Towards Closed-loop Maintenance Logistics for Offshore Wind Farms
Approaches for Strategic and Tactical Decision-making

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Towards Closed-loop Maintenance Logistics for Offshore Wind Farms:

Approaches for Strategic and Tactical Decision-making

Mingxin LI

Delft University of Technology

Towards Closed-loop Maintenance Logistics for Offshore Wind Farms:
Approaches for Strategic and Tactical Decision-making

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Mingxin LI
Master of Engineering in Naval Architecture and Ocean Engineering,
Harbin Engineering University, Harbin, China
geboren te Harbin, China.

Dit proefschrift is goedgekeurd door de promotoren:
Prof.dr. R.R. Negenborn
Dr. X. Jiang

Samenstelling promotiecommissie:

Rector Magnificus	voorzitter
Prof.dr. R.R. Negenborn	Technische Universiteit Delft, promotor
Dr. X. Jiang	Technische Universiteit Delft, copromotor

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Everyone has a cross to bear, so they must bear it by themselves.

Preface

As I write this preface and look back on my PhD, inside I have mixed and complicated feelings.

First of all, I would like to thank my supervisors. I am very grateful to my promoter, Prof. Rudy R. Negenborn for his guidance and care for me in the past four years, and thank you for accepting me as your PhD student. I was most impressed when I received the revisions to my manuscripts from you, which were full of handwriting that surprised and touched me. Your guidance has been one of the greatest help to me in completing my PhD. I am also grateful to my daily supervisor, Dr. Xiaoli Jiang, for all the help and guidance I have received. We first met in Madrid in 2018, where we discussed the possibility of doing a PhD at TU Delft, and I was lucky enough to end up in the Netherlands. In addition, I would like to thank Prof. Liping Sun, my Master's supervisor, for guiding me during my three years of Master's studies, for supporting my idea of studying abroad, and for helping me in applying for scholarships.

Also, thanks to the friends, colleagues and officemates I met in the Netherlands, I think I will never forget the aurora we watched in Iceland, the hotpot and fireworks at the New Year celebrations, the Tyrannosaurus rex fossils we saw in Leiden, and the beach in The Hague at sunset. These memories have made up four wonderful and impressive years of my life.

After that, I would like to thank my parents, Chaocan Li and Huimin Feng, you are the biggest motivation to support me to complete my PhD and make me full of hope for my future life.

Finally, I am grateful to myself that I have been able to get through my PhD successfully. These years have been filled with satisfaction, excitement, joy and anticipation, but also depression, pain, insomnia and anxiety. These four years have completely changed my personality, my perspective on life, and perhaps accelerated my perception of the world. Standing at a crossroads in life, no one could predict the butterfly effect of a choice on the future. In the long run, I feel that these four years will probably have a positive impact on my life, but I am not sure whether it is worth it, and perhaps time will tell me the final answer.

Hope is a good thing that gives you the motivation to move forward no matter what the situation. May each of us have it.

Mingxin Li,
Delft, New Year's Eve, January 1, 2023

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Chapter 1

Introduction

1.1 Background

The 2021 United Nations Climate Change Conference, more commonly referred to as COP26, has highlighted the significance and urgency of curbing greenhouse gases through enhancing climate action. The target is to reach net-zero CO_2 emissions around 2050 for the purpose of limiting global warming to 1.5 °C, which is resented by the Intergovernmental Panel on Climate Change (IPCC) [132]. In order to effectively address climate crisis, considerable effort has been devoted to developing renewable energy as a sustainable and reliable alternative to conventional energy sources, such as wind energy, solar energy, ocean energy, and hydrogen energy.

Over the past few decades, wind energy has grown into one of the most important renewable energy solutions, which can be attributed to both high wind resource availability and high technology maturity when compared to other renewable energy sources [53]. This indicates that wind power will play a more important role in achieving the target of net-zero CO_2 emissions. However, as pointed out in Fig. 1.1, only about 64% of the wind power required by 2030 will be reached to stay on-track for a netzero/1.5 °C goal according to the current growth rates, indicating more efforts and achievements are still required in wind energy development.

As illustrated in Fig. 1.2 and Fig. 1.3, *offshore* wind energy is experiencing a notable increase, especially in 2021. Although the total capacity of offshore wind energy is still less than onshore wind energy now, its potential is more considerable depending on several main decisive factors: the higher quality of the wind resource; more suitable free areas on the sea; less influence on environment [53, 96]. In Europe, the Netherlands is one of the leading countries in new installation of offshore wind energy. The Dutch Government has raised the offshore wind energy target to about 21 GW around 2030 [4]. By then, offshore wind energy is expected to supply 16% of the Netherlands' energy needs and 75% of our current electricity requirements.

With the significant increase in annual new installation and operational capacity of offshore wind power, maintaining the operation of offshore wind farms has become more vital and challenging. The global total installation has risen to 57 GW in 2021, which is 4 times larger than in 2016 and is 14 times larger than in 2011 [64]. Actually, according to the

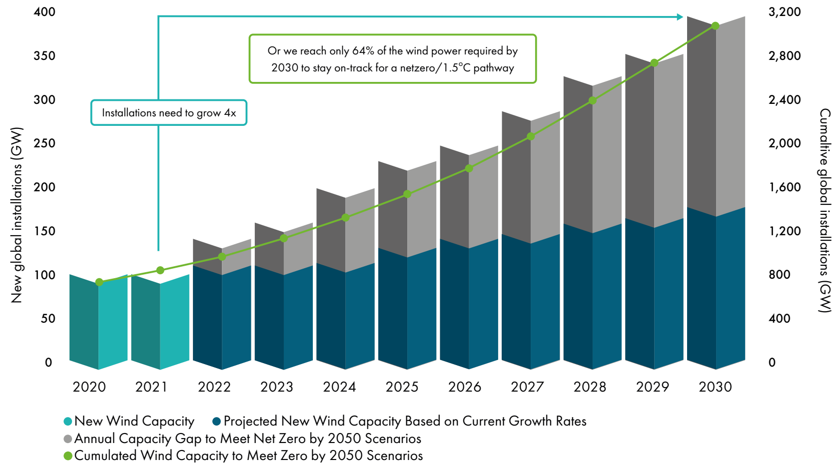

Figure 1.1: Lagging growth leads to wind energy shortfalls in this decade [64]

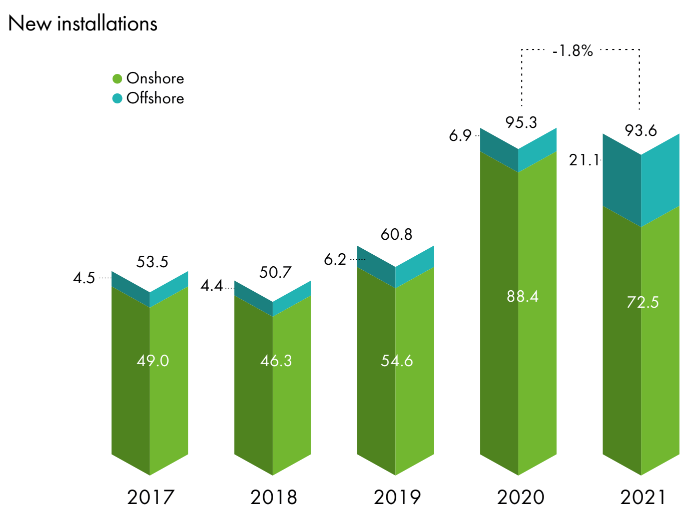

Figure 1.2: Global new installation [64]

existing studies [70], the economic performance of offshore wind energy does not overwhelm other electricity technologies and renewable energies. Many efforts are devoted to reducing the Levelized Cost of Energy (LCOE) of the offshore wind energy to enhance its competitiveness. In 2018, the average global LCOE for offshore wind energy is estimated at 140 $/MWh, and this value is expected to continually decrease to about 60 $/MWh in 2040 [73]. This achievement is attributed to increase in wind turbine and plant size [149], improvements in manufacturing, turbine design, and capacity factors, as well as reduction in Operation and Maintenance (O&M) costs [62]. O&M is a combination of general maintenance, management, training, budgeting, and business processes that are designed to

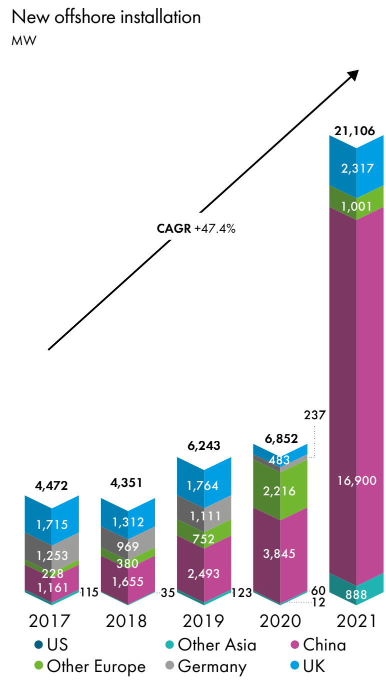

Figure 1.3: New installation of wind energy [64]

maintain wind turbines in a stable operating condition. Fig. 1.4 shows the breakdown of LCOE for a typical fixed-bottom offshore wind farm operating for 25 years. Among them, O&M constitutes the biggest share, about 30%.

1.2 Research motivation

In the near future, given that significant increase in installed capacity, more costs are expected to be invested in O&M for offshore wind farms than before. Maintenance activities and logistics organization account for the largest portion (43%) of O&M [49]. Given the high portion of O&M costs in LCOE, the improvement of O&M management, especially maintenance logistics, represents a significant cost reduction opportunity and will continue to be a primary factor in shaping the future development of the offshore wind sector.

The maintenance logistics for onshore and offshore wind farms have many differences. Once maintenance activities of an onshore wind farm are planned, the transportation means (e.g., trucks) transport the spare parts, technicians, tools, and hoisting equipment to the location. Since the base and wind farm are all on land, these activities will not be much disturbed. Compared to onshore wind farms, the marine environment where offshore wind farms are located presents many challenges for maintenance logistics. First, the failure rates of offshore wind turbines are obviously higher than onshore [20]. It can be explained that harsh environmental conditions, namely typhoon, sea ice, salt-fog and humidity, lead to more failure probability [99]. In addition, difficulties in the maintenance logistics mean

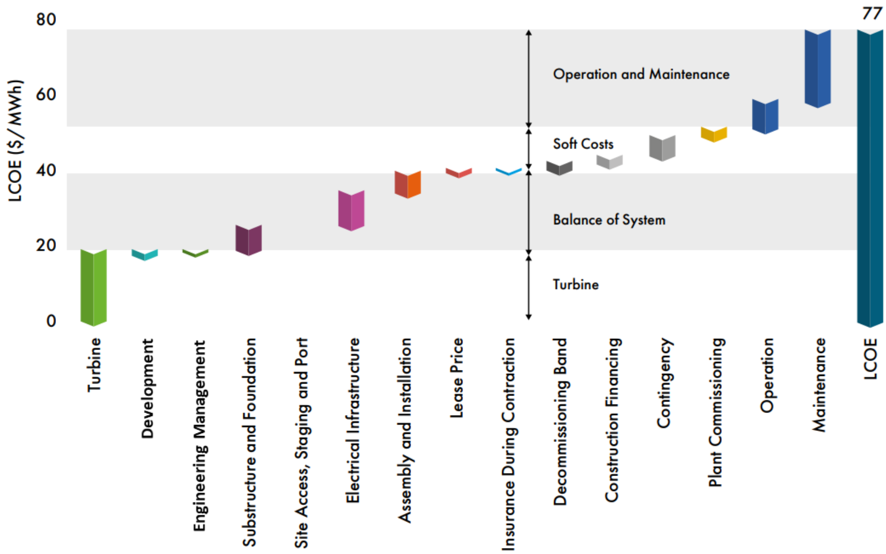

Figure 1.4: LCOE breakdown for typical fixed-bottom offshore wind farm [64]

that the turbines cannot be effectively maintained in good operating condition. Second, the distance to shore is expected to keep increasing and the water depth trends to be higher [41], which generate many difficulties in maintenance logistics. Transportation costs increase with distance, and disruptions due to weather are more obvious, especially for floating wind turbines which are installed in deep water. Once the water depth exceeds a certain limit, vessels, such as jack-up boats, cannot operate in this condition. The turbines need to be pulled to shore with the help of tugs. Therefore, the offshore maintenance logistics is more complicated and challenging, requiring more attention and research.

The research relevant to wind energy maintenance logistics has started around the end of last century. The discussion about offshore wind farm maintenance began with a proposal that no maintenance at all is necessary for offshore application or it may be beneficial to perform maintenance to replace failed turbines every 5 years. Obviously, these solutions have been proven as inadequate and unacceptable options due to the low availability of the offshore wind farm [163]. Since then, more efforts from industry and academia have been invested in this issue, driving maintenance logistics management to become more mature and diverse.

In the past, the major strategies employed in wind farms are corrective and time-based maintenance [177]. Maintenance actions are undertaken after a wind turbine failure, or at specified dates (one or two visits per year). Maintenance actions include replacement, major repair, and minor repair. Replacement is to replace the component with a new one and to recover the component state to ‘as good as new’. Major repair improves the component condition back to a state between ‘as good as new’ and ‘as bad as old’, done by replacement of major constituent parts that have deteriorated. Minor repair cannot change the component condition, so the component is still ‘as bad as old’. Following these maintenance strategies, a number of maintenance logistics models and tools, both commercial and scientific, have been developed to improve the cost efficiency of the offshore wind farm, for example, O&M Cost Estimator [128], and NRELS O&M cost model [125]. These tools and models are capable of supporting the development of solutions and strategies for asset managers and researchers [72].

In recent years, the maintenance logistics for offshore wind farms has gained benefits from novel technologies, such as condition monitoring systems, intelligent fault diagnosis and prognosis technologies, enabling decision-makers to know what is going on and what will happen in the wind farm. Maintenance plan based on the condition of the components is created in this context. Component failures can be predicted in advance and further perform as a decision basis to trigger maintenance actions.

Meanwhile, challenges come with the urgent need to better plan maintenance logistics. First, multiple dependencies existing among sub-systems in large systems are bringing about opportunities to improve the current maintenance logistics for large-scale offshore wind farms, which has already been agreed upon and seen as the future trend. A visual of wind turbine system is given in Fig. 1.5. While a maintenance action is performed on a single component, a maintenance opportunity arises where the other components in this system can be repaired preventively, instead of repairing each component separately, which is economic dependence. Capturing these maintenance opportunities reduces maintenance cost and effort. Thus, it is necessary to develop a maintenance strategy based on component condition and maintenance opportunities to reduce costs and efforts in O&M.

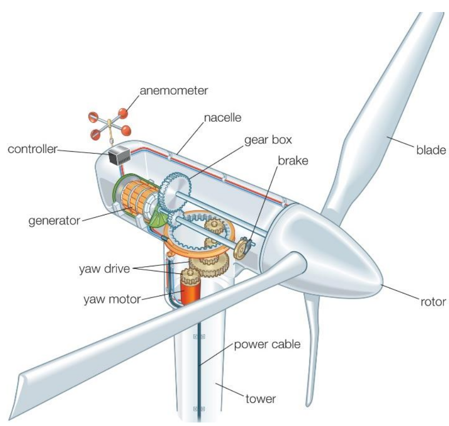

Figure 1.5: Visual of wind turbine systems [150]

Second, various types of uncertainties exist in maintenance model parameters when determining maintenance strategies, due to the inadequacy or inaccuracy in the available data. The existence of uncertainties is very likely to affect the maintenance performance and consequently leads to an unsuitable maintenance strategy. It is important to identify these uncertainties and quantify their influence. Furthermore, in order to mitigate the negative influence of uncertainty, it is necessary to develop a method that employs feedback information generated from the wind farm system to update uncertain model parameters, and adapt the maintenance strategy periodically based on updated parameters and the current monitored state of the wind farm. Such a process from information collection and use, to decision-making, action-taking, and back again to information, is achieved in this way and called a ‘closed-loop’ solution. This method also provides the feasibility and direction for the future realization of the entire closed-loop manner to improve the maintenance logistics, utilizing reliability, availability, maintainability (RAM) data to update maintenance decisions under uncertain decision-making environments.

Third, decision-making for maintenance logistics organization is classified into three echelons, i.e., strategic, tactical, and operational [143]. Among them, in terms of the level of planning, the strategic decisions are the highest, followed by tactical decisions and operational decisions. Moreover, compared to the operational decisions which are commonly day-to-day, the strategic and tactical decisions have longer lasting influence which may affect the maintenance logistics for offshore wind farms from several years to even over the entire farm’s lifetime. The decisions in different echelons are interrelated and interacting. It is necessary to develop maintenance resource management strategies aiming to support and interact with a determined maintenance strategy, in order to organize maintenance logistics more effectively and efficiently and bring about long-lasting economic benefits.

For example, a maintenance strategy is a crucial strategic decision. Maintenance resource organization, including spare parts inventory management and maintenance vessel fleet management, are significant decisions in the tactical echelon. The execution of maintenance decisions relies on the availability of spare parts, and the replenishment of spare parts depends on maintenance requirements. The maintenance and inventory management are therefore interrelated processes that can be integrated and then improved in a joint manner. Once necessary parts are prepared, different vessels are required to transform inventory and technicians and perform maintenance depending on the type of the maintenance action. As shown in Fig. 1.6, various types of vessels are used for maintenance implementation. A heavy lift vessel (HLV) is a vessel with a specific crane that has a large lifting capacity of up to thousands of tonnes to handle the huge offshore wind turbine parts. A service operation vessel (SOV) operates as a means of transport containing large quantities of spare parts and tools, but it also operates as in-field accommodations for workers and platform assist for wind turbine servicing and repair work. A crew transfer vessel (CTV) is used to transport wind farm technicians and other personnel out to sites on a daily basis. Different from onshore wind farms, the organization of vessel fleet consists a large portion of offshore wind farm maintenance logistics costs, so cost-effective management for maintenance vessels is very significant for offshore wind farms and directly affect the performance of maintenance strategies.

(a) (b) (c)

Figure 1.6: Different types of vessels: (a) HLVs [2], (b) SOVs [3], (c) CTVs [1]

In this context, it is worthy and significant to help decision-makers, such as offshore wind farm owners and operators or maintenance service providers, develop closed-loop maintenance logistics correlating strategic and tactical decisions to instruct the maintenance activities and logistics organization for offshore wind farms. This is the motivation of this thesis.

1.3 Research questions

The overall research question of this thesis is:

How to improve effectiveness of maintenance strategies and resource organization for offshore wind farms and move towards a closed-loop decision-making approach?

To answer the main question above, the following sub-questions should be addressed:

Q1: *What is the state-of-the-art of maintenance strategies and resource organization in offshore wind farms?*

Q2: *How to develop a maintenance strategy for an offshore wind farm that uses predicted component failure times and captures various types of maintenance opportunities?*

Q3: *How to quantify the influence of model parameter uncertainty on maintenance strategy and corresponding performance?*

Q4: *How to periodically update the maintenance strategy based on new data and wind farm state to realize a closed-loop decision-making manner?*

Q5: *How to manage the maintenance inventory to support the implementation of the maintenance actions?*

Q6: *How to make suitable leasing decisions to configure the maintenance vessel fleet?*

1.4 Contributions

The main contributions of this thesis are summarized as follows:

(1) Overview of the maintenance logistics for offshore wind energy, and summary of the current status and future trends in maintenance strategy optimization and maintenance resource organization. The existing research is summarized to provide more clear insights about this area for researchers. Moreover, research gaps are identified to achieve the improvement of the maintenance logistics for offshore wind farms [101].

(2) Proposal of a closed-loop approach to determine the optimal maintenance strategy for offshore wind farms. In the process, an open-loop maintenance strategy utilizing predicted component failures and maintenance opportunities is developed. Then the influence of unknown model parameters is quantified. Finally, the open-loop maintenance strategy gradually develops towards a closed-loop maintenance strategy mitigating the model parameter uncertainties [103–106, 108].

(3) Establishment of the planning models that organize the primary maintenance resources to support the implementation of the maintenance strategies. A multi-echelon and multi-unit inventory network is developed to manage the spare parts for maintenance. A vessel fleet configuration model is developed to assist a decision-maker to make leasing decisions on various types of vessels. Following the decision at the strategic level, the maintenance inventory and vessel fleet are controlled and adjusted correspondingly in order to minimize costs [107, 109–111].

1.5 Thesis approach and outline

The outline of this thesis is shown in Fig. 1.7.

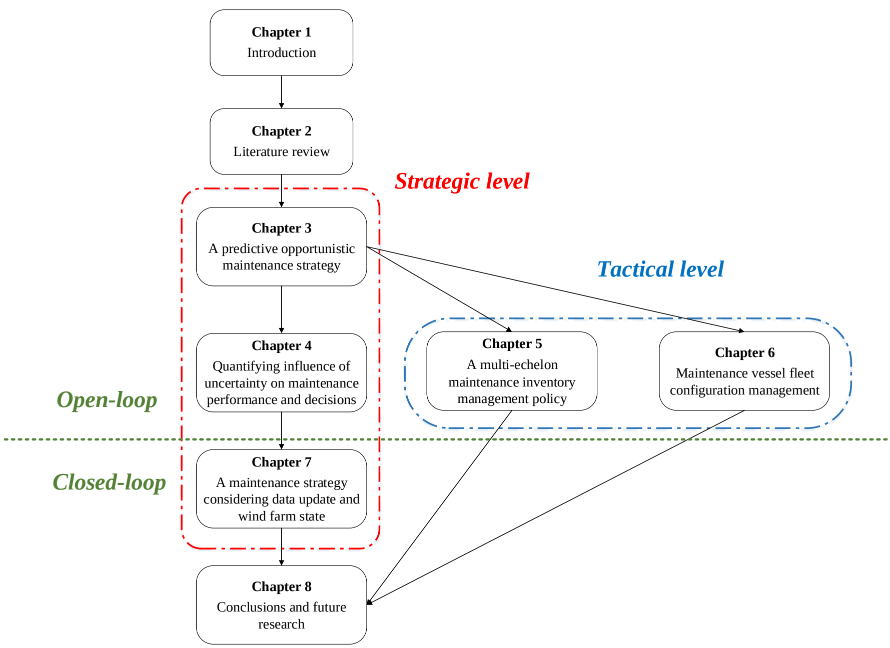

Figure 1.7: Thesis outline

In Chapter 2, a literature review on existing maintenance logistics for offshore wind energy is conducted. This chapter also identifies the main research gaps and answers research sub-question Q1.

In Chapter 3, we propose a new maintenance strategy for offshore wind farms considering component condition and economic dependence. The component is subject to degradation and environmental impact simultaneously. Three types of maintenance opportunities are introduced to determine the trigger of maintenance cycles. The proposed model is the basic model for the subsequent chapters. This chapter addresses research sub-question Q2.

In Chapter 4, an integrated decision-making framework is proposed that incorporates a maintenance model used to estimate maintenance performance, a probabilistic uncertainty modelling approach used to characterize different types of uncertainty and generate stochastic scenarios, and a multi-objective optimization method used to find optimal decisions. This framework is developed to quantify the influence of uncertainties on maintenance strategies and corresponding performance. This chapter addresses the research sub-question Q3.

In Chapter 5, a joint maintenance strategy and spare part inventory policy optimization model is proposed. The entire wind turbine is simplified to multiple critical components, and each component is composed of multiple critical subcomponents. The connection between maintenance model and inventory model is realized through referring to the Failure Mode and Effects Analysis (FMEA) and Fault Tree Analysis (FTA). This chapter addresses the research sub-question Q5.

In Chapter 6, a model is proposed to investigate the most cost-effective allocation of maintenance vessel fleet consisting of various types of vessels. A time-domain simulation method is used to simulate the scenarios where the maintenance activities are performed under the specific configuration of the maintenance vessel fleet. By varying the number of different vessels, the most economical configuration of the vessel fleet is determined. This chapter addresses the research sub-question Q6.

In Chapter 7, a closed-loop maintenance strategy is proposed, where model parameter uncertainties are gradually mitigated by using the collected reliability and maintainability data to update uncertain parameters. A rolling-horizon approach is applied to decompose the life-cycle maintenance optimization problem into a finite sequence of sub-optimization problems covering a multi-period of time. A series of sub-strategies is determined to minimize the revenue losses. This chapter addresses the research sub-question Q4.

Overall, Chapters 3, 4 and 7 focus on the maintenance strategy, that is the strategic decision. Chapters 5 and 6 address spare part inventory and vessel fleet configuration, which are tactical decisions. The models in Chapters 3-6 use an open-loop decision-making approach for maintenance strategy and resource organization. In Chapter 7, the decision-making approach for maintenance strategy is developed from open-loop to closed-loop based on Chapters 3 and 4.

In Chapter 8, the main findings of this thesis are concluded, and the directions for future research are provided.

Chapter 2

Literature Review

Chapter 1 emphasizes the necessity to improve the maintenance logistics for the offshore wind sector. In recent years, more researchers have started paying attention to this issue. In this chapter, we generally overview the classification scheme of offshore wind energy maintenance logistics, then give a detailed review on state-of-the-art in maintenance strategy optimization and maintenance resource organization. Significant research gaps are identified and summarized in this process to motivate the following research. With that, this chapter addresses the first question (**Q1**):"What is the state-of-the-art of maintenance strategies and resource organization in offshore wind farms?"

This chapter is organized as follows. Section 2.1 briefly overviews the maintenance logistics for offshore wind energy from three levels: strategic, tactical, and operational. Section 2.2 summarizes the current status and future trends in maintenance strategy optimization. It includes the types of maintenance strategies, uncertainty in the maintenance models, and decision-making approaches. Section 2.3 surveys existing studies focusing on maintenance resource organization including spare parts inventory and vessel fleet management. Section 2.4 concludes this chapter and highlights the research gaps.

Parts of this chapter have been published in [101][1].

2.1 Maintenance logistics for offshore wind farms

2.1.1 Classification framework

In [143], a classical framework to identify the various issues and challenges related to maintenance logistics of offshore wind farms in different decision-making levels is presented Hereby, we select key issues that have gained much attention from this framework and use a similar structure to overview this field in more detail (Fig. 2.1). Furthermore, we supplement the description of the synergy among different decision-making levels and recent research progress.

[1] M. Li, X. Jiang, H. Polinder, and R. R. Negenborn. A review of maintenance strategy optimization for wind energy. In *Proceedings of the 4th International Conference on Renewable Energies Offshore*, pages 469–480, Lisbon, Portugal, 2020.

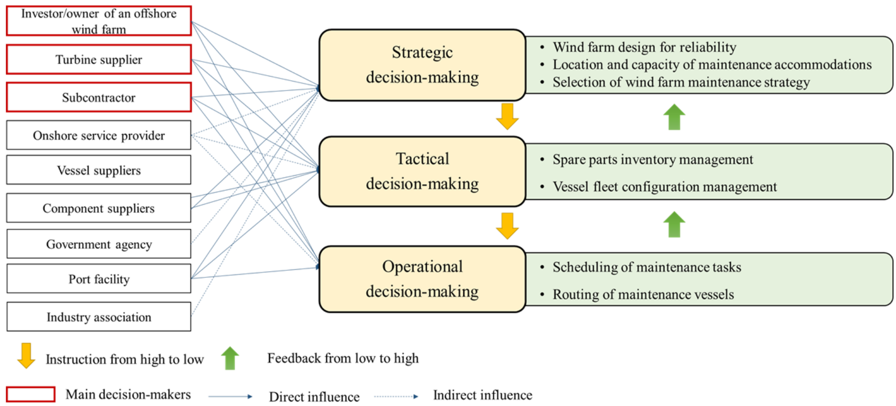

Figure 2.1: Decision-making levels in maintenance logistics for offshore wind energy systems and related stakeholders

From the perspective of the planning horizon, three decision-making levels are considered. Strategic (long-term) decisions have a long-lasting effect (5-20 years) on wind farms. For example, the influence of wind farm design lasts over the lifetime. Compared to the strategic decisions, the influence of tactical (medium-term) decisions is shorter, less than five years. At the operational (short-term) level, the decisions are updated on a daily basis. In terms of decision-making sequence, strategic decisions deal with the big picture of maintenance logistics, laying the groundwork for the entire process. Following strategic decisions, tactical decisions involve the establishment of key initiatives to achieve the overall strategy. Finally, operational decisions determine how activities are actually performed.

Multiple stakeholders are involved in the decision-making process, as illustrated in Fig. 2.1. Wind farm owners, turbine suppliers, and service providers are the principal decision-makers of the maintenance logistics activities. An Original Equipment Manufacturer (OEM) or turbine supplier usually provides a maintenance service contract lasting from 2 to 5 years. In this period, the OEM is responsible to handle any system failures caused by design, manufacturing, and quality assurance problems as well as to provide technicians over a specified period of time [77]. When the service contract has expired, the maintenance expenditures are borne completely by the wind farm owners. In this case, the wind farm owners can choose to employ an independent service provider to perform the maintenance tasks [52]. The contracts usually set a specific target for the wind turbines availability. The wind farm owner pays the service provider a one-time fee, and in return, the service provider must service all failures over the duration of the contract with no additional cost, or the service provider charges a fixed amount per maintenance activity.

In addition, the organization of life-cycle maintenance logistics is dependent on the efforts from various sectors. Different stakeholders, such as vessel suppliers and component suppliers, are directly involved in the decision-making. Other stakeholders like onshore service providers, government agencies, industry association, are also be involved, but may not directly influence the decision-making.

2.1.2 Strategic decisions

Strategic decisions mainly include determination of wind farm design, maintenance strategies, and location and capacity of maintenance accommodation. Wind farm design involves the design of the layout of the wind farm, cable routing, location of installations with respect to wind and wave direction, geographical location, etc [58]. Designing a large offshore wind farm is a very complicated task. In the development phase, a large amount of time is spent on designing the wind farm. In this process, significant factors including wind energy resource estimation and wake effect losses are considered for a more reliable and robust design to reduce production losses during operation [90] and service support cost during maintenance.

In terms of maintenance logistics, the location of the wind farm affects the accessibility of the maintenance vessels. Obviously, an offshore wind farm located in deep water in a remote area far from the shore brings an inevitable increment in maintenance logistics costs, which has been explained before. The layout of the wind farm, on the one hand, affects the routing and scheduling of maintenance vessels [168]. On the other hand, wind energy production influenced by the wind farm layout is an important factor affecting determination of maintenance strategies [151].

A maintenance strategy is a kind of decision rule or a set of criteria that determines the appropriate maintenance actions that should be performed on wind turbines in order to keep the wind farm operating properly [59]. Maintenance strategies are generally categorized into two types: reactive maintenance and proactive maintenance [177]. Reactive maintenance indicates the situation in which the maintenance action is performed after a component failure occurs and the located wind turbine stops working. On the contrary, proactive maintenance refers to the situation in which the maintenance actions are carried out before the failure occurrence to control the rate of degradation and prevent severe failure events.

Reactive maintenance is the simplest strategy to implement, but this strategy can only be practical and suitable for onshore wind farms or offshore wind farms that are located close to shore at shallow water [143]. The reason is that transportation vehicles and vessels are easier to access the sites to perform maintenance and recover the wind turbine operation as soon as possible. However, future offshore wind farms tend to be installed in far sea and deep water [41]. Under a reactive maintenance strategy, the turbines fail more often and require more frequent replacement of parts. Once the turbine is far from the coast and in deep water, the operation of vessels such as HLVs needed to replace parts will be in a more severe environment, making it more difficult for O&M. In this case, offshore wind turbine maintenance has become a much more challenging task, so it is preferred to carry out repair in advance to prevent failure instead of waiting for failure occurrence passively.

Integrating condition monitoring technology into maintenance strategies and utilizing data to make decisions has been recognized as a feasible and promising solution to maintain effective and efficient wind farm operations [157]. These technologies and methods are capable to support the decision-making for carrying out maintenance at a proper timing before failure. A more detailed literature review is given in Section 2.2.

Most of the wind turbine failures are addressed with an appropriate maintenance action on-site. For the cases in which the wind turbine failures cannot be handled immediately, the failed components/subcomponents are delivered to a designated maintenance accommodation. On-site and off-site repair facilities may both be required to repair failed components. The location and capacity sizing of maintenance accommodations are two critical factors affecting the implementation of maintenance services. When determining the optimal location and capacity of accommodations, the elements that should be considered include coverage of each maintenance accommodation, the distance between the offshore wind farm and corresponding transportation time, set-up and operating costs, wind farm reliability, etc [16, 36].

2.1.3 Tactical decisions

Tactical decisions mainly concern decisions controlling the organization of maintenance resources, namely spare parts inventory and vessel fleet management. A wind turbine is composed of hundreds of different components and subsystems, including rotor hubs, blades, bearings, shafts, gearboxes, and generators [11]. A spare part is an unit of inventory that is used to replace a failed or aged component/subcomponent. As one of the main cost drivers for O&M of offshore wind farms, keeping an appropriate stock level of spare parts is important.

The stock level of spare parts in inventory is determined by the maintenance requirements for each spare part. Meanwhile, implementing maintenance is dependent on the availability of spare parts in order to reduce failure downtime and costs. Therefore, maintenance and inventory management are interrelated and should be considered simultaneously [179].

Past research usually considered maintenance and inventory separately. The few existing papers assume that the inventory network follows a single-unit and single-echelon pattern [178, 189], which is not adequate enough to model the complicated spare parts inventory management. Joint optimization of maintenance strategy and a multi-unit and multi-echelon inventory is deemed as a significant issue gaining attention. More research regarding spare parts inventory management is summarized in Section 2.3.1.

In addition to the available spare parts, the maintenance tasks for offshore wind turbines are conducted employing different types of vessels, such as HLVs, field support vessels (FSVs), CTVs, and helicopters [44]. This is different from onshore wind farm maintenance. The maintenance implementer usually owns a mixed fleet of vessels to carry out maintenance activities. The vessels transfer the necessary heavy spare parts, maintenance crew, and maintenance tools from ports to on-site locations.

Unavailable transportation means or lack of technicians lead to a delay in maintenance activities and subsequently, long downtimes of the wind farm and excessive rental costs. Maintaining an excessive vessel fleet results in significant original investment and chartering costs. A sound configuration of a mixed maintenance vessel fleet involves finding a trade-off between excessive and insufficient vessels, so as to complete the required maintenance tasks in a timely manner [27]. The purchase of vessels, especially HLVs, is too expensive for the maintenance implementer to afford. When facing a large number of maintenance tasks that exceed the current work capacity of the fleet, new vessels should be supplemented into the vessel fleet. Compared to purchasing vessels, it may be more cost-effective to lease vessels from the spot market or even share the available vessels [162]. More research relevant to vessel fleet management is summarized in Section 2.3.2.

2.1.4 Operational decisions

Maintenance scheduling involves determining a detailed schedule of maintenance tasks: which maintenance team and vessel is dispatched to repair which component/turbine at what time [26]? The scheduling should consider the metocean conditions and availability of various maintenance resources (vessels, spare parts, equipment, and technicians) [74]. The routing of the vessels involves determining the route that a particular vessel will take in an offshore wind farm to dispatch and pick up technicians on the day [140]. The scheduling and routing of the service vessels are strongly correlated, so these two problems are commonly considered simultaneously.

A scheduling and routing model typically considers the following factors: Metocean conditions; size, type, and housing of the fleet; nature and location of maintenance demands; varying specifications of vehicle types; route time; costs (routing costs, fixed costs, penalty costs, downtime costs, technician costs, equipment costs), etc [130]. The optimization objectives can be minimizing downtime, minimizing total routing costs, minimizing environmental impact, etc.

2.1.5 Types of models, optimization objectives, and solution techniques

Regardless of the level of the problem solved, the process is to build a model and use solution techniques to obtain solutions in order to satisfy optimization criterion. The possible methods which are used to model maintenance logistics problems are simulation models [42], Markov models [100], analytical models [184], mathematical programming methods [186], Bayesian networks [66], etc. Different methods have strengths and weaknesses. For example, the simulation method has the potential to tackle the challenging optimization problems involving nonlinearities, combinatorial relationships, and uncertainties [8], especially when wind energy maintenance logistics problems are too complicated to be given tractable mathematical formulations. In addition, it allows experimenting and better understanding of systems with increasing complexity [7]. For another example, in a Markov model, the system is separated into initial perfect state, degradation states and failure states. Compared to conventional modelling methods only considering binary states, working state and failure state, Markov methods is able to illustrate the complicated degeneration process more effectively. More details about types of models can be found in [142, 145].

Based on the developed models, the solving methods are adopted to find optimal solutions to minimize/maximize the optimization objective. The optimization objectives are minimum costs, minimum production loss, maximum availability/reliability, combinations of several objectives, etc. More details can be found in [145]. When solving the problem with a small solution space, exact solutions can be used [137]. If the problem is developed using analytical models, the solution to the equations describing any changes in the system can be expressed as a mathematical analytic function which can assist solving the problem [145]. If the optimization problem has a huge solution space due to a large number of solutions concerning the variations in decision variables or the problem is too complicated to obtain mathematical analytic functions, it is difficult and time-consuming to find exact solutions. Heuristic algorithms are problem-solving methods designed to find approximate solutions to theses complex problems when facing the situations where exact solutions are too time-consuming or too difficult to obtain. Heuristic algorithms aim to find good solutions in a reasonable amount of time, using various approaches to explore the search space and guide the search towards promising areas, while avoiding unpromising areas. Therefore, in order to find the solutions efficiently, the application of heuristic algorithms is necessary [104]. The common heuristic algorithms are Genetic Algorithm (GA) [25], Simulated Annealing (SA) [135], Particle Swarm Optimization (PSO) methods [86], etc. These methods are widely used in the maintenance logistics related problems.

2.1.6 Summary

Section 2.1 overviews the maintenance logistics for offshore wind farms, summarizes the past studies into a multi-level scheme as shown in Fig. 2.1, and gives a brief description of each issue. The maintenance logistics are categorized into strategic, tactical, and operational levels. Although the decisions at different levels determine maintenance logistics organization at different time horizons, the decisions are not independent. In contrast, some decisions are interrelated. For instance, the implementation of the maintenance strategy (strategic) is affected by the available spare parts resource (tactical), and the spare parts inventory management relies on the maintenance requirement of the determined maintenance strategy. The configuration of a vessel fleet (tactical) is subject to the workload of maintenance tasks determined by maintenance strategies. The decisions for scheduling and routing (operational) is simultaneously subject to configuration of the vessel fleet and the workload determined by maintenance strategies. In this context, interaction exists and influences decisions at different decision-making levels. Lower-level decisions are made on the basis of upper-level decisions, and upper-level decision-making should consider the influence of lower-level decisions. The transfer of decisions and the consequent improvement of their results becomes an important issue.

The decisions at the strategic level determine the maintenance logistics over the lifetime, indicating that improvements to strategic decisions may lead to more long-lasting effect on offshore wind farm O&M, followed by tactical decisions. Operational decisions are made on a daily or weekly basis, having the least scope of influence over the life cycle of offshore wind farms. Among the strategic decisions, the maintenance strategy is the most significant issue which has gained much attention. Moreover, the implementation of the maintenance strategy is directly related to the maintenance resource organization at the tactical level. Therefore, in this thesis, we study the maintenance strategy at the strategic decision level and maintenance spare parts and fleet management at the tactical decision level. To address these issues, we conduct a literature review in the following sections to identify research gaps.

2.2 Maintenance strategies

2.2.1 Categories of maintenance strategies

As stated in Section 2.1.2, maintenance strategies are typically categorized into reactive maintenance and proactive maintenance. Subcategories of maintenance strategies are provided in Fig. 2.2. The reactive maintenance strategy, which is also called “corrective maintenance”, refers to recovering the wind turbine system after failure. Compared with other strategies, the implementation of reactive maintenance is the easiest, and unnecessary repairs are controlled to the lowest. However, in this case, downtime will be the highest, which will bring a noticeable negative influence on wind farm operations.

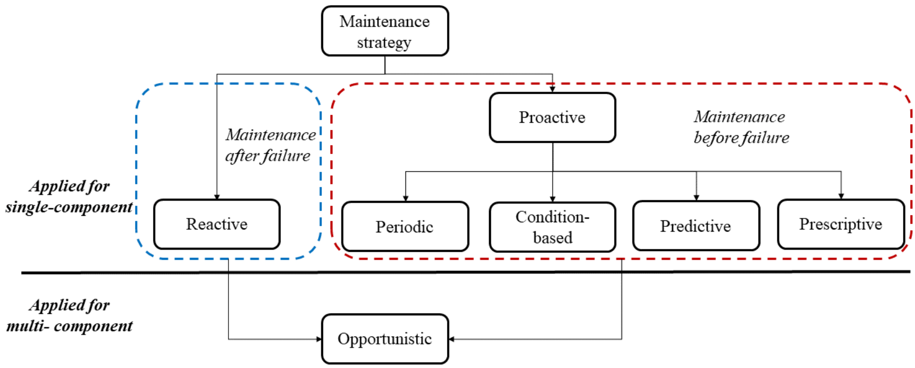

Figure 2.2: Subcategories of maintenance strategies

Proactive maintenance involves conducting maintenance in advance, which is further classified into periodic maintenance, condition-based maintenance, predictive maintenance, and prescriptive maintenance. Periodic maintenance is based on maintenance intervals recommended by the OEM. Wind turbines are repaired at regular time intervals (time-based), or after a fixed period of time depending on the age of a component (age-based), or according to the amount of electricity produced (use-based). With the development of condition monitoring technology over the last decades, the data collected by sensors offers the possibility of a maintenance approach using the condition of components as a basis for decision-making.

Although condition-based maintenance, predictive maintenance, and prescriptive maintenance all rely on component condition to make decisions, differences exist between these strategies [60]. Condition-based maintenance is performed when sensors alert you that the component condition has changed after something goes wrong, but before the wind turbine stops working. In predictive maintenance, operational data is analyzed to predict when failure will occur and maintenance will be needed. Prescriptive maintenance evolved from predictive maintenance, moving a step forward to make specialized O&M recommendations to reduce operational risks. In the field of wind energy, these three concepts are not distinguished very clearly in the past literature [145].

A novel maintenance strategy, opportunistic maintenance, has started to gain attention in recent years. A large-scale offshore wind farm is made up of a number of turbines. Besides, as a type of complicated electromechanical system, an offshore wind turbine system is composed of hundreds of components and subsystems [127]. The economic dependence among turbines and components applies when combined maintenance leads to a different cost than repairing individually [75]. It plays a positive role when travelling to the location where maintenance activities have to be executed is costly [84]. Simultaneously performing several maintenance activities is more cost-effective than repairing only individual turbines. Opportunistic maintenance is a type of strategy taking advantage of this economic dependence to reduce maintenance costs.

There are no norms, standards or consensually accepted meanings of 'opportunistic maintenance' [158]. It is systematic research to determine at what time to perform maintenance activities for what reason, and what components or turbines can be repaired by making use of the opportunities. From the perspective of triggering maintenance decisions, opportunistic maintenance is considered as a hybrid maintenance strategy mixing reactive and proactive maintenance [130], because the maintenance cycles are triggered more flexibly based on component condition rather than only after failures or at regular intervals. Maintenance cycles refer to the sequence of events that make up maintenance tasks, from the definition to the completion. Since the trigger of the maintenance opportunities is on the basis of component state, the opportunistic maintenance strategy is usually developed considering condition monitoring technology and predictive analytics.

2.2.2 Opportunistic maintenance

In 2009, [15] applied the opportunistic maintenance strategy to offshore wind energy. Maintenance opportunities appear when corrective maintenance has to be performed on a wind turbine or wind speed is low. The case study shows that taking these opportunities into account can effectively reduce maintenance costs. Due to the considerable potential, the number of literature focusing on opportunistic maintenance of wind energy sector has been increasing. We make a comparative analysis after reviewing the following representative papers, as shown in the Table 2.1. In the table, we mainly conclude the studies according to the following indicators: (1) scope modelling, ranging from a single wind turbine to a wind farm; (2) failure modelling, which include degradation and environmental impact; (3) maintenance modelling, including maintenance thresholds, preventive dispatch for maintenance; (4) accounting for uncertainties in model parameters; and (5) the decision-making approach used.

In [42], an opportunistic maintenance model with two-level repair actions for wind turbine systems is proposed. The failures of the components are caused by the degradation. Perfect and imperfect maintenance actions are performed depending on component states. Then, [43] introduced different maintenance thresholds in their model to distinguish the failed turbines and working turbines. In [167], the model also considered different maintenance thresholds under different maintenance opportunities to distinguish the failed/operating wind turbines.

Instead of the two-level maintenance threshold, [137] proposes the concept of multi-level maintenance in their work. Degradation results in the component failure. The interval between maximum and minimum maintenance thresholds is divided into multiple groups. After discussing the relationship between maintenance costs and the number of maintenance levels, the optimal number of level is selected to minimize the total costs. Similarly, the failures of the components are also assumed to be caused by degradation processes in [6, 12, 51, 117, 188].

In [177], the hybrid hazard rate method is introduced into the opportunistic maintenance model. The method describes the degradation processes causing failures, where the increase of operation time will accelerate the degradation and weaken the maintenance improvement.

In [102], a nonhomogeneous continuous-time Markov process is used to represent the multi-state model of offshore wind turbine subsystems. The subsystems transfer from one state to another state as the operation time increases. The most cost-effective combination

Table 2.1: Previous research of wind energy opportunistic maintenance

Year	Literature	Scope modeling		Failure modelling		Number of maintenance thresholds				Trigger of preventive dispatch		Model parameter uncertainty	Decision-making approach	
		Turbine	Farm	Degradation	Environmental impact	0	1	2	≥3	Single component	Multiple component		Open-loop	Closed-loop
2009	[15]		✓			✓							✓	
2011	[42]		✓	✓				✓					✓	
2012	[43]		✓	✓					✓				✓	
2015	[147]	✓		✓	✓		✓						✓	
2016	[137]		✓	✓					✓				✓	
2016	[6]		✓	✓				✓		✓			✓	
2017	[177]	✓		✓				✓		✓			✓	
2018	[117]	✓		✓				✓		✓			✓	
2019	[188]		✓	✓				✓		✓			✓	
2020	[175]		✓	✓				✓		✓			✓	
2020	[102]	✓		✓			✓						✓	
2021	[167]	✓		✓					✓	✓			✓	
2021	[171]		✓	✓		✓							✓	
2022	[114]	✓		✓				✓					✓	
2023	This thesis		✓	✓	✓				✓		✓	✓	✓	✓

of qualified components is selected to reduce the maintenance costs when compared with individual maintenance.

As stated in Secion 2.2.1, the opportunistic maintenance strategy is usually developed considering condition monitoring technology and predictive analytics. Studies [117, 171, 188] use Artificial Neural Networks (ANNs) and real-time prognostic updating to make the decisions to determine which component is repaired in the maintenance opportunities.

In [175], the model considered the prospective opportunity caused by low wind speed period besides component failure. In [114], the maintenance model considered stochastic, structural and economic dependence simultaneously to plan the maintenance for wind turbines.

Degradation and environmental impact

It is remarkable that in the models in Table 2.1, most of the wind turbines are assumed to only experience degradation. Only [147] considers degradation and environmental impact simultaneously when developing opportunistic maintenance for wind energy. An opportunistic condition-based maintenance policy is proposed for rotor-blade systems. The multi-blade systems are subjected to stress corrosion cracking and environmental impact. In order to avoid expensive failure replacement, a maintenance team is dispatched to repair critical blades before failure occurs, and other blades are preventively repaired as well.

The maintenance model considering random environmental shocks has been increasingly considered in the field of reliability and engineering in the past years. Many industrial systems operate in an environment where various types of impact (e.g., electrical, thermal, seismic shocks) arrive randomly and suffer from damage of these shocks which trigger state transitions of the system. The impact may result in the abrupt increase of degradation [134], the increasing degradation rate [129], or even the sudden incidents. The intensity or the magnitude of impact may also be dependent on the degradation process of the system [56, 57].

In a harsh marine environment, the wind turbine system deteriorates over time due to wear, erosion, fatigue, corrosion and so on. This normal degradation process applies when the operation condition is ideal. However, the offshore structures suffer from impact resulting from harsh marine environment (e.g., sea ice, atmospheric icing, typhoons, sea wave, lightning strike, sudden change in wind speed or direction). The harsher the environment is, the impact will arrive more frequently and the influence will be more serious. When the turbine works in practical environments, it is not only subject to degradation processes, but also the environmental impact throughout the whole service life. The presence of this environmental impact on the critical components, especially rotor blades, has an effect on the performance of O&M and the overall economics of wind energy systems [14, 124]. With future wind farm addresses spread across different regions of the world, environmental conditions are one of the most important factors affecting the reliability of turbines in different regions. If environmental impact is taken into account, a foundation can be laid for designing specific maintenance strategies for future wind farms in specific regions. Therefore, it is essential to consider to consider degradation and environmental impact when modelling wind turbine failure.

Maintenance opportunities

The models in [42, 43, 102, 137] in Table 2.1 assume that the occurrence of a component degradation failure can be considered as a type of maintenance opportunity (failure-based opportunity). This failure-based maintenance opportunity can trigger a maintenance cycle, where the maintenance teams are dispatched to simultaneously replace the failed components and perform preventive maintenance on the components needing repair.

As we know, failure should be avoided as much as possible given the fact that the cost of failure replacement is very expensive. Therefore, it is not necessary to start a maintenance cycle only waiting for the occurrence of the turbine failure. In [117, 177, 188], a preventive maintenance threshold is set to determine if a turbine component is in a defective or almost unacceptable state. In addition to the maintenance cycle triggered by failure, a maintenance cycle can also be triggered if any turbine component in the farm exceeds this preventive maintenance threshold. Actually, this preventive maintenance decision can be regarded as the preventive dispatch of maintenance teams. In [6, 12, 51], the preventive dispatch of maintenance teams is clearly addressed, i.e., not waiting until the failure occurs, a maintenance opportunity can also emerge preventively when a component satisfies the maintenance requirement (reach the threshold). Generally, the maintenance opportunity will appear in these two occasions: a failure occurs; a component reaches the preventive maintenance threshold.

However, although the preventive dispatch of maintenance teams has been introduced in the models, this action may not be as cost-effective as we expect. The maintenance team has to move to the wind site if even a single component reaches the predetermined threshold. This may be feasible when the farm is located onshore. Considering the effort and cost to dispatch the vessels and staff to the remote location away from the shore, the execution of preventive dispatch triggered by a single component is not economic enough for offshore wind farms. These decisions may induce over-maintenance. Furthermore, in these existing opportunistic maintenance models for wind energy, the consequences of environmental impact have not been considered, as discussed in Section 2.2.2. The critical impact may also result in the incident that the suffering turbine stops operating and requires maintenance, which can also provide the opportunity to repair the other turbines in the farm.

2.2.3 Uncertainty in determining maintenance strategies

The organization of maintenance logistics for offshore wind farms is a problem involving various types of uncertainty because of the diversity of assets and their corresponding damage mechanisms and failure modes, weather-dependent transport conditions, unpredictable spare parts demand, insufficient space or poor accessibility for maintenance and repair, limited availability of resources in terms of equipment and skilled manpower, etc [145]. The types of influential uncertainties considered at different decision-making levels in maintenance logistics are also different. For instance, statistical uncertainty of component reliability estimations [138] is an important type of uncertainty at the strategic level. Insufficient maintenance sources to support maintenance [162] and inaccessibility for maintenance affected by weather variety [141] are mainly considered in tactical and operational levels respectively. When determining a maintenance strategy, it is important to develop maintenance models capable of considering and incorporating uncertainties.

Only limited papers have paid attention to maintenance models along with uncertainty. In [31], it is mentioned that the lack of reliability data and inaccuracy in maintenance cost estimation is a common issue. A probabilistic sample method is used to derive failure data from reference reliability databases. Fuzzy numbers and a fuzzy inference system are used to model the uncertain repair related costs. The impact of uncertainty on performance indicators of an offshore wind turbine (availability, energy production, LCOE) is estimated. In [138], the uncertainty in collecting reliability data for offshore wind turbine components is investigated. The uncertain component failure distributions are input to an O&M simulation tool. Results for a specific case show that wind farm availability may vary in the range up to 20%. The uncertainty in component health prediction is mentioned in the papers [117, 160], but these studies cannot reflect the impact of varying degrees of this type of uncertainty and how maintenance decisions are altered because of this uncertainty.

It is noted that the above papers only study the impact of one or two types of uncertainty on the maintenance performance. In general, the maintenance models cover aspects including the modelling of the deterioration of the system, the description of the available information about the system state, the possible actions and consequences [148]. Various types of uncertainty are sequentially associated with these aspects in the model, including statistical uncertainty of component reliability [33], uncertain performance of component lifetime prediction [45], and ambiguous estimation of maintenance consequences [87, 115]. All these types of uncertainty deserve our attention to quantify their influence and compare the significance. However, this research still lacks in the past studies. Moreover, in the papers studying uncertainty in wind energy maintenance, it is still unknown that how the design of a maintenance strategy is affected and then adjusted due to uncertainty, which is an important research gap requiring investigation.

2.2.4 Maintenance strategy update

Section 2.2.3 has pointed out that designing a sound maintenance strategy covering the long lifespan of a wind farm is a complicated problem involving a high degree of uncertainty. The uncertainty in model parameters may lead to a maintenance strategy that is not suitable for target wind farms. Up to now, the limited number of papers [31, 117, 138, 160] studying uncertainty in wind energy maintenance strategies still adopt a passive manner. The passive manner means the influence of uncertainty is quantified, but no solution is proposed to gradually mitigate the negative influence of uncertainty. In comparison, a proactive manner is to consider the feasibility of gradually mitigating or eliminating uncertainty.

When determining a maintenance strategy, it is helpful to distinguish between open-loop, reactive, and closed-loop strategies [61, 133]. An open-loop strategy involves finding the optimal maintenance strategy at the beginning of operation and to implement it over the entire lifetime. This open-loop strategy is the most widely used in the earlier literature [104, 147, 177]. Compared to an open-loop strategy that is applied over the entire optimization horizon blindly, a reactive strategy is determined step by step. The current strategy is formulated on the basis of the current state, and it is implemented until the next step in which a new strategy is determined again. The reactive maintenance strategy has the capacity of making decisions based on the present situation. This method has been used in some earlier research [23, 116, 122, 176], but these studies usually focus on a component-level state rather than a farm-level state. The reactive strategies are incapable to handle the uncertainty in the model parameters as the feedback generated from wind farm systems, including new RAM data and monitored wind farm state, is not utilized to update strategies.

In this context, in order to improve the performance of maintenance strategies, it is necessary to develop a closed-loop strategy, referring to a process from information collection and use, to decision-making, action taking, and back again to information collection. The closed-loop strategy is not only able to respond to the feedback information generated from the wind farm when compared to open-loop and reactive strategies, but also to observe the dynamic wind farm state, that is similar to reactive strategies. This method has been commonly used in other areas, such as control engineering [24, 185], energy management [83], and transportation planning [112], but it has rarely been proposed for use in wind energy maintenance.

2.2.5 Research gaps

Because the decision determining whether a component should be repaired is made based on the component state, opportunistic maintenance is usually combined with condition monitoring technology to form a predictive opportunistic maintenance strategy, namely determining maintenance actions on the component based on its predicted failure time. According to the literature review, it can be concluded that there are several research gaps to be filled in maintenance strategy optimization.

First, the earlier models consider the situation in which the wind turbines only experience degradation. However, offshore wind turbines are subject to the impact resulting from the marine environment, indicating the turbines suffer from degradation processes and random environmental impact simultaneously. In addition, maintenance opportunities in the earlier opportunistic maintenance strategy are commonly triggered by failure events of a wind turbine or the scenario in which a wind turbine component is so old that it should be preventively replaced. This action may not be as cost-effective as we expect. The maintenance team has to move to the wind site even if a single component reaches the predetermined threshold. These maintenance decisions may induce over frequent maintenance activities. Therefore, it is necessary to develop a predictive opportunistic maintenance strategy considering multiple-component age-based preventive dispatch and environmental impact.

Second, although the maintenance decision-making is confronted with various types of uncertainty in the model, few papers paid attention to this issue before. The limited research concentrates on the influence of uncertainty on maintenance performance, but ignores how the optimal solutions are affected by uncertainty. Considering the determined maintenance strategy may become sub-optimal due to uncertainty, it is important to study the influence of uncertainty on maintenance strategies in an uncertain decision-making environment besides quantifying the influence on maintenance performance.

Third, compared to the passive manner of quantifying the influence of uncertainty, a proactive manner of mitigating uncertainty could be a more effective solution to reduce its negative influence. The maintenance strategy should be further improved to realize a closed-loop decision-making approach. The new RAM data is integrated into the decision-making process to assist in updating the maintenance strategy. The determination of maintenance strategy also considers the periodic wind farm states. Such a closed-loop strategy aims to reveal the economic benefit of data on offshore wind farm O&M.

2.3 Maintenance resource organization

2.3.1 Spare parts inventory management

As stated in Section 2.1.3, the maintenance strategy and spare parts inventory are interconnected, and are better to be considered simultaneously when optimizing an OEM or service provider's operations. However, earlier studies [160, 165] usually study them separately. In the maintenance model, a strong assumption is made that the required spare parts are always available while a maintenance decision is made [137]. This assumption may be applicable to a realistic situation where the system components are relatively homogeneous and the stock of spare parts on site is very sufficient.

Obviously, this situation does not apply to the wind energy industry. The wind turbine components are diverse, e.g., blades, gearboxes, generators[127]. Each of these components has its own subcomponents. All components and subcomponents are different in size, weight and shape. This brings difficulty in spare parts management. In addition, the holding costs of large wind turbine components are costly, which indicates that the amount of spare parts should not be kept at a very high level to avoid unnecessary holding costs [85]. Moreover, the components of small size can be stored in a warehouse close to the wind farm, but the larger components are likely to be stored further away from the target wind farm [173]. The long distances involved in transporting the components can lead to further maintenance downtime.

Spare parts inventory is an important and challenging issue in the area of the manufacturing industry. With the operational capacity of wind energy, the spare parts supply for wind farms becomes more significant and gains more interest. It is necessary to integrate the spare parts inventory management model and maintenance strategy model to formulate a more holistic plan.

We review the literature on joint optimization of maintenance and inventory for wind energy, as shown in Table 2.2. The key concepts in maintenance and inventory models are introduced according to [33, 46, 164], and we further make some extensions and additions. In the table, the studies are concluded based on the following indicators: (1) system level, ranging from onshore to offshore and component to farm; (2) maintenance characteristics, including maintenance strategies, maintenance effect; (3) objective; and (4) inventory characteristics, which encompass inventory policies, component characteristic, transport delays, diversity of units, inventory echelon.

The most common inventory policies adopted in the inventory management include Min/Max policy and Reorder Point/Order Quantity policy. In Min/Max policies, orders are placed as soon as the inventory drops to or below the minimum level, and the level is recovered to maximum level [178]. In Reorder Point/Order Quantity policies, orders with a fixed quantity are placed as soon as the inventory drops to or below the reorder point [174]. The (0,1) policy means ordering a new unit once the current unit is consumed, which is simplified from the Min/Max policy and Reorder Point/Order Quantity policy [182]. The adoption of (0,1) policy is because the object is a single wind turbine and there is no need to store a large number of spare parts. Safety inventory level and economic order quantity policies are also simplified from Min/Max and Reorder Point/Order Quantity policies, but are not commonly used in existing inventory models. Economic order quantity is a given quantity ordered at a constant periodicity [5]. In safety inventory level policies, an order is

Table 2.2: Literature on joint optimization of maintenance and inventory for wind energy

Year	Literature	System level					Maintenance characteristics					Objective
							Strategy			Effect		
		Onshore	Offshore	Component	Turbine	Farm	CBM	OM	Other	Perfect	Imperfect	Min cost
2017	[180]	✓		✓			✓	✓		✓		✓
2018	[182]	✓			✓		✓	✓		✓		✓
2019	[178]	✓				✓		✓		✓		✓
2020	[174]	✓				✓	✓			✓	✓	✓
2021	[166]		✓		✓		✓		✓	✓		✓
2021	[183]	✓			✓		✓	✓		✓		✓
2022	[5]	✓				✓			✓	✓	✓	✓
2022	[189]	✓				✓	✓	✓		✓		✓
2022	[179]	✓				✓	✓	✓		✓		✓
2023	This thesis		✓			✓	✓	✓			✓	✓

Table 2.2 Continued: Literature on joint optimization of maintenance and inventory for wind energy

Year	Literature	Policy	Inventory characteristics							
			Components		Delay		Unit		Echelon	
			Consumable	Repairable	Regular	Emergency	Single	Multi	Single	Multiple
2017	[180]	Safety inventory level	✓		✓		✓		✓	
2018	[182]	(0, 1)	✓			✓		✓	✓	
2019	[178]	Min/Max	✓			✓	✓		✓	
2020	[174]	Reorder Point/ Order Quantity	✓	✓	✓		✓		✓	
2021	[166]	(0, 1) and Min/Max	✓		✓	✓		✓	✓	
2021	[183]	(0, 1)	✓		✓	✓		✓	✓	
2022	[5]	Economic order quantity	✓	✓			✓		✓	
2022	[189]		✓				✓		✓	
2022	[179]	Min/Max	✓				✓		✓	
2023	This thesis	Min/Max	✓	✓	✓	✓		✓		✓

placed when the spare parts inventory cannot satisfy the maintenance requirements or the remaining spare parts after maintenance are smaller in number than the safety inventory level [180]. The quantity ordered is set to ensure that the inventory level of the next inspection time is safe. Minimizing total maintenance and inventory cost is the most important performance indicator of policies, so all the models set minimum costs as the objective. The delay in the inventory characteristics represents that there are lead times for regular and emergency orders to be prepared and delivered. Regular orders are the orders placed following the adopted inventory policy [156]. Replenishment with emergency orders occurs when the current stock level is insufficient to satisfy demands [78]. The adopted maintenance strategies are mostly condition-based maintenance (i.e., 'CBM'), opportunistic maintenance (i.e., 'OM'), and the combination of these two strategies.

Here, we identify the following research gaps related to spare parts inventory management after conducting literature review in Table 2.2. First, the system level represents the level of the system the model is concerned about, from component level (e.g., bearings) to turbine level and finally farm level. Most of the models concern onshore wind energy while offshore wind energy has received less attention. The only paper on offshore wind energy investigates the model of an offshore wind turbine system where only two components are considered [166]. A model involving an offshore wind farm with a number of wind turbines and various types of components and subcomponents is still missing.

Second, the components in the inventory characteristics are categorized into consumable and repairable [161]. A consumable component can only be repaired by replacing it. If a consumable part breaks down, it is removed and replaced by a new unit [164]. In comparison, a repairable component is capable of being repaired and returned to service. A repairable unit can be repaired without the necessity to replace the entire unit [37]. This concept corresponds to the concept of maintenance degree including perfect maintenance and imperfect maintenance. Most of the studies consider that components can only be replaced (perfect maintenance). A few papers using a hybrid (consumable and repairable) component concept without considering subcomponents, ignoring the fact that a component can be decomposed into subcomponents at lower-level and the subcomponents also require maintenance actions.

Third, all the papers adopt a single-echelon inventory network. The network structure entails the structure of the logistics system structure, which can be grouped into two categories; single-echelon and multi-echelon [71]. A single-echelon network structure is comprised of a single warehouse location that serves the system. Comparatively, a multi-echelon network structure contains a multitude of warehouses and/or depots. For example, in the offshore industry, a multi-echelon system can comprise a main warehouse which is possibly associated with the OEM, which consecutively serves smaller on-shore depots which in turn finally serve off-shore warehouses close to the wind farm location [143]. The distinction between a single- or multi-echelon logistics system can be considered influential in joint optimization focused on the offshore wind energy industry. This is due to the fact that each location in a multi-echelon network might have its own restriction in terms of available space and distance to the operational area in this case.

Last, the inventory network can be considered either single-unit or multi-unit [164]. A unit refers to a product or item that can be used for maintenance and managed within the inventory system. A single-unit inventory contains or considers only a single type of component or subcomponent, whereas a multi-unit inventory considers several types. Even though some papers have claimed that a wind turbine system is composed of multiple components/subcomponents [178], the models actually adopt a single-unit inventory. The reason is that the diversity of components/subcomponents is not considered and the number of different parts is aggregated without allocating a separate storage level. In this case, the stock is still optimized in a single-unit pattern.

In summary, the existing studies adopt a single-unit and single-echelon inventory model ignoring the diversity and complication of wind turbine structure and the various types of maintenance actions. It is necessary to improve the model to make it be more adequate for the offshore wind industry. In addition, the inventory model and maintenance model should be integrated to facilitate the coordination between the decisions in different models. Such a joint optimization could provide more comprehensive suggestions for decision-makers to organize the maintenance logistics plan.

2.3.2 Maintenance vessel fleet management

In this section, the literature on the fleet size and mix problem for the maintenance of offshore wind farms is reviewed. Different types of vessels are needed to support maintenance activities. For example, CTVs can transport technicians to the site to conduct minor repair activities. When lifting activities are required, a HLV is needed to lift the heavy components to the height of the cabin. The wind farm operator (or maintenance service provider) usually owns some vessels to conduct maintenance tasks, but the number of these vessels may not be sufficient when a high number of maintenance tasks must be completed. In this case, additional vessels must be chartered to make up for the insufficient number of vessels, but the number of chartered vessels should be controlled to a suitable value in order to avoid excessive costs. Therefore, the determination of the optimal fleet size and mix to support maintenance activities at an offshore wind farm is crucial, involving optimizing a vessel chartering strategy.

The literature on fleet size and mix to support offshore wind farm maintenance is concluded in Table 2.3. In the table, the studies are concluded based on the following indicators: (1) maintenance strategies; (2) variety of vessels used; (3) methods and tools for modelling and solving; (4) accounting for uncertainty factors; and (5) performance.

It is found that all the fleet size and mix problems consider corrective maintenance or time-based maintenance strategies. The optimization objective is mainly set as minimum costs, including fixed costs of maintenance bases, chartering costs of vessel resources, variable costs of executing maintenance tasks, downtime costs, penalty costs, transportation costs, and technician costs [29, 69, 154]. In [27, 50], the objectives are also relevant to revenue loss, power production, and availability. Downtime, vessel utilization, hazard rates and mean time to failure are also used to evaluate the performance of the vessel fleet [27, 30]. The fleet size and mix problem involves various types of uncertainty factors, metaocean conditions, component failures, vessel chartering rates, electricity prices, working shift, etc [65, 153].

From the perspective of vessel types in the fleet, most of the studies focus on a hybrid fleet composed of CTVs/helicopters (represented by 'HL'), FSVs/offshore assistance vessels (OAVs)/supply vessels (SVs)/SOVs, and HLVs/Jack-up vessels. The vessel types concerned in the studies relies on the requirement of maintenance tasks. If the model involves multiple types of maintenance, such as replacement, major repair, and minor repair, a

Table 2.3: Literature on vessel fleet management for offshore wind farm maintenance

Year	Literature	Maintenance Strategy			Vessel Type				Modeling methods		Solving tools /methods
		CM	TM	other	CTV/HL	FSV/OAV /SV/SOV	HLV/ Jack-up	Others	Mathematical programming	Simulation	
2013	[16]	✓	✓		✓			✓	Queuing		
2013	[68]	✓	✓		✓	✓	✓	✓	MIP		FICO Xpress
2014	[50]	✓	✓		✓	✓	✓			✓	
2015	[27]	✓	✓		✓	✓	✓	✓		✓	
2015	[65]	✓	✓		✓	✓	✓	✓	SP		FICO Xpress
2015	[29]	✓	✓		✓					✓	
2015	[30]	✓					✓			✓	
2015	[28]	✓			✓		✓	✓		✓	
2016	[152]	✓	✓		✓	✓	✓	✓	SP		FICO Xpress
2017	[153]	✓					✓		SP		SAA
2017	[69]	✓	✓		✓			✓	MILP		GRASP
2017	[67]	✓	✓					✓	MILP		CPLEX
2019	[154]	✓	✓		✓	✓	✓		SP		FICO Xpress
2019	[162]	✓					✓			✓	
2020	[155]	✓	✓		✓				SP		L-shaped
2022	[18]	✓	✓		✓				SP		GRASP
2023	This thesis			✓	✓	✓	✓			✓	SA

Table 2.3 Continued: Literature on vessel fleet management for offshore wind farm maintenance

Year	Literature	Uncertainty factors					Performance					
		Failure	Weather	Vessel charter	Electricity price	Other	Cost	Revenue loss	Power yield	Availability/ downtime	Vessel utilization	Other
2013	[16]	✓	✓			✓	✓	✓		✓		
2013	[68]	✓	✓	✓	✓		✓					
2014	[50]	✓	✓				✓		✓	✓	✓	
2015	[27]	✓	✓				✓	✓	✓	✓	✓	
2015	[65]	✓	✓	✓	✓		✓					✓
2015	[29]	✓	✓				✓	✓	✓			
2015	[30]	✓	✓				✓				✓	✓
2015	[28]	✓	✓				✓			✓	✓	
2016	[152]	✓	✓				✓					
2017	[153]	✓	✓		✓		✓					
2017	[69]	✓	✓				✓					
2017	[67]	✓	✓				✓					
2019	[154]	✓	✓			✓	✓			✓		
2019	[162]	✓	✓				✓			✓	✓	
2020	[155]	✓	✓		✓	✓	✓					
2022	[18]	✓	✓			✓	✓					
2023	This thesis	✓	✓				✓	✓				

hybrid vessel fleet is necessary. In case that only minor repair is considered, the vessel fleet is mainly configured by CTVs. Moreover, various types of novel transportation methods can be introduced to discuss about their influence on maintenance logistics. Helicopters are usually used to perform minor maintenance tasks [28]. Compared to CTVs, helicopters are able to bring and hoist the technicians and the material needed to maintain the wind farm quickly, and handle the rough sea condition, but the drawback is that the helicopter is a kind of costly tool. Multi-purpose crane vessels, surface effect ships, small accommodation vessel, mother vessels, and daughter vessels are also introduced in the vessel fleet [16, 69, 152]. A mother vessel, which is a large vessel that can accommodate multiple CTVs alongside, can provide a possible solution for operators with daughter vessels. Surface effect ships are special types of vessels that are a combination of hovercrafts and catamarans, allowing them to have greater speed on sea water. Multi-purpose crane vessels are designed to carry a wide diversity of cargo types. They are combined with crane capacity, offering a wide operational flexibility depending on the mission. Accommodation vessels are primarily used to provide accommodation for personnel during the establishment or maintenance of an offshore structure/wind farm. Accommodation vessels are moored or floating close to the construction site to minimize transport time to the offshore structure and maximize personnel work time.

The modelling methods of the maintenance vessel fleet size and mix problems are categorized as mathematical programming methods and simulation methods. In mathematical programming methods, a mathematical model involving variables and constraints is formulated and solved by minimizing/maximizing an objective function. The mathematical programming methods are further classified into solving deterministic problems [68] and stochastic problems [65]. In deterministic problems, all the parameters are assumed to be known. In [67–69], deterministic vessel fleet optimization models for offshore wind farms are developed by using mixed-integer programming (MIP), mixed-integer linear programming (MILP), aiming to give offshore wind farm operators a tool to determine which types of vessels to buy, which and how many vessels to charter, and which vessel bases (onshore and offshore) to use. A MIP problem is one where some of the decision variables are constrained to be integer values, and a MIP problem without any quadratic features is often referred to as a MILP problem. In MIP/MILP problems, factors including weather conditions, electricity price, vessels' charter rates, and maintenance tasks are all treated as deterministic parameters which have been known in advance.

The deterministic problems assume that all the parameters are known, which is a simplification of the real maintenance planning full of uncertainty. The large changes in vessel fleet caused by different scenarios with uncertainty will bring difficulties for decision-makers. Several work tends to investigate the optimal fleet configuration in the scenarios incorporating uncertainty, namely as stochastic problems. In [65], a stochastic programming (SP) model for the fleet size and mix problem for offshore wind farms is proposed. SP is a framework for modeling an optimization problem in which some or all problem parameters are uncertain, but follow known probability distributions. This framework contrasts with deterministic optimization, in which all problem parameters are assumed to be known exactly. The uncertainty in charter rates of vessels and helicopters, weather conditions (wind speed and wave height), electricity prices, and failures is introduced. The SP model is solved by transforming it into its scenario tree node-based deterministic equivalent, where all decision variables affected by the uncertain parameters are transferred into node-based equivalents. Each realization of the uncertain parameters is referred to as a scenario in which all the parameters are deterministic. Similarly, in [18, 152–155], SP models are developed to consider various types of uncertain including weather conditions, components failures, electricity prices, and vessel chartering rates. The study [65] reveals that, compared to a stochastic approach, deterministic methods where all uncertain parameters are replaced by their expected value underestimates the required vessel fleet result in fewer maintenance tasks being completed in rougher weather conditions.

Simulation methods are typically used to model and analyze the complex organization of vessel fleet in order to understand how they work and make predictions about the output. For one specific realization of the decision variables (configuration of the vessel fleet), the outputs (e.g., total costs and wind farm availability) are estimated after simulating the maintenance activities. By performing simulations for different fleet configurations, the most favourable fleet size and mix can be determined. In [29], 65 different fleet compositions are evaluated and 100 scenarios (with realizations of the stochastic parameters involving weather conditions and turbine failures.) are simulated for each fleet composition. The objective was to find the fleet composition resulting in the minimum total O&M costs. Simulation methods have also been used in [27, 28, 30, 50, 162] to investigate the optimum chartering strategies for jack-up vessels, mother vessels, and hybrid vessel fleet consisting of helicopters, CTVs, OAVs, and jack-up vessels.

According to the literature review on the different modelling methods for fleet management of offshore wind farms, two main differences (advantages and disadvantages) are identified. First, the deterministic models solve a certain problem where all information is known priorly. For example, the corrective maintenance tasks (sudden failures) of wind turbines and weather conditions are assumed to be known over the planning horizon. Thus, optimal decisions can be determined by anticipating future events, while in practice the failures and weather conditions are not known in advance. Consequently, deterministic methods may underestimate the required fleet size and costs of O&M since in practice there is incomplete information. Simulation methods and SP methods can deal with information to be revealed over time, so the problem can be modelled more realistically. Second, the results of using a specific fleet can be analysed in much greater detail with simulation methods compared to mathematical programming methods. A simulation method allows the results of multiple fleet configurations to be evaluated and compared, whereas with an mathematical programming method only the result of the optimal solution is obtained. For example, one specific fleet composition resulting in the lowest expected costs may have significantly more risks in extreme cases than another fleet composition with somewhat higher average costs. These considerations can be taken into account by analyzing the results of a simulation model, useful for assessing the risks versus the benefits of different fleets.

The solving methods/tools selected in the studies is related to the modelling methods. When using mathematical programming methods, metaheuristic algorithm, such as GRASP (greedy randomized adaptive search procedure), commercial optimization tool, such as FICO Xpress and CPLEX, and SAA (Sample Average Approximation) are the commonly used solving methods and tools [67, 152]. When dealing with the problems using simulation methods, the common approach is to use an exhaustive method or a large number of comparisons of different fleet configurations to determine the optimal solution [27].

In summary, when solving the maintenance vessel fleet configuration problem, the modelling methods are categorized into mathematical programming methods and simulation methods. This problem in practice is full of uncertain factors including failures and metocean conditions, which brings about many difficulties in the modelling and solving. The simulation methods play an important role in addressing this kind of problem. However, all the past studies using simulation methods still use an exhaustive method or a large number of comparisons of different fleet configurations to determine the optimal solution. As the scale of the future offshore wind farm increases and more factors (e.g., various types of uncertainty) are considered, it can be predicted that the model will become more complex, and the computation time will increase significantly. In this case, such exhaustive methods will be very time-consuming. Combining the simulation modelling methods with heuristic solving methods will provide a good capacity to solve these problem. In addition, the past studies study the fleet configuration under a corrective or time-based maintenance (represented by 'TM') strategy, but no paper before developed the model under a novel maintenance strategy such as condition-based or opportunistic maintenance strategy. Although there is no difference between tasks under opportunistic maintenance strategy and time-based maintenance for the vessels from the point of view of vessel dispatching, previous studies lacked the ability to integrate vessel fleet configuration with maintenance strategies and failed to realize the interaction between tactical and strategic decisions. A holistic model that integrates the maintenance strategy model with the vessel fleet management model is necessary.

2.3.3 Research gaps

The organization of the maintenance resource aims to support the maintenance strategy. After reviewing the related literature, two main research gaps are summarized here.

First, maintenance and inventory management can be considered simultaneously to improve an OEM or service provider's operations. The limited papers studying joint inventory and maintenance optimization commonly only notice component-level spare parts, and adopt a single-echelon inventory warehouse and a conventional corrective or time-based maintenance strategy. It is not adequate enough for offshore wind turbines, such a typical complex system consisting of many components in different hierarchical levels, and the potential application of condition monitoring technology is also not considered. A joint multi-unit and multi-echelon inventory and predictive opportunistic maintenance optimization problem is a necessary topic deserving attention.

Second, the past studies using simulation methods combined with an exhaustive method or a large number of comparisons of different fleet configurations to determine the optimal solution. With the increase of wind farm size and problem complexity, it is more challenging to use exhaustive methods or compare different fleet configurations to solve the problems. Therefore, more efficient methods, such as metaheuristic methods, are required to solve the optimization problems more quickly. Moreover, the past studies study the fleet configuration under a corrective or time-based maintenance strategy. It is necessary to develop the model under a novel maintenance strategy, integrating vessel fleet configuration with maintenance strategies and realizing the interaction between tactical and strategic decisions. These are research gaps to be filled in the vessel fleet size and mix problem.

2.4 Conclusions

This chapter begins with an overview of the classification scheme of the offshore wind energy maintenance logistics. The maintenance logistics are categorized into strategic, tactical, and operational levels. The decisions at different levels are not independent. In contrast, some decisions are interrelated. The decisions at the strategic level determines the maintenance logistics over the lifetime, indicating that improvements to strategic decisions may lead to more long-lasting effect on offshore wind farm O&M, followed by tactical decisions. Thus, a detailed review on state-of-the-art in maintenance strategy optimization and maintenance resource organization is then given. The research gaps are summarized in Section 2.2.5 and 2.3.3. Therefore, this chapter addresses the first research question **Q1**: What is the overview of maintenance logistics and state-of-the-art in the maintenance strategy and resource organization?

Based on the identified research gaps and findings, Chapters 3, 4, and 7 aim to bridge the research gaps in maintenance strategies in Section 2.2.5. Chapters 5 and 6 aim to address the research gaps in resource organization in Section 2.3.3.

Chapter 3

A Predictive Opportunistic Maintenance Strategy

As Chapter 2 concludes, a sound maintenance strategy is able to take component condition and maintenance opportunities into account to instruct maintenance actions. The trigger of maintenance cycles can also be improved to avoid over frequent maintenance. In addition, random environmental impact on wind turbines should be considered in the model besides degradation processes. Therefore, in Chapter 3, a maintenance strategy for offshore wind farms integrating three types of maintenance opportunities is proposed, where the maintenance decisions are made based on component failure times. The turbines suffer from degradation processes and random environmental impact simultaneously, and a multiple-component age-based preventive dispatch is introduced to improve the trigger of maintenance cycles.

The remainder of this chapter is organized as follows. Section 3.1 introduces the background of the problem. In Section 3.2, a mathematical model is developed to formalize the proposed maintenance strategy. In Section 3.3, a numerical example is used to illustrate the potential of the proposed strategy. The optimization results and comparative study are presented. Finally, conclusions are presented in Section 3.4.

Parts of this chapter have been published in [104][1].

3.1 Introduction

As wind energy systems are growing both in capacity and complexity, there are ongoing efforts to improve reliability, availability, maintainability and safety, aiming to enhance its marketability and competitiveness [120]. O&M costs account for 12%-30% of the total life cycle cost for onshore wind farms [76], and the portion is estimated to rise to more than 32% for offshore wind farms [113, 119]. Optimizing the O&M strategy, especially maintenance activities, is thus an effective pattern to reduce O&M costs and gain more profits.

[1] M. Li, X. Jiang, and R. R. Negenborn. Opportunistic maintenance for offshore wind farms with multiple-component age-based preventive dispatch. *Ocean Engineering*, 231:109062, 2021.

As a strategic decision made by wind farm owners and operators, the determination of the long-term maintenance strategy has a straightforward influence on wind farm O&M. A large-scale offshore wind farm is made up of a number of turbines. Besides, as a type of complicated electromechanical system, an offshore wind turbine system is composed of hundreds of components and subsystems [127]. The economic dependence applies when the combined maintenance leads to a different cost than repairing individually [75], especially it will has a positive effect when travelling to the location where maintenance activities have to be executed is costly [84]. The predictive opportunistic maintenance is a type of strategy using predicted component failure to make maintenance decisions and taking advantage of the economic dependence to reduce maintenance cost .

As discussed in Chapter 2, the earlier models consider the situation in which the wind turbines only experience degradation. However, offshore wind turbines are subject to the impact resulting from the marine environment, indicating the turbines suffer from degradation processes and random environmental impact simultaneously. In addition, maintenance opportunities in the earlier opportunistic maintenance strategy are triggered by failure events of a wind turbine or the scenario in which a wind turbine component is so old that it should be preventively replaced, which may induce over-maintenance. To address the above issues, a predictive opportunistic maintenance model considering the influence of environmental impact is developed in this chapter, and the trade-off between the frequency of preventive dispatch of maintenance teams and maintenance costs is analyzed.

3.2 Model description

In this section, a mathematical model is developed to formalize the proposed maintenance strategy. In the model, three types of maintenance opportunities can trigger maintenance cycles referring to the sequence of events that make up maintenance tasks, from the definition to the completion. More specifically, when a maintenance cycle is triggered, the following steps are to make preparation for maintenance implementation, dispatch the the maintenance teams to the site, and repair or replace the components satisfying the maintenance requirements. This series of activities then constitutes a maintenance cycle. After finishing the maintenance actions on qualified components, the maintenance cycle will end until the maintenance opportunity appears next time. The total costs represent the sum of money generated from repair activities during the maintenance cycles.

3.2.1 Assumptions

In the offshore wind farm, it is assumed that all the turbines are of the same type. After a wind farm maintenance decision is made, sufficient preparation is done to ensure the execution of maintenance activities is as successful as we expect. Therefore, the following assumptions are made on the offshore wind farm:

1. A specific component is of similar nature for all the turbines in the farm. The same maintenance activity performed on the specific component spends the same money, no matter the component contained in which turbine.

2. The time spent on performing maintenance activities is negligible when compared to the long service time of farms.

3. The maintenance resource and capacity, including staff, tools, spare parts, transportation means, are always available to complete all the maintenance tasks in the farm.

4. The accessibility to the location of the farm will not be affected by any negative factor such as weather conditions.

For an individual offshore wind turbine, it can be regarded as a series system, because the failure of subsystem may result in the entire system breaking down. For the mechanical or electromechanical components in the turbine, Weibull distribution is appropriate to model the failure times. Poisson process is a completely random process and each point is stochastically independent of all the other points in the process. The impact from marine environment arrives randomly with the average rates varying with time, so non-homogeneous Poisson process is suitable to describe this process. Hence the following assumptions are made on every individual turbine:

1. Offshore wind turbine system is simplified to a series system of critical components.

2. The degradation failure times of components are modelled as a two–parameter Weibull distribution with scale parameter and shape parameter. The arrival times of the environmental impact are modelled as a non-homogeneous Poisson process.

3.2.2 Failure of component

Suppose that there are K offshore wind turbines consisting of I critical components connected in series. The particular type of components in different turbines would undergo the same degradation process if they operate under the same ideal condition. This process can be defined as the normal degradation process. The environmental impact arriving at the turbines may incur failure or have an influence on the component degradation. The arrivals of environmental impact and the deterioration of the system are independent in this model.

The component gradually degrades as the age increases until failure. Suppose that the failure time of component i at turbine k is modelled as a Weibull distribution with scale parameter σ_{ik} and shape parameter ε_{ik}, the component has the probability density function $f_{ik}^{\mathrm{p}}(t)$ as

$$f_{ik}^{\mathrm{p}}(t) = \frac{\varepsilon_{ik}}{\sigma_{ik}}\left(\frac{t}{\sigma_{ik}}\right)^{\varepsilon_{ik}-1} e^{-\left(\frac{t}{\sigma_{ik}}\right)^{\varepsilon_{ik}}}. \tag{3.1}$$

The reliability function can be expressed as

$$R_{ik}^{\mathrm{p}}(t) = e^{-\left(\frac{t}{\sigma_{ik}}\right)^{\varepsilon_{ik}}}. \tag{3.2}$$

The degradation degree increases as the time passes. The mean time to failure, $MTTF_{ik}$, denotes the expected time to failure for the component, and can be represented as

$$MTTF_{ik} = \int_0^{\infty} t f_{ik}(t) = \sigma_{ik}\Gamma\left(\frac{1}{\varepsilon_{ik}}+1\right), \tag{3.3}$$

with $\Gamma(*)$ denoting the Gamma function. The lifetimes of components are randomly generated by employing the Weibull distribution. A inverse Weibull model is used to generate Weibull distributed random numbers, where $\alpha_{ik} = \sigma_{ik}^{-\varepsilon_{ik}}$. A random number, γ, is generated in the range from 0 to 1. Then the following equation is used to obtain new independent random numbers which have the Weibull distribution with the mean and variance depending on

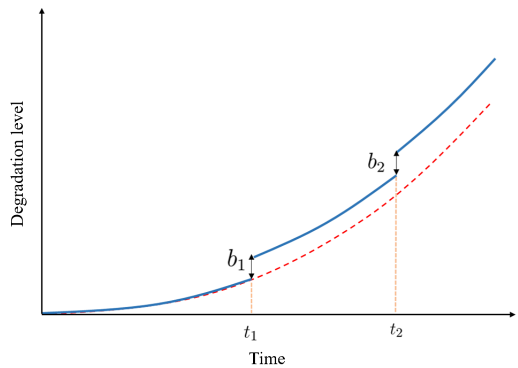

Figure 3.1: Abrupt increases of degradation caused by influential impact

shape and scale parameters [32]. These random numbers will be assigned to corresponding components to represent their failure ages [160] as

$$v_{ik} = \left[-\frac{1}{\alpha_{ik}} \ln(1-\gamma) \right]^{\frac{1}{\varepsilon_{ik}}}. \tag{3.4}$$

The degradation process of components may also be affected by some factors, such as environmental impact. For example, at time point t_1 and t_2, two times of impact arrive, resulting in the component degradation increasing abruptly with the magnitude of b_1 and b_2 respectively (Fig. 3.1).

The impact arrives randomly, modelled as a non-homogeneous Poisson process. A non-homogeneous Poisson process $\{N_k(t) : t \geq 0\}$ is a counting process where $N_k(t)$ is the number of load arrivals during time $(0,t]$, and the intensity function $\lambda_k(t)$ varying with time is a non-negative, integrable function satisfying the Poisson postulates [95]. The Poisson random variables are given by:

$$\Lambda_k(t) = \Lambda_k(0,t) = \int_0^t \lambda_k(z)dz. \tag{3.5}$$

In order to simulate the occurrence times of impact, the thinning algorithm is used to simulate the points in the non-homogeneous Poisson process [89, 172]. The procedure starts with the determination of the maximum intensity value λ and with the generation of a realization of a homogeneous Poisson process with intensity value equal to this maximum intensity value. After that, the generated points of the homogeneous Poisson process at location t are retained and discarded based on the probability $\lambda_k(t)/\lambda$ [97].

3.2.3 Failure of offshore wind turbine

Considering the offshore wind turbine is a series system, the system fails once a component failure occurs. In other words, the component failures caused by degradation and environmental impact will make the turbine where the component is located stop working

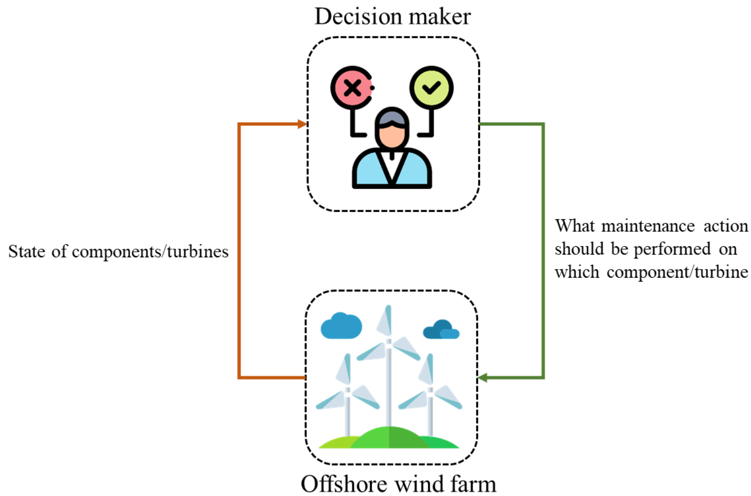

Figure 3.2: Decision-making process of offshore wind farm maintenance

immediately.

Not every environmental impact induces the failure of turbines. The impact can be generally categorized into three types depending on the severity, that is critical impact, influential impact and minor impact. The critical impact means the impact is so disastrous that the turbine will break down until the failed component is completely replaced. The influential impact will cause an abrupt increase in the degradation. The minor impact has a slight influence on component conditions and will not make the component break down. Correspondingly, the occurrence probability of critical impact P_k^{C} $(0 \leq P_k^{\mathrm{C}} \leq 1)$ is the least, because this incident rarely happens. The probability of minor impact P_k^{M} $(0 \leq P_k^{\mathrm{M}} \leq 1)$ is the most, and the probability of influential impact P_k^{I} $(0 \leq P_k^{\mathrm{I}} \leq 1)$ is intermediate. The sum of P_k^{C}, P_k^{I} and P_k^{M} is equal to 1.

3.2.4 Opportunistic maintenance model

After studying the failure mechanism of turbines in the offshore wind farm, the opportunistic maintenance model is developed to determine what time to activate maintenance activities and how the components will be repaired. The maintenance cost is refer to the corresponding money spent on these maintenance-related activities.

Fig. 3.2 demonstrates the decision-making process of the wind farm maintenance. The decision maker, such as the offshore wind farm owner and operator or the independent service provider, decides if the maintenance cycle should start according to the state of components/turbines. If the maintenance cycle begins, what maintenance action should be performed on which component/turbine will also be decided.

There are three types of maintenance opportunity in the model, namely failure-based opportunity, age-based opportunity, and incident-based opportunity. The maintenance opportunities emerge when the corresponding situations happen. Every type of maintenance opportunity can initiate a maintenance cycle in the offshore wind farm. In Fig. 3.3, the detailed flow chart of the proposed opportunistic maintenance strategy is introduced. Only in the case that no opportunities happen, the wind farm is determined to be without maintenance.

1. *Failure-based opportunity*. When the component i at turbine k breaks down because of the degradation, the maintenance opportunity will be triggered.

2. *Age-based opportunity*. If no component fails, but a certain number of components reach the specific age threshold, the maintenance opportunity will arrive.

3. *Incident-based opportunity*. If the arriving environmental impact is critical so that the component fails, the maintenance opportunity will appear.

When the offshore wind farm begins to operate, all of the components are brand new, their ages u_{ik} are certainly 0. The inverse Weibull model is adopted to generate the random failure age v_{ik} of each component. Once the age reaches the failure age, this component will break down due to degradation. After every period of time $\{T_1^{\text{period}}, T_2^{\text{period}}, ..., T_y^{\text{period}}, ...\}$, the information of wind farm is inspected to determine if maintenance actions are needed. The inspection is supposed to be perfect and non-destructive.

During time T_{y-1}^{period} to T_y^{period}, the environmental impact is firstly checked. For each component subject to the environmental impact, the arrival time of impact is w_k^{E}. If $T_{y-1}^{\text{period}} < w_k^{\text{E}} \leq T_y^{\text{period}}$, the turbine k has to endure the environmental impact (X_k^{EI}=1). Considering the impact is critical, influential or minor, the Binomial distribution can present whether the impact can induce the incident. If the impact is minor, the turbines will maintain in the previous state. If the impact is influential, it causes the component age to increase by a portion b_m ($0 < b_m$) from the current age. The interval between maximum age percentage threshold $A^{\max}$ and minimum age percentage threshold $A^{\min}$ is separated into groups of equal lengths, $\{A^{\min}$, ..., A^m, ..., $A^{\max}\}$. If the component is younger than $A^{\min}$, the age will be updated to $u_{ik}(1+b_1)$. The age of components in the group between $A^{\min}$ and A^1 will increase with a coefficient b_2, and so on. The younger the component is, the age increase will be less, because it is in a better state to withstand the impact. If the impact is so catastrophic to destroy the turbine (X_k^{c} =1), the incident-based opportunity is generated (X^{i}=1).

If no incident happens, then the failure times F_{ik} are compared with the real time. If $T_y^{\text{period}} < F_{ik}$, that means the component won't fail during this period and no failure replacement is needed, the binary variable X_{ik}^{FR} is equal to 0. Only for all the components, the $X_{ik}^{\text{FR}} = 0$, the value of X^{f} is 0. Otherwise, the $T_{y-1}^{\text{period}} < F_{ik} \leq T_y^{\text{period}}$, the degradation failure occurs on one component. In this case, $X_{ik}^{\text{FR}} = 1$, the failure-based opportunity appears (X^{f}=1) and one maintenance cycle will launch. If no failure occurs during this time period, the third maintenance opportunity, age-based opportunity, should be estimated. For component i at turbine k, if its age u_{ik} is more than a specific percentage of failure age v_{ik}, the component is regarded as an aged component. In other words, the component is judged as aged because it exceeds the maximum age threshold $A^{\max}$. We assume ζ is the percentage threshold of number of aged components. If the total number of aged components in the wind farm is greater than or equal to B, $B = \zeta IK$, the age-based opportunity is triggered (X^{a}=1). As introduced in Section 3.2.2, there are K offshore wind turbines consisting of I critical components in the wind farm. If X^{a}, X^{i}, X^{f} =0, no maintenance is needed during the

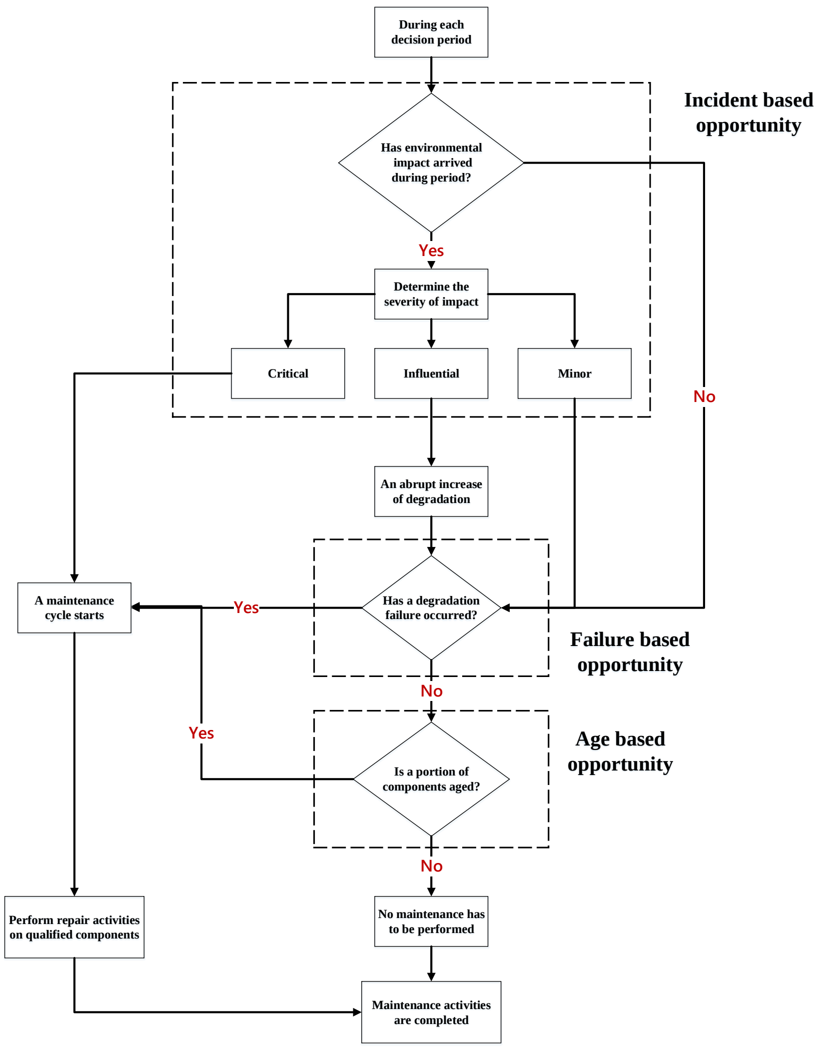

Figure 3.3: Flow chart of the proposed opportunistic maintenance model

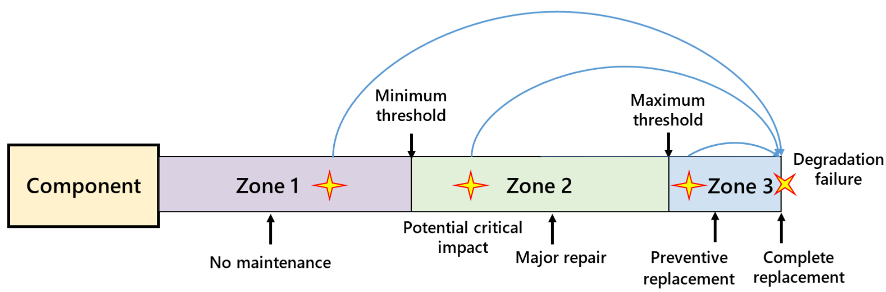

Figure 3.4: Maintenance actions for the components of different stages

period. The time moves to the next period, and values of time and age are updated.

An occurrence of a failure-based opportunity, age-based opportunity, or incident-based opportunity triggers a maintenance cycle, where all the components requiring maintenance are required or replaced. Three maintenance actions are considered in one maintenance cycle. Failure replacement is conducted on the failed component due to degradation or critical impact. The failure replacement means the component is completely replaced with a component of similar nature, implying the component is brand new with the age reset to zero. If the component is about to fail because of the degradation, it is qualified for a preventive replacement. The preventive replacement can also restore the age of component to zero. Because it is preventively carried out before the failure to avoid potentially serious damages, so the cost is less when compared with failure replacement. The major repair will be carried out on the components satisfying the requirements (between maximum and minimum age threshold). The major repair can effectively improve the component health. The maintenance actions for components of different stages are illustrated as Fig. 3.4.

The sth maintenance cycle begins after the maintenance opportunity emerges. The starting time of this cycle is T_s. The component states in the site can be classified into four cases: failed, aged, mature, and young. The Kijima type II virtual age method proposed in [88], where the age accumulates with time going and the repair can remove the damages incurred before repair, is introduced here to describe the influence of maintenance on component condition.

1. Failed component.

As introduced above, the failed components caused by degradation or critical impact should be completely replaced, and their corresponding binary variables X_{ik}^{FR} is equal to 1. Accordingly, their ages are reset to 0, as

$$u_{ik}^{\mathrm{new}} = 0. \tag{3.6}$$

By sampling from Weibull distribution, the lifetimes of these new components are obtained, then their new failure ages v_{ik}^{new} is known. The next failure times can be obtained as follows:

$$F_{ik} = v_{ik}^{\mathrm{new}} + T_s. \tag{3.7}$$

2. Aged component.

In the maintenance cycle, the ages of running components are compared with the predetermined age thresholds. Two percentages of failure ages are set as maintenance thresholds, $A^{\max}$ and $A^{\min}$. If $u_{ik}^{\text{old}} > v_{ik}^{\text{old}} A^{\max}$, it is determined as the aged component to be replaced and X_{ik}^{PR} is equal to 1. Similar to a failed component, the age will be restored to 0 after preventive replacement, as follows:

$$u_{ik}^{\text{new}} = 0. \tag{3.8}$$

The new failure ages of these components v_{ik}^{new} are obtained. The occurrence time of next failure can be obtained as:

$$F_{ik}^{\text{new}} = v_{ik}^{\text{new}} + T_s. \tag{3.9}$$

3. Mature component.

For the running components with ages between maximum and minimum thresholds, namely $v_{ik}^{\text{old}} A^{\min} < u_{ik}^{\text{old}} \leq v_{ik}^{\text{old}} A^{\max}$, these components are judged as mature components which major repair should be conducted on (X_{ik}^{MAR}=1). Multi-level maintenance thresholds [137] are used to present the maintenance effect. The components in the group between $A^{\min}$ and A^1 will undergo the l_1 level maintenance action. The l_2 level maintenance action is performed on the components between A^1 and A^2, and so on. For the mth maintenance level, l_m, there is a maintenance quality, θ_{l_m}. The maintenance quality means the age of components can be improved to a fixed percentage [121]. Therefore, the ages of component will be updated after major repair as follows:

$$u_{ik}^{\text{new}} = \theta_{l_m} u_{ik}^{\text{old}}. \tag{3.10}$$

The failure age keeps the same value:

$$v_{ik}^{\text{new}} = v_{ik}^{\text{old}}. \tag{3.11}$$

The occurrence time of next failure is as follows:

$$F_{ik}^{\text{new}} = v_{ik}^{\text{new}} - u_{ik}^{\text{new}} + T_s. \tag{3.12}$$

4. Young component.

For the components younger than the minimum threshold ($u_{ik}^{\text{old}} \leq v_{ik}^{\text{old}} A^{\min}$), they do not require maintenance. During the maintenance cycle, the components still retain the previous state, so the degradation process and failure age do not change, as follows:

$$v_{ik}^{\text{new}} = v_{ik}^{\text{old}}. \tag{3.13}$$

After the maintenance cycle, their ages are updated as follows:

$$u_{ik}^{\text{new}} = u_{ik}^{\text{old}}. \tag{3.14}$$

The occurrence time of next failure is as follows:

$$F_{ik}^{\text{new}} = v_{ik}^{\text{new}} - u_{ik}^{\text{new}} + T_s. \tag{3.15}$$

The objective is to reduce the total maintenance costs of offshore wind farms. After developing the maintenance model, the cost generated in the procedure is calculated to estimate economic. The first step is to calculate the money spent on four types of components (failed, aged, mature, and young) in each maintenance cycle.

For the failed component, it should be completely replaced, so the total cost of failure replacement of the wind farm, M^{FR}, is as follows:

$$M^{\mathrm{FR}} = \sum_{k=1}^{K} \sum_{i=1}^{I} R_{ik}^{\mathrm{FR}} X_{ik}^{\mathrm{FR}}, \tag{3.16}$$

where R_{ik}^{FR} represents the cost of failure replacement of component i at turbine k, and X_{ik}^{FR} is the binary variable to determine whether this component needs to be replaced.

For the aged components reaching the maximum age threshold, they are replaced as well. The money spent on activities of preventive replacement, M^{PR}, is calculated as:

$$M^{\mathrm{PR}} = \sum_{k=1}^{K} \sum_{i=1}^{I} R_{ik}^{\mathrm{PR}} X_{ik}^{\mathrm{PR}}, \tag{3.17}$$

where R_{ik}^{PR} represents the cost of preventive replacement of component i at turbine k, and X_{ik}^{PR} is the binary variable to check if preventive replacement is required.

The mature components with ages between the maximum and minimum age thresholds are qualified for major repair. In the present work, it is commonly assumed that the cost M_{ikm}^{MAR} of intermediate maintenance level performed on component is function of the expected value θ_{l_m} of the improvement coefficient of l_m in addition to the age and the operating state of the component [123]. According to literature [47, 87], the cost of major repair can be obtained as:

$$R_{ikm}^{\mathrm{MAR}} = r_{ikm} R_{ik}^{\mathrm{PR}} (1-\theta_{l_m})^{d_{ikm}\eta_{ikm}}, \tag{3.18}$$

where r_{ikm} and d_{ikm} are the characteristic constants that determine how the improvement coefficient affects the corresponding intermediate maintenance cost. Variable η_{ikm} represents the stability level of the maintenance quality. The $d_{ikm}\eta_{ikm}$ is smaller, then the major repair will be more expensive. Therefore, the total costs of major repair is:

$$M^{\mathrm{MAR}} = \sum_{m=1}^{M} \sum_{k=1}^{K} \sum_{i=1}^{I} R_{ikm}^{\mathrm{MAR}} X_{ikm}^{\mathrm{MAR}} = \sum_{m=1}^{M} \sum_{k=1}^{K} \sum_{i=1}^{I} r_{ikm} R_{ik}^{\mathrm{PR}} (1-\theta_{l_m})^{d_{ikm}\eta_{ikm}} X_{ikm}^{\mathrm{MAR}}, \tag{3.19}$$

where X_{ikm}^{MAR} is the binary variable to indicate if major repair is necessary.

Moreover, some extra cost exists along with the cost for maintenance tasks when conducting maintenance. Fixed cost M^{f} is the money used to make some preparation and trigger maintenance activities [27, 119]. R_{k}^{TR} is the transportation cost to turbine k in one maintenance cycle, thus more turbines are visited and repaired, the transportation cost is higher. Therefore, the total transportation cost is:

$$M^{\mathrm{TR}} = \sum_{k=1}^{K} M_{k}^{\mathrm{TR}} X_{k}^{\mathrm{TR}}, \tag{3.20}$$

where X_{k}^{TR} is the binary variable to indicate if the turbine is visited, as follows:

$$X_k^{\mathrm{TR}} = \begin{cases} 1 & X_{ik}^{\mathrm{FR}} = 1 \text{ or } X_{ik}^{\mathrm{PR}} = 1 \text{ or } X_{ikm}^{\mathrm{MAR}} = 1 \\ 0 & \text{otherwise} \end{cases} \tag{3.21}$$

Finally, the total cost of maintenance cycle s is calculated as follows:

$$\begin{aligned} M_s &= M^{\mathrm{f}} + M^{\mathrm{TR}} + MT^{\mathrm{PR}} + M^{\mathrm{FR}} + M^{\mathrm{MAR}} = \\ & M^{\mathrm{f}} + \sum_{k=1}^{K} M_k^{\mathrm{TR}} X_k^{\mathrm{TR}} + \sum_{k=1}^{K}\sum_{i=1}^{I} M_{ik}^{\mathrm{PR}} X_{ik}^{\mathrm{PR}} + \sum_{k=1}^{K}\sum_{i=1}^{I} M_{ik}^{\mathrm{FR}} X_{ik}^{\mathrm{FR}} + \\ & \sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{i=1}^{I} r_{ikm} M_{ik}^{\mathrm{PR}} (1-\theta_{l_m})^{d_{ikm}\eta_{ikm}} X_{ikm}^{\mathrm{MAR}}. \end{aligned} \tag{3.22}$$

The offshore wind farm operates for L years (lifetime) which S cycles of maintenance are carried out during. The total costs during L years can be calculated, and further the annual cost A_{c} is obtained, as follows:

$$\begin{aligned} \min \quad & A_{\mathrm{c}}(A^{\min}, A^{\max}, \zeta) = \frac{\sum_{s=1}^{S} M_s}{L} \\ \text{s.t.} \quad & 0 < A^{\min} < A^{\max} < 1 \end{aligned} \tag{3.23}$$

where $A^{\min}$ (minimum age percentage threshold), $A^{\max}$ (maximum age percentage threshold), and ζ (percentage threshold of number of aged components) are the decision variables of the proposed model. Actually, the values of $A^{\min}$ and $A^{\max}$ can be regarded as the criterion to determine whether a component is qualified for the repair. If it is older than $A^{\min}$ but less than $A^{\max}$, a major repair is needed. If it is more aged than $A^{\max}$, it should be preventively replaced. By varying the thresholds, the number of components which should be repaired will change accordingly. The variable ζ can determine how many aged components can trigger the age-based opportunity. The objective is to determine the optimal combination of variables which can minimize the annual maintenance cost over the lifetime. The simulation framework is established for the maintenance model of the offshore wind farm, as shown in Fig. 3.5.

The expression of the objective function and constraints is linear, as shown in Equation 3.23. However, it should be noted that the terms in the objective function represent various costs and do not directly include decision variables. The purpose of this simulation model is to input a set of decision variables and calculate the corresponding overall costs, which is the value of the objective function. This simulation model includes non-linear relationships, such as Equation 3.19. Therefore, this problem is considered to be a non-linear problem. A GA method is used to solve the model. It is proposed according to the evolution of organisms in nature, which has been widely used to tackle the multi-variable and non-linear maintenance optimization issue [25]. GAs involve iteratively generating a population of candidate solutions, evaluating their fitness, and then selecting individuals for reproduction based on their fitness. The steps involved in GA are initialization, fitness evaluation, selection, crossover, mutation, termination and repeat. These steps are repeated iteratively until the algorithm converges to a satisfactory solution. GA has its advantages when compared with other optimization methods, such as: avoid being trapped in local optimal solution by searching parallel from a population of points; use probabilistic selection

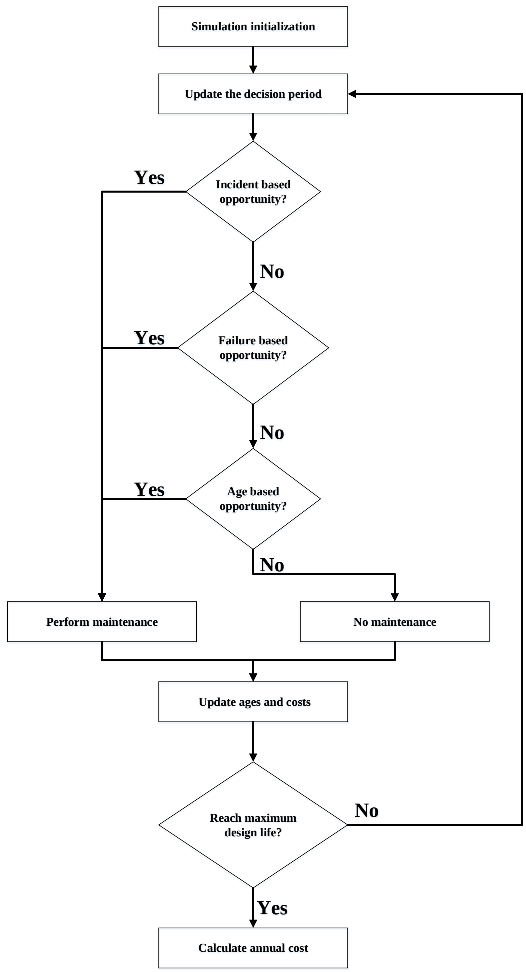

Figure 3.5: Simulation process of the maintenance strategy

rules instead of deterministic ones, etc.

3.3 Case study

In order to illustrate the effectiveness of the proposed opportunistic maintenance method, a numerical example of the offshore wind farm is used in this section. The optimization results of three strategies are represented. A comparative study with the conventional opportunistic maintenance strategies under the same parameters demonstrates the advantage of the proposed strategy in reducing the maintenance cost.

3.3.1 Scenario set-up

The proposed approach is applied in a generic offshore wind farm with a 20-year lifetime, as shown in Fig. 3.6. This case is unified, applied throughout the thesis. Subsequent chapters are also based on this case, and the details are modified and explained for specific problems and models. It is located in the North Sea, about 20 km away from the Netherlands shore. The scale of the farm is 50 3-MW turbines. The technical specification of the turbine is shown in Table 3.1. Considering the turbine is a type of complicated electromechanical system containing hundreds of components, it is difficult to take every subsystem into account. Previously published results in peer-review journals [9, 80, 81, 98, 139, 144, 181, 187] have revealed the criticality ranking of wind turbine components by using the methods, such as FMEA, Failure mode effects and criticality analysis (FMECA), two-stage FMEA, etc. In this model, every turbine is simplified to a multi-component series system with five critical subsystem (gearbox, generator, rotor&blade, pitch system, and main bearing). Due to the extremely low failure rates, tower and support structure are not considered in this model. The blade is the component more subject to the environmental impact, and the influence of critical impact on other components are ignored because of the protection of cabin. The failure and maintenance parameters are collected and estimated based on the studies [20, 91, 136], listed in Table 3.2, which represents the properties and parameters of the example of the offshore wind farm.

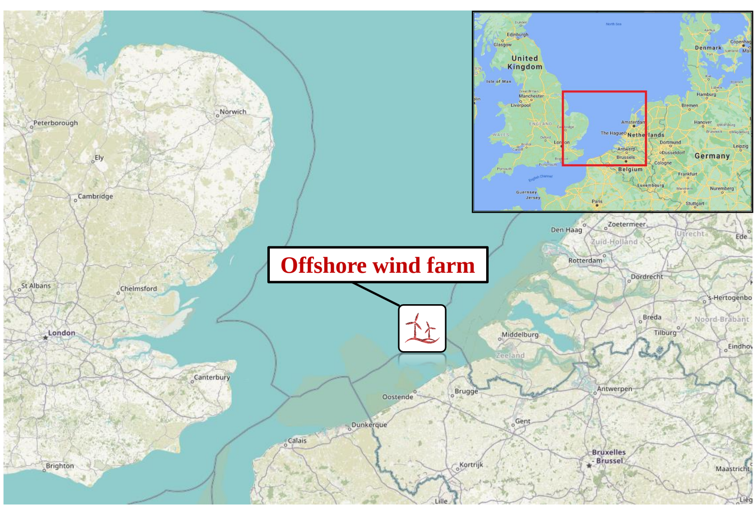

Figure 3.6: Geographical localization of the offshore wind farm located in the North Sea

The decision moments are assumed to be periodic, with an interval of 20 days. The fixed cost M^{f} and transportation cost M_k^{TR} are 50k€ and 10k€ respectively. The intensity function of external factor is assumed to be $2/27 * (t/27)$ [146, 147]. The value of P_k^{C}, P_k^{I}, P_k^{M} is assumed to be 0.001, 0.005 and 0.994. Three age thresholds, maximum threshold $A^{\max}$, intermediate threshold A^m, and minimum threshold $A^{\min}$, are considered in the model. The

Table 3.1: Technical parameter of 3MW offshore wind turbine

Parameter	Value
Rated power	3 MW
Rotor configuration	3 blades
Drivetrain	High speed, multiple-stage gearbox
Rotor diameter	90m
Hub height	80m
Cut-in speed	3m/s
Rated speed	12m/s
Cut-out speed	25m/s

maintenance improvement of two levels, l_1 and l_2, are 0.5 and 0.7 respectively, indicating the maintenance quality will be more significant for older components. Accordingly, the maintenance task of higher quality is more costly. The values of b_1, b_2, b_3 and b_4 are 0.025, 0.05, 0.075 and 0.1 respectively. The values of r_{ikm} and η_{ikm} are both 1, and d_{ikm} is 2.

Table 3.2: Failure distribution and cost parameters for critical components.

Component	Shape parameters	Scale parameters (days)	Failure replacement (k€)	Preventive replacement (k€)
Rotor&blade	3	1847	215	55
Bearing	2	1811	60	15
Gearbox	3	1477	260	65
Generator	2	1594	90	25
Pitch system	3	1144	46	10

3.3.2 Results

There have been three strategies, NABO Strategy, SABO Strategy, and MABO strategy, as follows:

1. NABO Strategy

In the first strategy, only failure and incident can trigger the maintenance opportunities and the age-based opportunity is not considered, similar as the model in the paper [137]. This kind of strategy is called as NABO Strategy (none age-based opportunity).

2. SABO Strategy

Failure and incident can trigger the maintenance cycle. Besides, if any component age reaches $A^{\max}$, the age-based opportunity will arise, like the model in the paper [117], the model is called SABO Strategy (single age-based opportunity).

3. MABO Strategy

The proposed strategy is called as MABO Strategy (multiple age-based opportunity). Failure-based, incident-based, and age-based opportunities exist in the strategy. If a predetermined number of components are aged, the maintenance decision can also be made to maintain the wind farm.

The decision variables of the model (MABO Strategy) are $A^{\min}$, $A^{\max}$, ζ. The annual maintenance cost is the function of these decision variables. The GA algorithm IS configured with a population size of 40 individuals and a maximum number of generations (G) of 50. The Monte Carlo simulation method is implemented to evaluate the outcome of the proposed maintenance strategy. The fitness value of each individual is evaluated by Monte Carlo simulation with 500 times. With this setting, the simulation in Fig. 3.5 should be run 1×10^6 times, which is implemented in MATLAB software. The GA optimization process results are represented in Fig. 3.7. The optimal combination of three decision variables is about (0.65, 0.94, 1.2%), with the lowest value 1956k€.

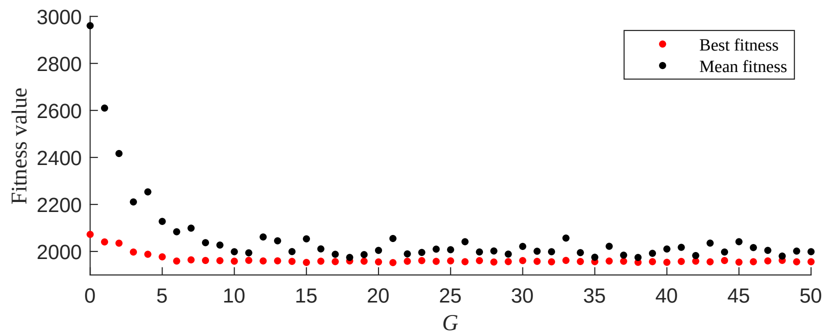

Figure 3.7: The genetic algorithm optimization process results

In order to illustrate how the varying variables affect the annual cost, we further test various combinations in Fig. 3.8 and show the effects of age percentage threshold under MABO Strategy when ζ equals 1.2% in Fig. 3.9. In Fig. 3.8, there exists an optimal combination of the decision variables which can minimize the annual maintenance cost. The variable ζ determines the exact number of the "multiple" in the MABO Strategy. We select and present four faces ($\zeta = 0.8\%, 1.2\%, 2.0\%, 2.8\%,$) in the figure where the lowest point is on the yellow face ($\zeta = 1.2\%$). The lowest point means the optimal combination of the variables (0.65, 0.94, 1.2%).

In Fig. 3.9, when changing $A^{\min}$ or $A^{\max}$, the trend is similar: the annual cost gradually drops as the increase of age threshold until the bottom, then increases to a high value. For the former, it can be explained that resulting from the lower threshold, more components are determined to be repaired in one maintenance cycle, contributing to more money. Then as the increase of threshold, the number of qualified components decreases, but the state of wind farm becomes worse due to less frequent repair. For the latter, the lower threshold indicates more components need to preventively replaced. More components are likely to fail due to insufficient preventive maintenance if the threshold is set at a higher percentage of the failure age.

In Fig. 3.10, the comparison among three strategies under different thresholds is illustrated. The MABO Strategy is the most cost-effective strategy after optimization as shown in Fig.3.10 and Table 3.3. In the figure, the blue face (MABO Strategy) is the lowest in almost half of the area. However, it is found that it is not always the most cost-effective when varying the maintenance thresholds. When $A^{\max}$ is very high, MABO and SABO both perform better than NABO, because the expensive failure replacement can be avoided

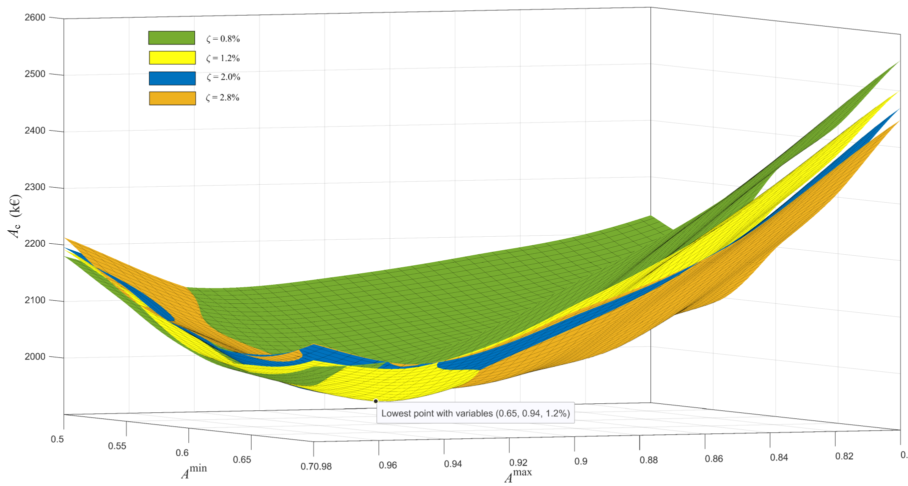

Figure 3.8: Annual costs versus combinations of decision variables A^{min}, A^{max}, ζ

due to the benefit of age-based opportunity. When A^{max} begins to decrease, it will become gradually easier to trigger the age-based opportunity, causing the increasing maintenance frequency and cost, especially for SABO (yellow face). In these occasions, the NABO Strategy has a better performance to reduce costs. Compared with MABO and SABO, the variance of annual cost is relatively stable when changing threshold for NABO Strategy (as shown in green face), because the change of thresholds does not affect the trigger of age-based opportunity.

Table 3.3: Optimized results of three strategies

Strategy	A^{min}	A^{max}	ζ	Annual cost (k€)
MABO	0.65	0.94	1.2%	1956
SABO	0.64	0.96	-	1984
NABO	0.60	0.90	-	1996

3.3.3 Comparative analysis

In order to study the differences among three strategies and discuss the reasons, all the parameters should be assumed the same, and the strategies are applied on the following base scenario: $A^{max} = 0.95$, $A^{min} = 0.5$, ζ=1.2% .

In Fig. 3.11, the Monte Carlo simulation of three strategies is presented, where the number of iterations is presented by W. The simulation is run independently in each iteration. The convergence analysis for the Monte Carlo simulation is conducted. After running the Monte Carlo simulation for 500 iterations, it can be seen that no significant variations of the intermediate mean value are obtained. It indicates that the 500 iterations provide a sufficiently accurate statistical analysis of the results. The final results at the 500 simulation

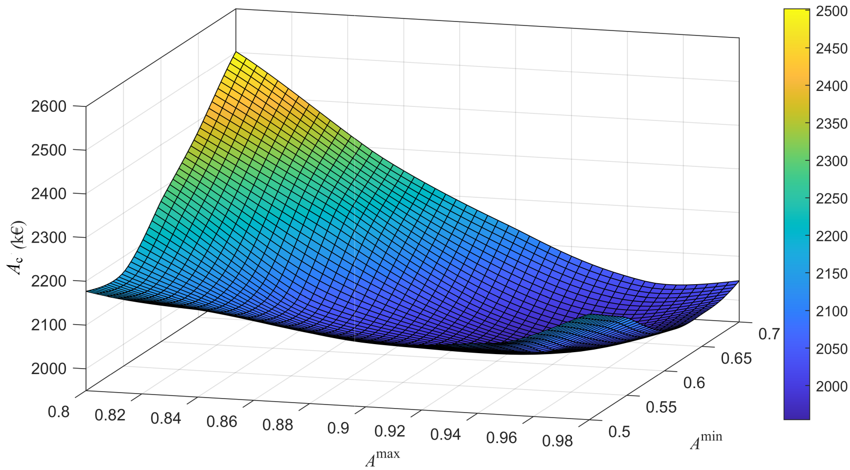

Figure 3.9: Annual cost with different age thresholds under MABO Strategy when ζ=1.2%

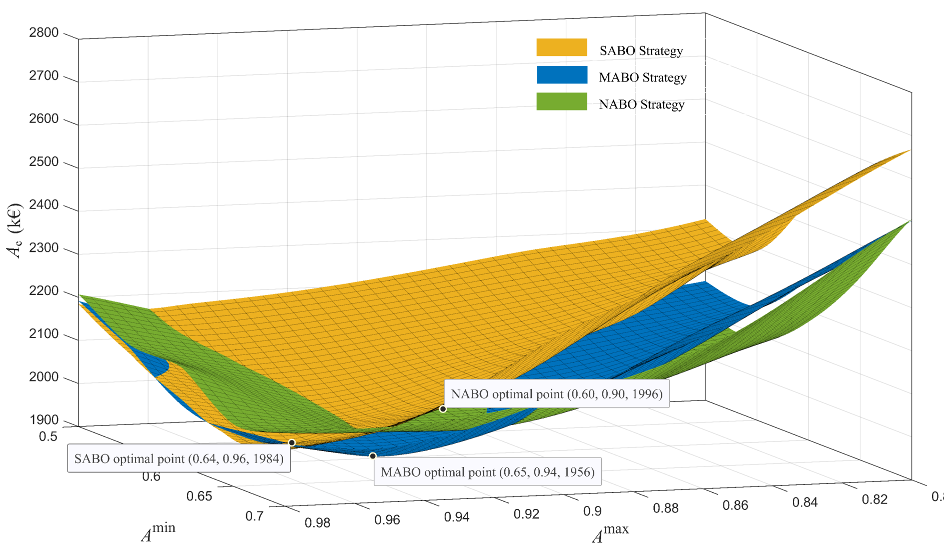

Figure 3.10: Annual cost with different age threshold under three strategies

times are used to estimate the economic of different strategies. As shown in Table 3.4 and Fig. 3.12, these results suggest that MABO strategy shows the economic advantage compared with other two strategies. By introducing the age-based opportunity, the cost of failure replacement decreases accompanied by a increase in the cost of major repair, fixed cost and transportation cost. In SABO strategy, the triggering condition is set as single component. The corresponding result is the offshore wind farm can be maintained to a good state, with the lowest costs of replacing failed components. However, more maintenance cycles and activities make the costs of major repair, fixed and transportation cost grow, inducing the strategy doesn't perform satisfactorily in the aspect of economic. The age-based opportunity reduces the occurrence of failure events at the expense of triggering preventive repair more frequently. The MABO strategy found a balance to reduce the replacement costs with a slight increase of the major repair, fixed and transportation costs. Overall, the proposed MABO opportunistic maintenance strategy can lower the total maintenance costs compared with the other two strategies.

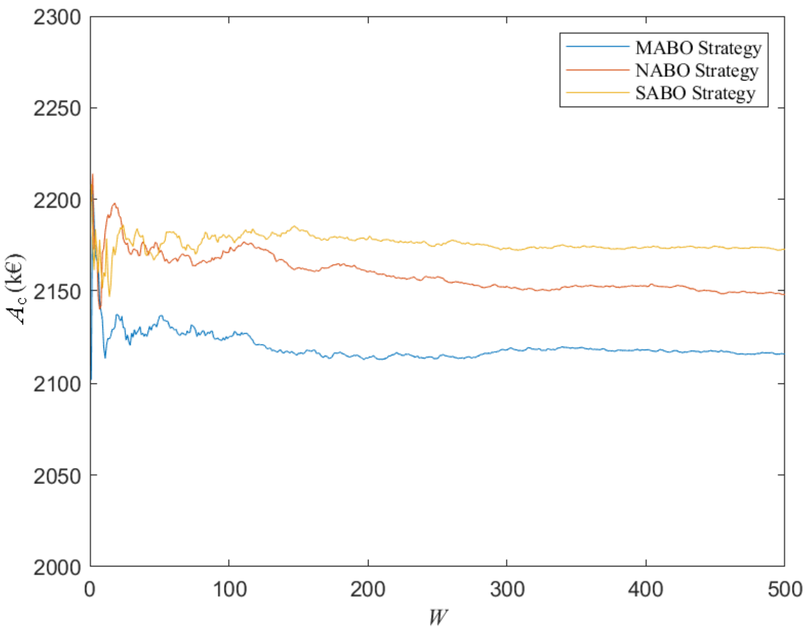

Figure 3.11: Comparison of different opportunistic maintenance strategy

Table 3.4: Breakdown of maintenance costs of different strategies

	Annual cost (k€)	Failure replacement (k€)	Preventive replacement (k€)	Major repair (k€)	Transportation and fixed cost (k€)
NABO strategy	2149	271	67	1070	741
SABO strategy	2173	126	54	1148	845
MABO strategy	2116	198	63	1089	766

The effects of following parameters on the MABO strategy: percentage threshold of number of aged components, ζ; the occurrence probability of critical, influential and minor impact, P_k^{C} , P_k^{I}, P_k^{M} ; the size of the offshore wind farm K, are further shown. The value of these parameters will change gradually and all other parameters remain fixed.

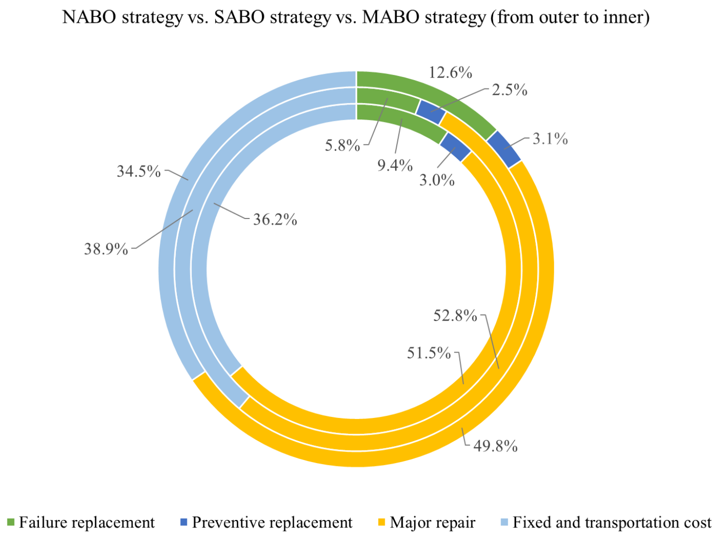

Figure 3.12: Comparison of maintenance cost percentage for different maintenance strategies

In Fig. 3.13, as the increase of percentage threshold ζ, the annual cost drops at first until the bottom, then gradually grows with slight fluctuation. The size of the wind farm is 50 turbines with 250 critical components. The range of percentage thresholds from 0.4% to 3.2% indicates the number threshold of aged components is from 1 to 8. When the number is 1, that means once one component is determined to be aged, the age-based opportunity will make the maintenance cycle start. The number is 2 means two or more than two aged components can trigger the maintenance. And so on, for each set of percentage threshold. At the threshold of 0.4%, the failure occurrence can be avoided as much as possible, but the frequency of maintenance is also the highest resulting from the easily triggered conditions. The frequent maintenance results in the highest total cost. Then, as the increase of threshold, the negative influence of maintenance frequency weakens, but component failure is more likely to occur, resulting in the costly repair. A balance considering these two factors is find out until the lowest point at 1.2%. Afterwards, the effect of failure occurrence becomes significant, causing the rise of annual cost.

Setting of the parameters of the environmental impact presents the harshness of the marine environment. In Fig. 3.14, it clearly shows that the annual cost rises as the increase of the probability of critical impact and influential impact. The value of P_k^C has the most significant influence. The higher probability results in more components have to be completely replaced, so the cost of failure replacement will increase obviously. The influential impact can only accelerate the degradation, so its effect is less significant.

As shown in Table 3.5, the opportunistic maintenance strategy is applied to the offshore wind farms with different number of turbines. When comparing MABO strategy with NABO strategy, for the small-scale farm, the results reveal that the cost saving is the most

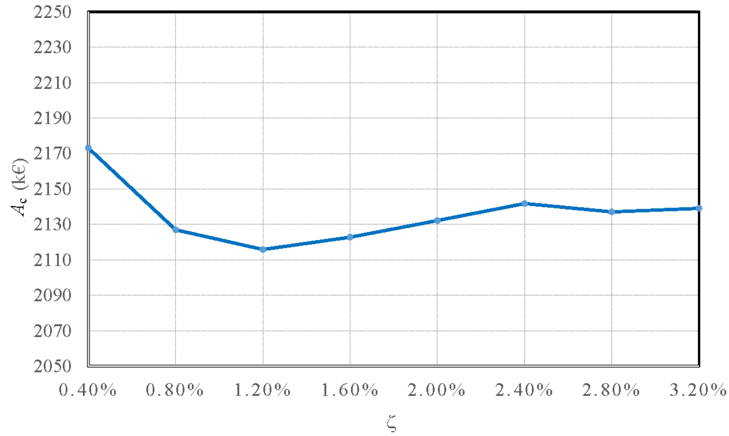

Figure 3.13: Annual cost with different percentage thresholds

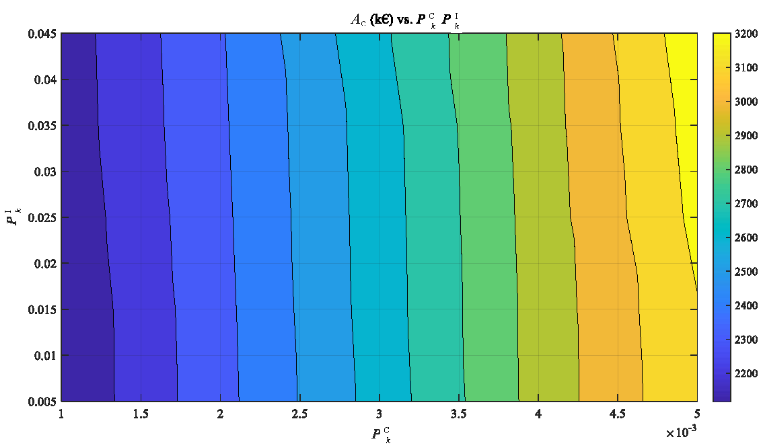

Figure 3.14: The effect of varying probability of impact on annual maintenance cost

significant, as high as 11.9%. However, as the expansion of farm the reduction of maintenance costs become less considerable. It is largely explained by the more occurrence of failure-based opportunities and incident-based opportunities with the increase of farm size. The number of failure and incidents is less for a small-scale farm. In this case, the age-based opportunity is more promising to trigger the preventive maintenance and avoid failure replacement, then save more money. When the farm gets larger with even 100 turbines, the failure because of degradation or environmental impact have provided a number of opportunities to start the maintenance cycles. The age-based opportunity could make the strategy perform better on this condition, but not as substantial as small-scale farm. When the size is small, the cost savings of SABO strategy and MABO strategy is the same, because the single component is the best option to trigger preventive dispatch. However, the execution of SABO strategy becomes more costly as the increase of the farm size, even exceeding the NABO strategy. More turbines mean the number of aged component is more, so the over frequent maintenance activities may result in much unnecessary costs. In summary, the MABO and SABO strategy can reduce maintenance costs for a small-scale offshore wind farm when compared with NABO strategy. As the increase of turbine number, the MABO strategy is still the best option, followed by NABO strategy and SABO strategy.

Table 3.5: The cost savings under different size of offshore wind farm

Farm size	NABO strategy (k€)	SABO strategy (k€)	MABO strategy (k€)	Cost savings (%)
10	463	408	408	11.9%/-
20	865	816	816	5.7%/-
50	2149	2173	2116	1.5%/2.6%
80	3574	3692	3507	1.9%/5%
100	4572	4731	4547	0.5%/3.9%

In Fig. 3.15, the number threshold of aged components, U, is changed under the MABO strategy when the size of wind farm is different. The annual cost of NABO strategy is seen as the comparison criterion, and the cost saving is presented by Q. When the threshold is only 1, the maintenance cost is minimized for the 10-turbine and 20-turbine farm. The preventive dispatch can significantly avoid the severe failure occurrence and high replacement costs. Furthermore, the case is also difficult to happen that more than 1 components reach the maximum age threshold at the same time for a small-scale farm. The more thresholds can only make the age-based opportunity happen more impossibly and the improvement weaken successively. When the number of turbines increase to 50, 80 and 100, the optimal number thresholds are obtained as 3, 5 and 7 respectively, showing that the optimal number of aged components increases as the wind farm enlarge.

3.4 Conclusions

In this chapter, a predictive opportunistic maintenance strategy for offshore wind farms is proposed, in order to answer the Research Question 2. The offshore wind turbines operating in the harsh marine environment do not only suffer from degradation, but also impact from environment. The failures due to ultimate degradation and critical impact will create maintenance opportunities, namely failure-based opportunity and incident-based opportunity. Another maintenance opportunity considering the number of aged components, age-based opportunity, is also considered to balance costly failure replacement and over frequent maintenance cycles. In these maintenance opportunities, wind turbine components are classified into failed, ages, mature, and young components according to the predicted failure times.

The proposed strategy is applied in a generic offshore wind farm to evaluate its performance. The comparative analysis shows the MABO and SABO strategies can both reduce about 11.9% cost than NABO strategy for a 10-turbine farm. When the scale of the farm enlarges, the MABO strategy still has the best performance. An economic benefit of 2.6%

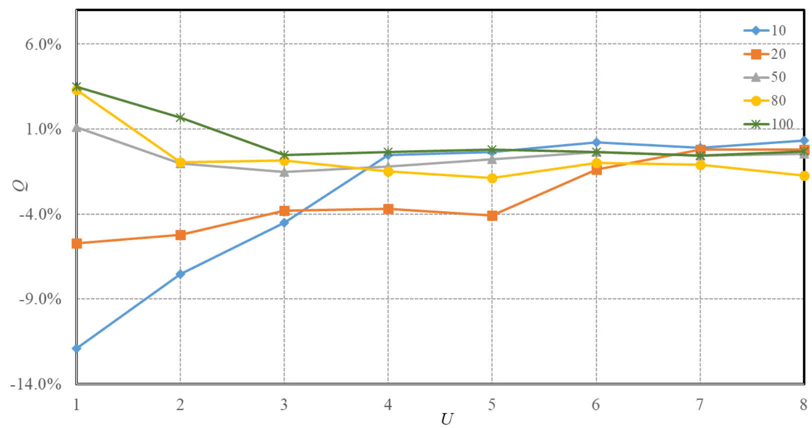

Figure 3.15: Strategy improvement under different size of offshore wind farm

and 1.5% respectively can be achieved for a 50-turbine farm when compared with SABO and NABO strategy. When the number of turbine increases to 100, MABO strategy saves 3.9% and 0.5% costs respectively in comparison to SABO strategy and NABO strategy.

In the model in this chapter, the model parameters are assumed to be accurately known in advance, which is not applicable in practice. It is necessary to identify the potential uncertainty existing in the model, and then quantify their influence on maintenance strategies and performance, which is addressed in Chapter 4.

Chapter 4

Influence of Uncertainty on Maintenance Strategies and Performance

In Chapter 3, a predictive opportunistic maintenance strategy is proposed to design a long-term maintenance strategy for offshore wind farms covering lifetime. However, the potential uncertainty in the model is not considered, but will be studied in this chapter. This chapter proposes a holistic framework to integrate maintenance strategy, decision-makers' objectives and uncertainty modelling, which is designed for a more realistic maintenance decision-making environment, aiming to quantify the impact that uncertainty has on maintenance performance and provide a series of maintenance strategies meeting decision-makers' different demands while considering uncertainties.

The remainder of this chapter is organized as follows. Section 4.1 introduces the background. In Section 4.2, the maintenance model is furthered developed based on the model in Chapter 3. In Section 4.3, the concerned uncertainties are characterized and modelled. The optimization method used to find the balanced solutions between multiple objectives is presented in Section 4.4. In Section 4.5, the proposed framework is applied in a generic offshore wind farm. The results and discussion are also presented. Section 4.6 concludes this chapter.

Parts of this chapter have been published in [105][1] and [103] [2].

4.1 Introduction

The optimization of maintenance strategy aims to provide decision-makers maintenance decisions to determine the necessary maintenance actions which should be performed on

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[1] M. Li, X. Jiang, J. Carroll, and R. R. Negenborn. A multi-objective maintenance strategy optimization framework for offshore wind farms considering uncertainty. *Applied Energy*, 321:119284, 2022.

[2] M. Li, X. Jiang, J. Carroll, and R. R. Negenborn. Influence of uncertainty on performance of opportunistic maintenance strategy for offshore wind farms. In *Proceedings of the OCEANS 2021*, pages 1–10, San Diego, USA, 2021.

the qualified components and turbine. The consideration of uncertainty in maintenance optimization is significant and challenging, but very few studies addressed this issue. As stated in Chapter 2, most of the existing research correlated to maintenance optimization is to build maintenance models in a deterministic scenario and perform optimization to purse a cost-effective solution.

However, the maintenance decision-making in reality is full of uncertainty. The determination of maintenance strategies relies on the development of maintenance model where various types of uncertainty are involved. For example, the exact values or distribution characteristics of input parameters are not deterministic due to insufficient information, but are assumed to be deterministic[34]. As another example, when the maintenance model is developed to explain real maintenance behaviours for offshore wind farms, the assumptions, simplifications, and generalizations involved make the maintenance model unable to accurately represent true characteristics [47]. The presence of uncertainty affects the estimation of maintenance performance along with the determination of maintenance strategy. In the context, the determined maintenance strategy may become sub-optimal and need adjustment. In addition, the maintenance objectives the decision-makers care about are often more than only maintenance costs. In reality, the decision-makers often focus on multiple maintenance objectives as opposed to a single objective such as minimum maintenance costs. The uncertainties have an impact on different maintenance goals, and the magnitude of the impact is likely to vary with the degree of uncertainty.

Therefore, to address the above issues, an integrated framework is proposed to quantify influence of uncertainties, incorporating i) a maintenance model which is applied to estimate maintenance performance, including maintenance costs and production losses, ii) a probabilistic uncertainty modelling approach which is used to characterize different types of uncertainty and a Monte Carlo method is adopted to generate stochastic scenarios, and iii) a multi-objective optimization method used to find the optimal decisions in the presence of conflict between multiple objectives.

4.2 Maintenance model

In this section, a mathematical model is proposed to formalize the maintenance model which is extended based on Chapter 3. In order to maintain the readability of the article and the continuity of research, the model will be briefly described and particular emphasis will be placed on the newly added elements. The purpose of the maintenance model is to evaluate the maintenance performance, including maintenance costs and production losses over the overall lifetime. The evaluation is then used in the optimization model to guide the search for the optimal solutions.

4.2.1 Maintenance opportunities and component condition

Suppose that an offshore wind farm consisting of K turbines, and each turbine is composed of I critical components. The failure time of component i at turbine k at yth decision point is predicted as $\widetilde{v}_{iky}$. According to the predicted failure time, the component condition is estimated by comparing its age u_{iky} with prediction result $\widetilde{v}_{iky}$.

In a maintenance cycle, the components are performed different types of maintenance on depending on their conditions. Four types of maintenance actions are considered: failure replacement, preventive replacement, major repair, and basic maintenance. The total number of maintenance cycles is S, and the arrival time of s-th maintenance cycle is T_s. After the s-th maintenance cycle, the age of component i at turbine k is u_{iks}. The maintenance action of mth level in the $(s+1)$-th maintenance cycle updates the component age as [88]

$$u_{ik(s+1)} = \theta_{l_m}(u_{iks} + T_{s+1} - T_s), \tag{4.1}$$

where $u_{ik(s+1)}$ is the new component age after repair; θ_{l_m} is maintenance quality for mth maintenance level. Failure replacement is performed on the failed components due to critical impact or degradation. Preventive replacement is preventively replacing the components which are aged. These aged components reaching threshold $A^{\max}$ are determined to be on the verge of failure and thus require preventive replacement ($m = 1$). Both failure replacement and preventive replacement reset the age of component to 0, which are regarded as perfect maintenance ($\theta_{l_m} = 0$).

In the maintenance cycle, the component below $A^{\min}$ is manually reset and checked with the capacity of ensuring the operation of components, such as lubricating, adjusting, tightening, and cleaning ($m = M$). This basic maintenance does not improve the state of the undertaken components, indicating the value of θ_{l_m} is 1 and the component age does not change after repair.

The components between these two thresholds $A^{\max}$ and $A^{\min}$ are determined as mature components. The entire range between $A^{\max}$ and $A^{\min}$ is uniformly divided into $(M-2)$ age groups. Component i at turbine k is performed the mth level of repair when the age falls into corresponding age groups [137]:

$$\tilde{v}_{iky}\left[A^{\max} - \frac{A^{\max} - A^{\min}}{M-2}(m-1)\right] \leq u_{iky} < \tilde{v}_{iky}\left[A^{\max} - \frac{A^{\max} - A^{\min}}{M-2}(m-2)\right], \tag{4.2}$$

where $m = 2, 3, \ldots, M-1$

4.2.2 Decision variables

There are three decision variables of the maintenance model: $A^{\max}$, $A^{\min}$, ζ. The variables $A^{\max}$ and $A^{\min}$ can be regarded as the criterion to determine whether a component is qualified for a specific type of repair. The number of different types of maintenance actions changes with the varying values of $A^{\max}$ and $A^{\min}$. In addition, the combination $A^{\max}$ and ζ determines the occurrence of ageing-based opportunity. Therefore, the decision vector is:

$$\vec{x} = [A^{\max}, A^{\min}, \zeta]. \tag{4.3}$$

4.2.3 Model output

Two kinds of output are concerned in the model. The first one is maintenance related cost, including the cost of the materials used for repair, mobilization cost, vessel costs and technician costs for the execution of maintenance tasks. In addition to maintenance related cost, another output is the production losses during the turbine downtime. Compared to the model in Chapter 3, the new output, production losses, is introduced, and the vessel costs and technician costs are used to replace the transportation cost. The introduction of these new elements further supplements the details of the model and better describes the consequences of wind farm maintenance.

The total cost of the materials used for repair C^{MAT} is obtained as follows:

$$C^{\mathrm{MAT}} = \sum_{s=1}^{S}\sum_{k=1}^{K}\sum_{i=1}^{I}\left(R_{iks}^{\mathrm{FR}}X_{iks}^{\mathrm{FR}} + R_{iks}^{\mathrm{PR}}X_{iks}^{\mathrm{PR}} + \sum_{m=2}^{,M-1} R_{iks}^{\mathrm{MAR}}X_{ikms}^{\mathrm{MAR}} + R_{iks}^{\mathrm{MIR}}X_{iks}^{\mathrm{MIR}}\right), \tag{4.4}$$

where R_{iks}^{FR}, R_{iks}^{PR}, R_{ikms}^{MAR} , and R_{iks}^{MIR} is the cost of failure replacement, preventive replacement, mth major repair, and basic maintenance of component i at turbine k in the sth maintenance cycle; X_{iks}^{FR}, X_{iks}^{PR}, X_{ikms}^{MAR}, X_{iks}^{MIR} determines whether the maintenance action is conducted. It is also the sum of (3.16), (3.17), (3.19), and the cost for basic repair.

Vessels are deployed to transport spare parts and technicians from shore to offshore sites. Considering the weight of the parts and maintenance requirements, different types of vessels are used for carry out maintenance. The replacement activities are implemented by using HLVs, because the lifting capacity of large equipment is necessary. A HLV is a kind of self-elevating barge with the capacity of raising its hull for heavy lifting and heavy component replacements [162]. A FSV is needed to perform major repair considering its capacity to transport heavy spare parts. For basic maintenance, a CTV is required to transport technicians and necessary tools.

In reality, maintenance service providers or asset owners usually own a number of specific vessels for O&M of offshore wind farms. When facing a high demand of vessels, service providers may also lease available vessels for a period of time from the market. Making purchasing/leasing decisions for vessels and optimizing fleet mix and size to support maintenance activities are usually regarded as tactical decisions in the O&M for wind energy. Further, the daily scheduling and routing of vessels is considered in the operational level. The tactical and operational decisions are not the concern of the paper. Here, the costs for vessels are approximately estimated according to daily cost rate of specific vessels and repair time of different maintenance categories. The total vessel cost is denoted by C^{VES} as follows:

$$C^{\mathrm{VES}} = \sum_{s=1}^{S}\sum_{k=1}^{K}\sum_{i=1}^{I}(N_{iks}^{\mathrm{FR}}X_{iks}^{\mathrm{FR}}Q^{\mathrm{J}} + N_{iks}^{\mathrm{PR}}X_{iks}^{\mathrm{PR}}Q^{\mathrm{J}} + N_{iks}^{\mathrm{MIR}}X_{iks}^{\mathrm{MIR}}Q^{\mathrm{C}} + \sum_{m=2}^{M-1} N_{ikms}^{\mathrm{MAR}}X_{ikms}^{\mathrm{MAR}}Q^{\mathrm{S}}), \tag{4.5}$$

where Q^{J}, Q^{S}, and Q^{C} is the daily cost of heavy-lift vessels, field support vessels, and CTVs respectively; N_{iks}^{FR}, N_{iks}^{PR}, N_{ikms}^{MAR}, and N_{iks}^{MIR} is repair time of failure replacement, preventive replacement, major repair and basic maintenance.

Similar to vessel costs, the technician costs is estimated according to the daily personnel rate, the repair time of different maintenance categories, and the number of technicians needed to execute a maintenance task. The total technician cost C^{TEC} is calculated as:

$$C^{\mathrm{TEC}} = T^{\mathrm{C}} \sum_{s=1}^{S} \sum_{k=1}^{K} \sum_{i=1}^{I} \left(\begin{array}{l} N_{iks}^{\mathrm{FR}} X_{iks}^{\mathrm{FR}} W^{\mathrm{FR}} + N_{iks}^{\mathrm{PR}} X_{iks}^{\mathrm{PR}} W^{\mathrm{PR}} + N_{iks}^{\mathrm{MIR}} X_{iks}^{\mathrm{MIR}} W^{\mathrm{MIR}} \\ + \sum_{m=2}^{M-1} N_{ikms}^{\mathrm{MAR}} X_{ikms}^{\mathrm{MAR}} W^{\mathrm{MAR}} \end{array} \right), \tag{4.6}$$

where T^{C} is daily personnel cost; W^{FR}, W^{PR}, $W^{\mathrm{MAR}}$and W^{MIR} is the number of required technicians of failure replacement, preventive replacement, major repair and basic maintenance.

When using HLVs to perform replacement, a large amount of cost is consumed to plan and prepare the marine operation before the vessel arrives at the wind farm, which is the mobilization cost. In each maintenance cycle, the mobilization cost of HLVs is only calculated for one time. The total mobilization cost C^{MOB} is:

$$C^{\mathrm{MOB}} = \sum_{s=1}^{S} M_s^{\mathrm{MOB}}. \tag{4.7}$$

The downtime is mainly caused by turbine failure and maintenance execution. Once a failure occurs in the farm, the failed turbine stops operating until it is recovered in the upcoming maintenance cycle. The running turbines are required to stop operating during the maintenance execution, resulting in the production losses. Each turbine is assumed to be subject to one maintenance activity at the same time. The failure time of the component i at turbine k failing between $(s-1)$th and sth maintenance cycle is denoted by F_{iks^-}. Because the offshore wind turbine is a series system, the failure of one component makes the turbine stop operating immediately. The failure time of the located turbine is represented by $F_{ks^-}^{\mathrm{T}}$. The total downtime thus can be calculated as

$$N^{\mathrm{T}} = \sum_{s=1}^{S} \sum_{k=1}^{K} (T_s - F_{ks^-}^{\mathrm{T}}) + \sum_{s=1}^{S} \sum_{k=1}^{K} \sum_{i=1}^{I} \left(\begin{array}{l} N_{iks}^{\mathrm{FR}} X_{iks}^{\mathrm{FR}} + N_{iks}^{\mathrm{PR}} X_{iks}^{\mathrm{PR}} + N_{iks}^{\mathrm{MIR}} X_{iks}^{\mathrm{MIR}} \\ + \sum_{m=2}^{M-1} N_{ikms}^{\mathrm{MAR}} X_{ikms}^{\mathrm{MAR}} \end{array} \right). \tag{4.8}$$

The production loss is evaluated based on the wind speed data and the design parameters of the wind turbine, The wind turbine is designed to have a cut-in wind speed (w_{in}), a rated wind speed w_{rated}, and a cut-out wind speed (w_{out}). When the wind speed is too low, wind speed is not strong enough to make wind turbine operate. As the wind speed increases to w_{in}, the turbine starts to generate electricity by rotating blades. When the wind speed reaches the range between w_{rated} and w_{out}, the turbine operates in a rated capacity (P_{rated}). Once the turbine suffers from a wind speed higher than w_{out}, it shuts shown to avoid the potential damage and risk. The detailed relationship between wind speed (w_t) and turbine capacity (P_{kt}^{w}) is [63]:

$$P_{kt}^{\mathrm{w}} = \begin{cases} 0, & 0 \leq w_t < w_{\mathrm{in}} \\ P_{\mathrm{rated}}(a + bw_t + cw_t^2), & w_{\mathrm{in}} \leq w_t < w_{\mathrm{rated}} \\ P_{\mathrm{rated}}, & w_{\mathrm{rated}} \leq w_t < w_{\mathrm{out}} \\ 0, & w_{\mathrm{out}} \leq w_t \end{cases} \tag{4.9}$$

where parameters a, b, and c are obtained as:

$$a = \frac{w_{\text{in}}}{(w_{\text{in}} - w_{\text{rated}})^2} \left[(w_{\text{in}} + w_{\text{rated}}) - 4w_{\text{rated}} \left(\frac{w_{\text{in}} + w_{\text{rated}}}{2w_{\text{rated}}} \right)^3 \right], \tag{4.10}$$

$$b = \frac{1}{(w_{\text{in}} - w_{\text{rated}})^2} \left[4(w_{\text{in}} + w_{\text{rated}}) \left(\frac{w_{\text{in}} + w_{\text{rated}}}{2w_{\text{rated}}} \right)^3 - (3w_{\text{in}} + w_{\text{rated}}) \right], \tag{4.11}$$

$$c = \frac{1}{(w_{\text{in}} - w_{\text{rated}})^2} \left[2 - 4 \left(\frac{w_{\text{in}} + w_{\text{rated}}}{2w_{\text{rated}}} \right)^3 \right]. \tag{4.12}$$

The offshore wind farms is designed with a L-year lifetime. During the overall lifetime, the total costs related to maintenance efforts is denoted by C^{T} which is estimated based on (4.4)-(4.7), and the total production losses in the downtime is denoted by P^{T} which is estimated based on (4.8)-(4.12).

4.2.4 Constraints

The constraints of the model are shown as follows:

$$X_{iks}^{\text{FR}}, X_{iks}^{\text{PR}}, X_{ikms}^{\text{MAR}}, X_{iks}^{\text{MIR}} \in \{0,1\} \qquad \forall i \in I, \forall k \in K, \forall m \in M, \forall s \in S \tag{4.13}$$

$$0 < A^{\min} < A^{\max} < 1 \tag{4.14}$$

$$KI\zeta \in \mathbb{Z}^{+} \tag{4.15}$$

$$F_{ks^-}^{\text{T}} = \min\{F_{iks^-}\} \qquad \forall i \in I, \forall k \in K, \forall s \tag{4.16}$$

In (4.13), the intermediate binary variables indicate whether the different type of maintenance action is performed on component i at turbine k in the s-th maintenance cycle. Constraint (4.14) determines the decision variable triggering preventive replacement is higher than the decision variable triggering major repair. Constraint (4.15) determines the threshold of the number of aged components in the farm must be a positive integer. Constraint (4.16) determines the date of turbine breakdown. Once a component fails, the entire turbine consequently stops working.

4.3 Uncertainty modelling

The maintenance model in Section 4.2 illustrates the maintenance strategy which is designed in a deterministic scenario. In this section, three types of uncertainty are characterized and modelled by using a probabilistic method. Given the probability distribution, the Monte Carlo method is adopted to generate stochastic values.

4.3.1 Statistical uncertainty of component reliability

The failure rate of components is usually described as a shape of bathtub curve throughout the lifetime. Although the failure rate is not constant, the available maintenance models mostly rely on the simplification of assuming it is constant. This model makes the same simplification. In order to model the degradation process and generate the failure events of each component, it is common to select and input a specific lifetime distribution and its parameter values which are estimated based on mean time to failure [122]. The lifetime distribution and parameters are typically assumed to be known accurately in the conventional maintenance models.

However, the estimates of lifetime distributions and parameters is very likely to be inaccurate in practice. The reasons include the incompatible vendor guidelines due to lack of knowledge of actual use and repair, and unreliable collected maintenance records and historic failure data for years [35]. Given the same value of MTTF, the mean value of the distribution function estimating the probability of a failure occurrence corresponds to the MTTF, but the shape of different distribution and parameters results in different failure probabilities in certain intervals. In other words, the observations of failure data may not follow a clear pattern, then failure of components can be modelled in various lifetime distributions and parameters generating different failure behaviour of components, and consequently affect the model output [34]. This is a type of uncertainty in the lifetime distribution function and parameters under the same MTTF, which decision-makers are confronted with when designing the maintenance strategy.

Weibull, Exponential, Uniform, and Normal distributions are selected as the examples. As shown in Fig. 4.1, various lifetime distribution functions have the same value of MTTF (2679 days). It means the simulated failure events occur every 2679 days on average, but failure characteristic follows different pattern. Even though it is assumed that the distribution function is certainly known, such as Weibull distribution, the varying shape parameter in the range of [2.5, 3.5] still lead to different dispersion.

Decision-makers need to input the lifetime distribution functions and parameters into the maintenance model to model degradation process of components and randomly reproduce the time to failure. The occurrence of maintenance opportunities depends on failure and condition of components in the offshore wind farm. The uncertainty of distribution functions and parameters may result in different model performance, and then influence decision-making.

4.3.2 Uncertain performance of component lifetime prediction

When a maintenance cycle is triggered, the number of components and turbines which are repaired or replaced is determined by comparing the component condition with maintenance thresholds. Because the real failure times of component is unknown in advance, remaining useful life (RUL) prediction technology is employed to make predictions which are regarded as the important decision basis to plan maintenance actions.

Diagnostic signals including vibration, acoustic emission, strain, torque, temperature, lubrication oil parameter, supervisory control and data acquisition (SCADA) system signals are provided by the sensors installed on critical components [126]. By analysing the signals, RUL prediction technology can provide information with respect to the time when the fail-

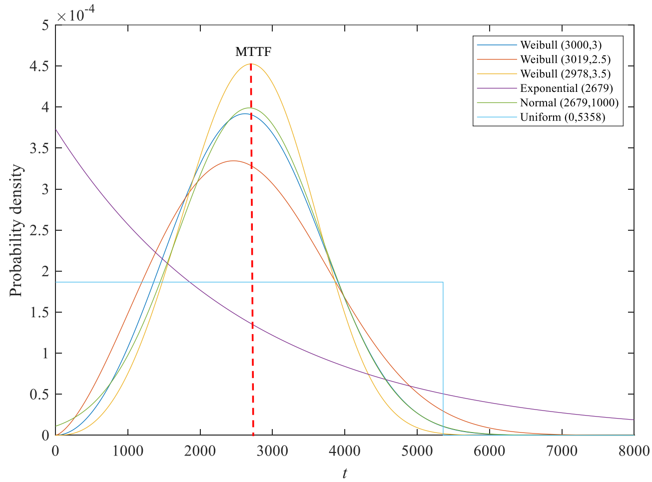


Figure 4.1: Probability density of various lifetime distribution and parameter

ure will occur. RUL prediction methods are basically classified into model-based methods and data-driven methods. Model-based methods use the knowledge of failure mechanisms to describe the system degradation process in a mathematical way. The operational data is collected to update the model parameters [93]. Data-driven methods use history data to derive the degradation process or match with history patterns to infer RUL [21].

These research mainly focuses on increasing the accuracy of prediction to provide more reliable information for the maintenance decisions. It would be ideal if the actual failure times can be accurately forecast, but the error between predicted and real failure times is inevitable. The inaccurate prediction indicates the component is maintained earlier or later than ideal timing, which is another type of uncertainty in the model.

The age of component i at turbine k at yth decision point is denoted by u_{iky}. At the decision point, RUL prediction is performed to obtain the predicted failure age by analysing condition information of component. The predicted failure age is represented by $\widetilde{v}_{iky}$. and the predicted RUL percentage $\widetilde{P}_{iky}$ is obtained as $(\widetilde{v}_{iky} - u_{iky})/\widetilde{v}_{iky}$. The real failure age of the component is represented by v_{iky}, and the real RUL percentage P_{iky} is represented by $(v_{iky} - u_{iky})/v_{iky}$.

In order to quantify the prediction performance, an indicator called average prediction error is usually used to evaluate the average prediction accuracy. If the total number of inspection during the lifetime is Y, average prediction error $\bar{e}$ is calculated as [159]:

$$\bar{e} = \frac{1}{Y} \sum_{y=1}^{Y} \left| P_{iky} - \tilde{P}_{iky} \right|. \tag{4.17}$$

Th average prediction error is not constant during the lifetime of component. As the component gradually degrades, the component age is close to the failure age. The prediction results become more accurate as the component gets closer to failure [131]. The error

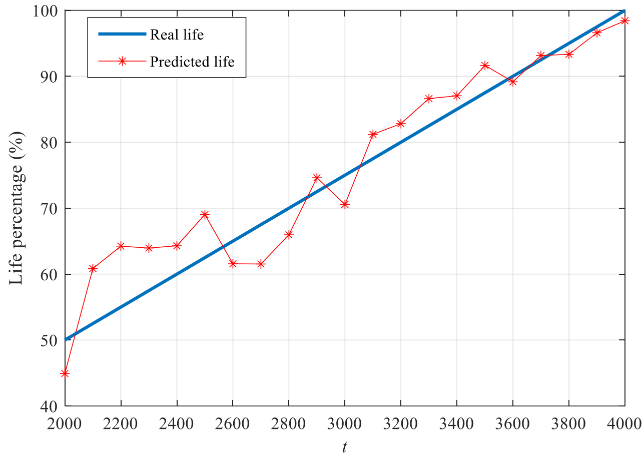


Figure 4.2: Simulated deviation between real and predicted component life

between real RUL percentage P_{iky} and predicted RUL percentage $\widetilde{P}_{iky}$ is denoted by e_{iky}, which is assumed to follow a Normal distribution:

$$e_{iky} = \left| P_{iky} - \widetilde{P}_{iky} \right| \sim N(\mu_{iky}^{\mathrm{R}}, {\delta_{iky}^{\mathrm{R}}}^2), \tag{4.18}$$

where μ_{iky}^{R} is expected value and $\delta_{iky}^{\mathrm{R}}$ is standard deviation. With the decrease of RUL, the prediction accuracy increases, meaning the error e_{iky} gradually becomes lower. Thus the magnitude of error is positively correlated with the RUL. Suppose that $\mu_{iky}^{\mathrm{R}} = \mu_{\mathrm{a}} + a_{\mathrm{p}} P_{iky}$ and $\delta_{iky}^{\mathrm{R}} = \delta_{\mathrm{a}} + a_{\mathrm{s}} P_{iky}$. Parameter μ_{a} and δ_{a} indicates the error always exists no matter how close the component is to fail. Positive parameters a_{s} and a_{p} depicts that the error increases with the increase of RUL. Hence the deviation between predicted and real failure times is presented in this way, as shown in Fig. 4.2, thereby simulating the situation where the maintenance decision is not ideal due to the prediction error.

4.3.3 Ambiguous estimation of maintenance consequences

After performing a maintenance action on the component, there is a corresponding cost and time consumed while the condition of the component is improved, which can be considered as the consequences of the maintenance action. The maintenance action is usually assumed to restore the state of component back to perfect, recover the stage with a certain degree, or not change the component age. However, the quality of maintenance is closely related to repairman's expertise, working environment, maintenance tools, etc., meaning the real value of maintenance quality varies from the expected maintenance effect. Meanwhile, the cost of the materials used for repair and the time spent on performing maintenance actions are closely related to maintenance quality, which are uncertain as well. The uncertain maintenance consequences is the third type of uncertainty concerned in the work.

Considering the consequences of replacement and basic repair are stable, the model mainly focuses on uncertainty relevant to major repair. The quality of major repair is often assumed as a fixed value in many studies of wind energy maintenance [43], indicating the major repair can successfully reduce the component age as expected. This assumption may disagree with the real-world maintenance situations. The real maintenance quality can not be specified precisely as a fixed value. It is more reasonable and realistic to model it as a variable which is close to an expected value but is uncertain. The value of maintenance quality is between 0 and 1, because major repair can recover the component to an intermediate state between as good as new and as bad as old. In probability theory and statistics, the beta distribution has been applied to model the behaviour of random variables limited to interval [0,1]. It is assumed that the random maintenance quality θ_{l_m} of mth maintenance level follows a beta distribution. The probability density function is:

$$f^{\mathrm{p}}(\theta_{l_m}) = \frac{\Gamma(\alpha^{\mathrm{r}}_m + \beta^{\mathrm{r}}_m)}{\Gamma(\alpha^{\mathrm{r}}_m)\Gamma(\beta^{\mathrm{r}}_m)} \theta_{l_m}^{\alpha^{\mathrm{r}}_m - 1} (1 - \theta_{l_m})^{\beta^{\mathrm{r}}_m - 1}, \tag{4.19}$$

where α^{r}_m and β^{r}_m are two positive shape parameters.

The expected value $\mu^{\mathrm{r}}_{\theta_{l_m}}$ and the standard deviation $\sigma^{\mathrm{r}}_{\theta_{l_m}}$ are:

$$\mu^{\mathrm{r}}_{\theta_{l_m}} = \frac{1}{1 + \frac{\beta^{\mathrm{r}}_m}{\alpha^{\mathrm{r}}_m}}. \tag{4.20}$$

$$\sigma^{\mathrm{r}}_{\theta_{l_m}} = \left(\frac{\alpha^{\mathrm{r}}_m \beta^{\mathrm{r}}_m}{(\alpha^{\mathrm{r}}_m + \beta^{\mathrm{r}}_m)^2 (1 + \alpha^{\mathrm{r}}_m + \beta^{\mathrm{r}}_m)} \right)^{\frac{1}{2}}. \tag{4.21}$$

The value of $\mu^{\mathrm{r}}_{\theta_{l_m}}$ is the age percentage which the component age is expected to reduce to. The value of $\sigma^{\mathrm{r}}_{\theta_{l_m}}$ characterises the instability of the maintenance quality. A higher standard deviation indicates the value of maintenance quality fluctuates in a larger range, as shown in Fig. 4.3.

The maintenance quality usually improves if more budget and time are allocated. In other words, the maintenance quality is positively correlated with the money and time spent on maintenance. The relationship between maintenance quality and cost is shown as [115, 123]:

$$R^{\mathrm{MAR}}_{ikms} = R^{\mathrm{PR}}_{iks} (1 - \theta_{l_m})^{\eta_{\mathrm{c}}}, \tag{4.22}$$

where R^{MAR}_{ikms} is the cost of mth level major repair of component i at turbine k in the s-th maintenance cycle; η_{c} is the coefficient determining the relationship between maintenance quality and corresponding repair cost.

Similarly, the relationship between maintenance quality and time is shown as [115, 123]:

$$N^{\mathrm{MAR}}_{ikms} = N^{\mathrm{PR}}_{iks} (1 - \theta_{l_m})^{\eta_{\mathrm{t}}}, \tag{4.23}$$

where N^{MAR}_{ikms} is repair time of mth level major repair of component i at turbine k in the sth maintenance cycle; η_{t} is the coefficient determining the relationship between maintenance quality and corresponding repair time.

(4.22) and (4.23) estimate the amount of cost and time invested in maintenance actions. The coefficients η_c and η_t influence how much more cost and time are needed with the

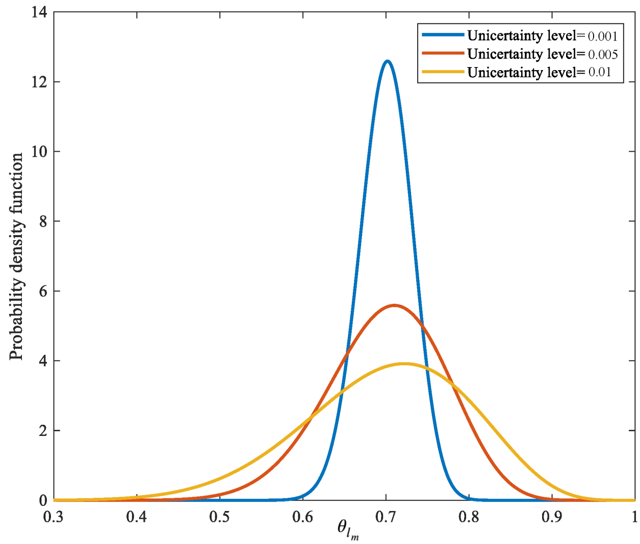


Figure 4.3: Maintenance quality under different uncertainty level

increase of maintenance quality. In other words, larger η_c and η_t means a more efficient maintenance action with less cost and time [115]. However, if these parameters are set as constant, the cost and time invested must be the same as long as the same quality of maintenance is achieved, which may not be realistic. Furthermore, the value of η_c and η_t are not explicit enough considering quality and quantity of historical maintenance record in wind industry is still insufficient. Instead of a fixed value, the coefficients η_c and η_t are assumed to be random values following a Normal distribution. Therefore, the coefficient η_c is represented as $\eta_c \sim N(\mu_c, \delta_c^2)$ and the coefficient η_t is represented as $\eta_t \sim N(\mu_t, \delta_t^2)$.

4.4 Multi-objective optimization method

The section illustrates the process of searching for the optimal solutions among the universe of possible options, that is, the optimization problem needs to be solved. The two objectives of the optimization problem are identified as minimizing annual maintenance costs A_c and minimizing annual production losses A_p, which are shown in the following form:

$$\min \qquad A_c(A^{\max}, A^{\min}, \zeta) = \frac{C^T}{L} \tag{4.24}$$

$$\min \qquad A_p(A^{\max}, A^{\min}, \zeta) = \frac{P^T}{L} \tag{4.25}$$

It is very difficult or even impossible to find an optimal solution to satisfy multiple objectives simultaneously, especially when these objectives may be conflicting. In order to obtain solutions which are appropriate from different perspectives, a multi-objective optimization method is used to provide decision-makers with a better position to make maintenance decisions.

The multi-objective optimization methods can be broadly categorized into: scalarization approaches and Pareto approaches [19]. Scalarization approaches are to translate a multi-objective optimization problem into a single or a series of single objective optimization problems. The typical scalarization approaches include weighted sum approach, ε-Constraint Method, etc. Pareto approaches aim to generate a set of Pareto optimal solutions for decision-makers to choose from.

Non-dominated Sorting Genetic Algorithm-II (NSGA-II) method, a kind of Pareto approach, has been one of the most popular multi-objective optimization methods and widely used in many real-world applications [118]. NSGA-II was proposed by [38]. As an improved version of NSGA, NSGA-II has the advantages including a fast non-dominated sorting approach which reduces high computational complexity, a crowding distance technique which provides diversity in solution, and an elitist-preserving approach retaining the current optimal solution to the next generation. Considering its fast running speed and good convergence of the solution set, it is selected as the multi-objective optimization method solving the model. More detailed description of the algorithm can be found in [38].

The proposed framework of optimizing maintenance strategy considering uncertainty is shown in Fig. 4.4, and the main steps are listed as follows:

Step 1: Initialize the necessary parameters for maintenance model, uncertainty model, and NSGA-II optimization method.

Step 2: The fist population containing Υ individuals are generated from the initial population after non-dominated sorting, selection, crossover, and mutation.

Step 3: Perform selection, crossover, and mutation to create the offspring population based on the first generation. The parent and offspring populations are merged as an intermediate population,

Step 4: Each individual containing decision variables is input into the maintenance model. In order to obtain reliable and stable results, the simulation of maintenance model is run for Θ times.

Step 5: In each simulation, the deterministic parameters are modelled by using a probabilistic method in the uncertainty model. The uncertainty scenarios are generated randomly by Monte Carlo method.

Step 6: The model outputs including annual maintenance cost A_{c} and annual production loss A_{p} is calculated in each simulation. After running the simulation for Θ times, the average results are calculated to represent the values of objective functions under a specific set of decision variables.

Step 7: Carry out fast non-dominated sorting and virtual crowding distance calculation for the merged population. The implementation of fast non-dominated sorting is based on the maintenance cost and production loss of individual, which is estimated in Step 6. The crowding-distance computation requires sorting the population according to each objective function value. The overall crowding-distance value is calculated based on the distance information of individual variables in the variable space.

Step 8: The new individuals are selected as the next generation according to fast non-dominated sorting and virtual crowding distance.

Step 9: The stopping criterion is checked. If the maximum generation is not reached, the population is updated with the new individuals. The updated population is expected to perform better than the previous generations. The new population undergoes the evolution process and is input to the maintenance model again. The number of generation increases until the maximum generation Ω.

Step 10: A set of non-dominated solutions is returned in the final step, which is regarded as the optimal solutions considering uncertainty.

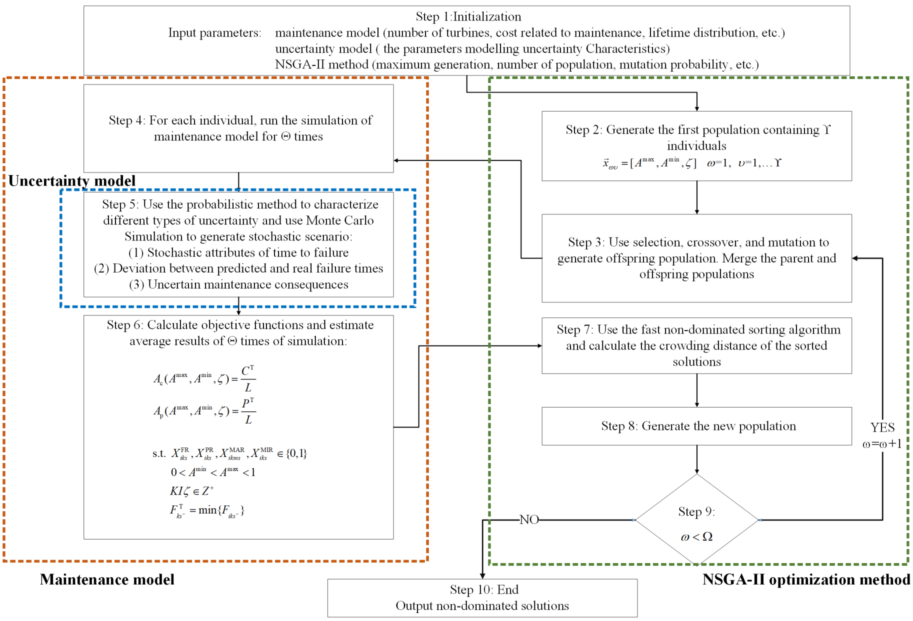


Figure 4.4: Flowchart of the proposed multi-objective optimization framework of maintenance strategy considering uncertainty

4.5 Case study

4.5.1 Scenario set-up

The case study is expanded based on the case in Section 3.3.1. The parameters related to wind speed, vessels and technicians, uncertainty modelling are added. The input data for wind speed in the simulation is taken from the Royal Netherlands Meteorological Institute (KNMI). The generation of daily wind speed data is based on the 34-year from 1979 to 2012 [170]. The graph illustration of the wind data and turbine design parameter is provided in Fig. 4.5. The parameters of vessel and technician are derived from [44, 91], as listed in Table 4.1. The repair time of failure replacement, preventive replacement, and basic repair is 70h, 50h, and 6h [91].

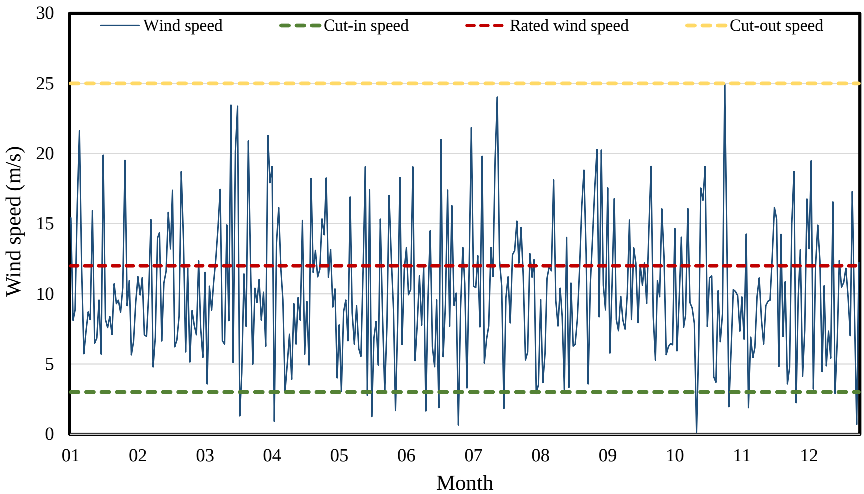


Figure 4.5: Wind speed and turbine design parameter

Table 4.1: Parameters of required vessels

Vessel type	CTV	Field support vessel	Heavy-Lift vessel
Mobilization cost (k€)	0	0	57
Daily vessel cost (k€)	8	18	50
Required technician	2	4	6-8
Daily technician cost (k€)		0.6	
Working shift (hours)		12 hours	

4.5.2 Optimization results disregarding uncertainty

In this section, the maintenance strategy is optimized disregarding the uncertainties. The deterministic input parameters have been provided in the Section 4.5.1. Table 4.2 reports the parameter settings for the NSGA-II algorithm used to obtain optimal solutions. The algorithm is configured with a population size of 60 individuals and a maximum number of 50 generations. The algorithm is implemented in Matlab® employed, using a computer equipped with 32 Intel Xeon Gold 5218 CPU 2.3GHz and 192 GB of memory. By implementing parallel computing, the time consumption is about 21 hours.

Fig. 4.6 represents the populations and Pareto front obtained in selected generation. Fig. 4.6(a) illustrates the convergence plot of populations versus the number of generations. The populations gradually converge with the increase of generation. A generation refers to a single iteration of the algorithm's main loop. Each generation consists of a set of individuals that are evaluated based on their performance on multiple objective functions. The figure indicates the front has converged well at the 50th generation, indicating the solutions on the front can be accepted as optimal solutions.

All the non-dominated solutions at the 50th generation are shown in Fig. 4.6(b). A se-

Table 4.2: Configuration of NSGA-II algorithm

NSGA-II parameter	Parameter value (type)
Maximum generation	50
Population size	60
Mutation operator	Gaussian mutation
Crossover operator	Intermediate crossover
Mutation probability	0.17
Crossover probability	0.67

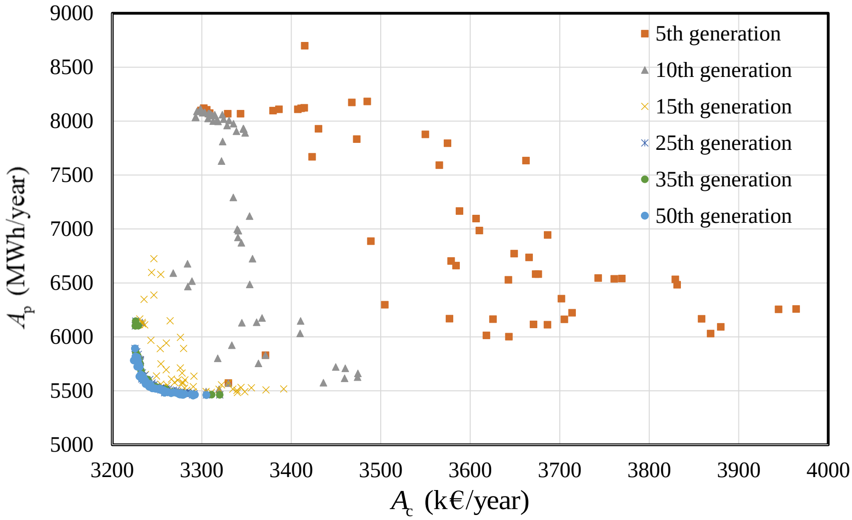
ries of solutions are found when approaching the multi-objective optimization, addressing trade-offs among values of the objective functions. These solutions are non-dominated to each other, but dominate the rest of solutions. It is found that these two objectives do not completely conflict. In other words, the decrease of one objective function does not necessarily cause the increase of another objective function. The range of annual cost is from 3.22×10^3k€ to 3.29×10^3k€, and the annual production loss is in the range of 5.46×10^3MWh to 5.78×10^3MWh. These solutions are helpful for decision-makers to select a feasible solution so as to satisfy their preferences and requirements. Three representative solutions are highlighted on the front, namely a maintenance cost priority solution, a production loss priority solution, and a compromise solution. The decision instructions based on different solutions are discussed in Section 4.5.3 and Section 4.5.4.

4.5.3 Influence of uncertainty

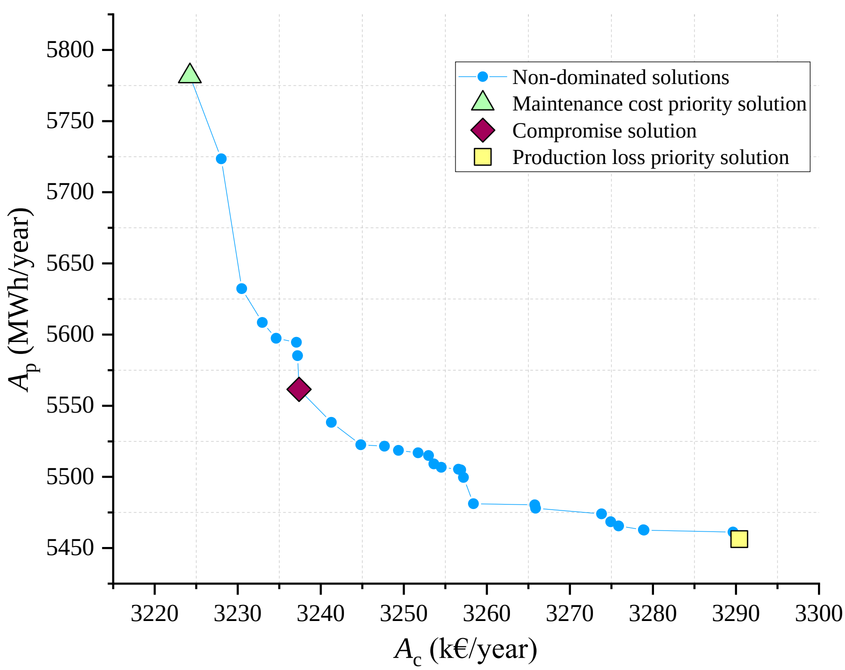
The three solutions marked in Fig. 4.6(b) represent the different preferences of the decision-maker. The solutions from cost priority to production priority are named as Solution 1-3, which are considered as the benchmark.

In Table 4.3, the cases are listed to represent different types of uncertainty. From Case 1-1 to 1-4, the shape parameter σ gradually rises from 2 to 3, and Case 1-3 represent the value of σ is uniformly distributed in the range of [2,3]. Case 1-5 to 1-7 show the Uniform and Normal distribution. Cases from 2-1 to 2-6 generally represent the increasing error between real and predicted failure time. Case 3-1 to 3-3, the uncertain maintenance quality is mainly concerned about, and Case 3-4 to 3-6 focus on the uncertain repair cost and time.

Fig. 4.7, Fig. 4.8, and Fig. 4.10 illustrate how the maintenance performance changes under different cases. Although minimum maintenance cost and minimum production loss are two different objectives, Fig. 4.6(b) has shown the conflict between the two goals is not serious, so the non-dominated solutions are located in a relatively small range. This results in the trend of Solution 1-3 changes similarly. In Fig. 4.7, from Cases 1-1 to 1-4, the values of A_c and A_p both tend downwards with the increase of shape parameter. In Weibull distribution, the shape with a higher shape parameters is more concentrated around the value of MTTF (shown in Fig. 4.1). In addition, the increase of standard deviation of Case 1-6 and 1-7 induces the increase of A_c and A_p. That reveals that when lifetime is modelled by using the distribution where the values tend to stay within a narrow range around MTTF, the model outputs are lower. It gives an explanation of the lower results when using the Weibull distribution with higher shape parameter and the Normal distribution with less standard deviation as the input. Moreover, when using Normal distribution and Uniform distribution,



(a)



(b)

Figure 4.6: Optimization results disregarding uncertainty: (a) Convergence of populations. (b) Non-dominated solutions at 50th generation

Table 4.3: Cases representing different types of uncertainty

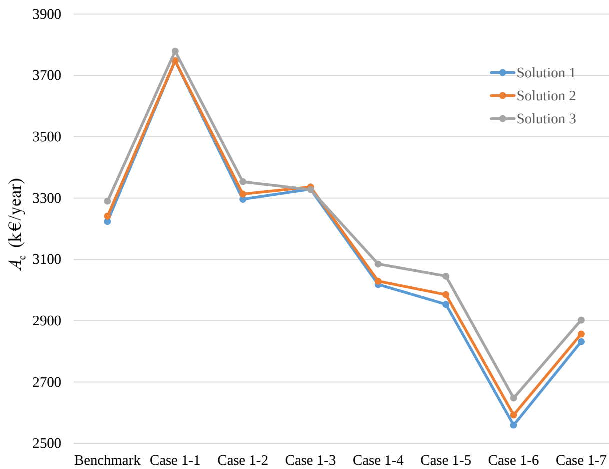
Case	Lifetime distribution and parameter	Case	Prediction error	Case	Maintenance consequences
1-1	Weibull (σ=2,$\varepsilon = \frac{\text{MTTF}}{\Gamma(1+\frac{1}{\sigma})}$)	2-1	μ_{a}, δ_{a} = 0.005, a_{s}, a_{p}=0.05	3-1	Quality ($\sigma_{\theta_{l_m}}$=0.001)
1-2	Weibull (σ=2.5, $\varepsilon = \frac{\text{MTTF}}{\Gamma(1+\frac{1}{\sigma})}$)	2-2	μ_{a}, δ_{a}=0.005, a_{s}, a_{p}=0.1	3-2	Quality ($\sigma_{\theta_{l_m}}$=0.005)
1-3	Weibull ($2 \leq \sigma \leq 3$, $\varepsilon = \frac{\text{MTTF}}{\Gamma(1+\frac{1}{\sigma})}$)	2-3	μ_{a}, δ_{a}=0.01, a_{s}, a_{p}=0.1	3-3	Quality ($\sigma_{\theta_{l_m}}$=0.01)
1-4	Weibull (σ=3, $\varepsilon = \frac{\text{MTTF}}{\Gamma(1+\frac{1}{\sigma})}$)	2-4	μ_{a}, δ_{a}=0.015, a_{s}, a_{p}=0.1	3-4	Cost and time (η_{c}, $\eta_{\text{t}} \sim N(2,0.1^2)$)
1-5	Uniform ($\frac{1}{2}$MTTF, $\frac{3}{2}$MTTF)	2-5	μ_{a}, δ_{a}=0.01, a_{s}, a_{p}=0.15	3-5	Cost and time (η_{c}, $\eta_{\text{t}} \sim N(2,0.3^2)$)
1-6	Normal (MTTF, 500^2)	2-6	μ_{a}. δ_{a}=0.015, a_{s}, a_{p}=0.15	3-6	Cost and time (η_{c}, $\eta_{\text{t}} \sim N(2,0.5^2)$)
1-7	Normal (MTTF, 700^2)				

the outputs are both lower than benchmark which uses Weibull distribution. This result is generally consistent with the findings in the [138].

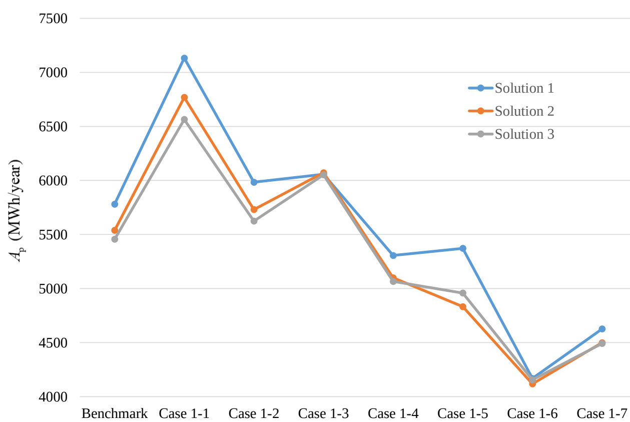
Fig. 4.8(a) illustrates the influence of prediction error on the maintenance cost. The values of A_{c} shows a growing trend when the deviation between real and predicted lifetime increases. Furthermore, the performance gap (A_{c}) between different solutions gradually widens, indicating the uncertainty strengthens the priority of the solutions. Solution 1 is the maintenance cost priority solution, and it always retain the lowest cost in the cases. However, this trend is not applicable in the aspect of production loss. As shown in Fig. 4.8(b), Solution 3 is the production loss priority solution with the lowest value of A_{p}. As the prediction error rises, Solution 3 gradually becomes the worst solution compared to Solution 1 and 2. Unlike maintenance cost, the performance gap of solutions in the aspect of production loss is reduced, even to the point where the priority solution becomes the worst solution.

The deviation between real value and prediction can be evaluated by using the average prediction error $\bar{e}$. The symbol $\widetilde{E}$ is used to denote the deviation percentage between results of cases and benchmark. Fig. 4.9 represent how the maintenance performance of solutions changes with the increase of average prediction error. It is found that as accuracy of prediction decreases (average prediction error grows), the deviation between output and benchmark increase at a growing rate. Furthermore, in comparison with maintenance cost, the production loss of solutions is more sensitive to prediction error because its greater tendency to rise. These results can provide a basis for estimating the benefits of improved accuracy of fault prognosis techniques

In Fig. 4.10, the benchmark represents the scenario where the maintenance actions can recover the component age with a fixed value as expectation. The relationship between maintenance quality, cost, and time is explicit, indicating the consumption according to maintenance effect can be accurately estimated. The maintenance quality becomes more unstable from Case 3-1 to 3-3 without considering the uncertain repair cost and time, then the values of A_{c} and A_{p} go up. In practice, the effect of maintenance actions is always



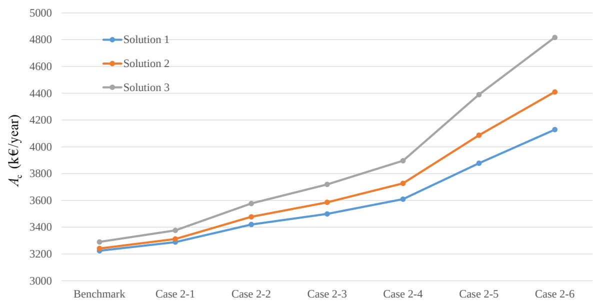
(a)



(b)

Figure 4.7: Comparison of Cases 1-1 to 1-7: (a) Maintenance cost (b) Production loss

stochastic, worse or better than the expectation. In order to reduce the consumption during maintenance activities, a suggestion is provided by enhancing the technicians' expertise, improving the maintenance conditions, and using more effective maintenance tools to ensure a more stable maintenance quality. Case 3-4 to 3-6 depict a growing uncertainty in the maintenance cost and time, representing a more ambiguous estimate of the maintenance resources expended to support the implementation of maintenance activity. Due to the functional relationship between maintenance cost and time and quality, this uncertainty can lead to an increase in maintenance consumption which can not be ignored. Compared to the benchmark, the increase of A_c and A_p is notable, and this change is certain to impact the potential decision-making.



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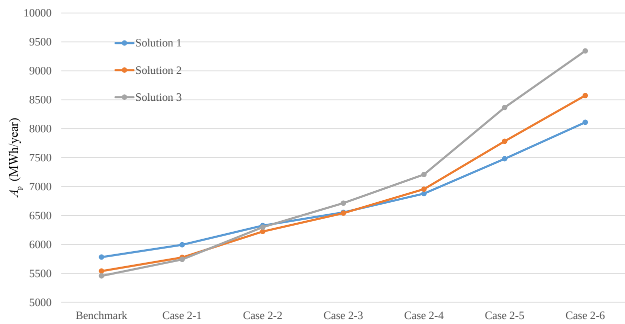


(b)

Figure 4.8: Comparison of Cases 2-1 to 2-6: (a) Maintenance cost. (b) Production loss

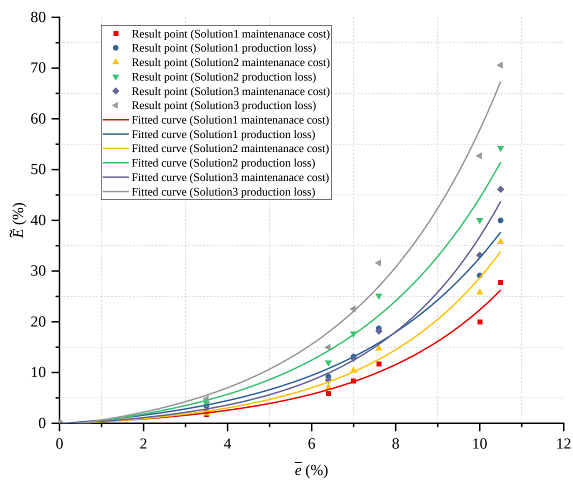


Figure 4.9: Average prediction error $\bar{e}$ versus maintenance performance

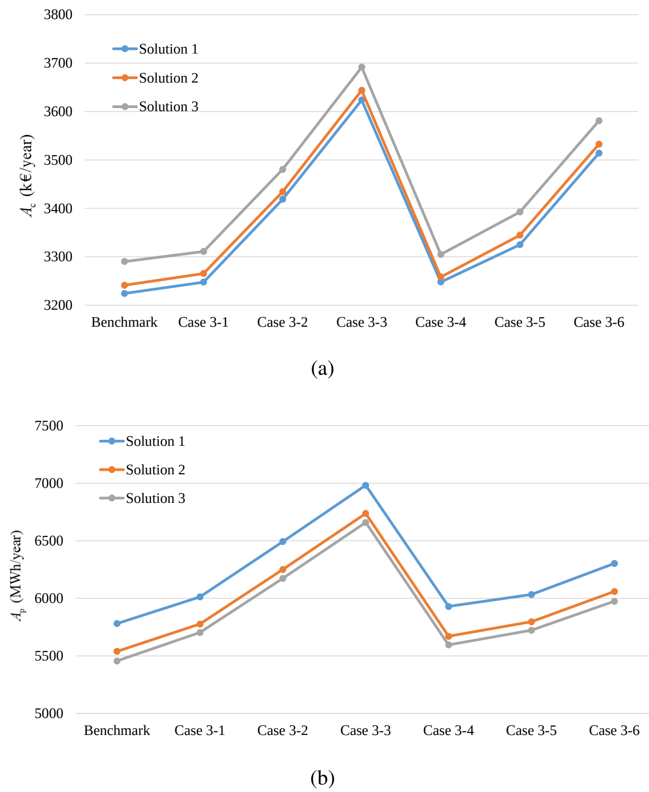
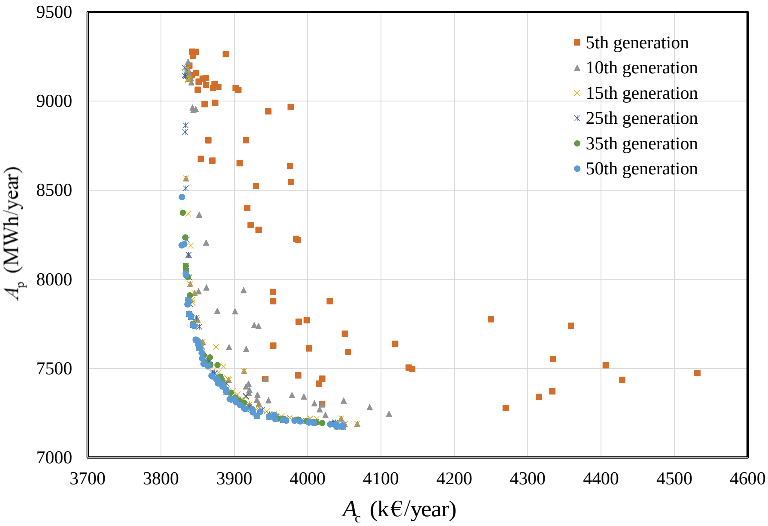


Figure 4.10: Comparison of Cases 3-1 to 3-6: (a) Maintenance cost. (b) Production loss

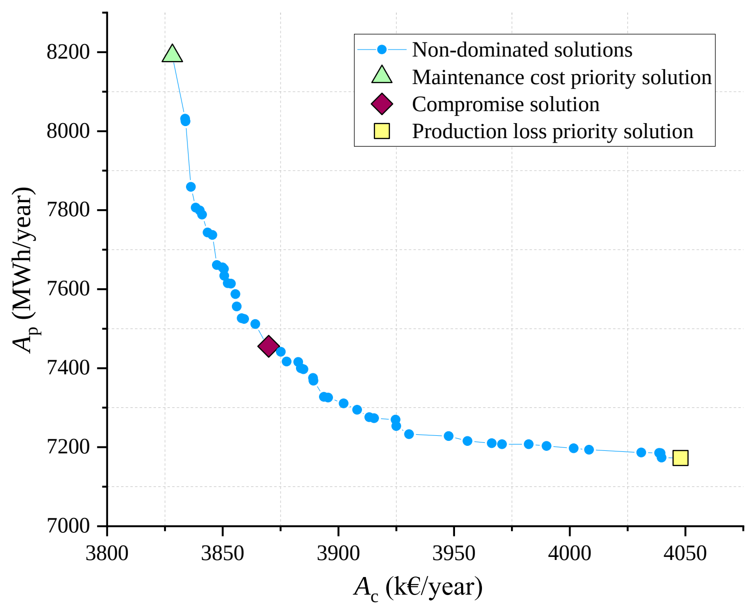
4.5.4 Optimization results under uncertainty

In this section, the proposed optimization framework incorporating three types of uncertainty model is implemented. The configuration of NSGA-II algorithm is the same as Section 4.5.2, and the time consumption is about 70 hours. The decision-making environment includes the uncertainty represented in Case 1-3, 2-3, 3-2 and 3-5. Fig. 4.11(a) illustrates the trend of convergence of populations with the increase of generations. The Pareto front at 50th generation is provided in Fig. 4.11(b), which has converged well.

In Fig. 4.12, a comparison of the two Pareto fronts in Fig. 4.6(b) and Fig. 4.11(b) is made. The Pareto front 1 (yellow line) is the optimal solutions disregarding uncertainty, and the Pareto front 2 (blue line) is obtained considering uncertainty. The Pareto front 2 lays to the upper right of the Pareto front 1, indicating the existence of uncertainty results in higher maintenance cost and more production loss. In addition, the range of front 2 is wider than front 1. Pareto front 1 shows that the maintenance cost and production loss are not completely conflicting objective functions, so the solution that is good for one objective may also be beneficial to another objective. However, uncertainty exacerbates the conflict between the two goals, indicating the maintenance decisions can no longer effectively reduce the two objectives at the same time. That results in the range of front 2 becomes



(a)



(b)

Figure 4.11: Optimization results under uncertainty: (a) Convergence of populations. (b) Non-dominated solutions at 50th generation

wider. The red plots illustrate the performance of applying the solutions obtained in a certain environment (the non-dominated solutions on front 1) to an uncertain decision-making

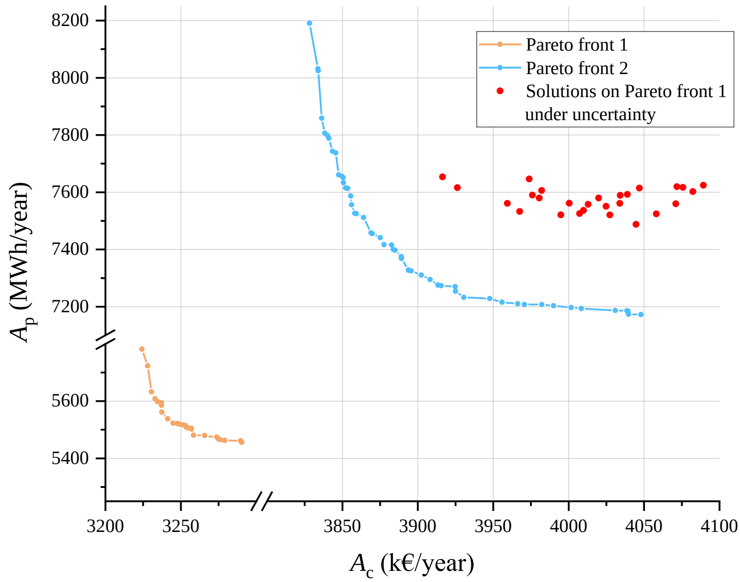


Figure 4.12: Comparison of non-dominated solutions disregarding and considering uncertainty

environment. It is found the points are located at the upper right of front 2, meaning the solutions are dominated by the solutions on front 2. The existence of uncertainty renders the maintenance decisions determined under certainty sub-optimal.

The solutions representing different interests are marked in Fig. 4.6(b) and Fig. 4.11(b). The top leftmost point corresponds to the solution with lowest maintenance cost and highest production loss, while the bottom rightmost point represents the highest maintenance cost with lowest production loss. A compromise solution is selected in the knee of the front.

These solutions can provide some instructions at the different strategic environment in which decision-makers manage an offshore wind farm project. (1) If the decision-maker adopts a cost priority strategy, the maintenance cost is set as the first consideration and it is reduced to the minimum. At the same time, the pursue of lowest cost indicates the production loss can not reach the lowest value. The decision-maker is willing to execute the Solution 1 with the lowest cost and the high but acceptable production loss. (2) If both the maintenance cost and the production loss are equally significant for the decision-maker, the compromise solutions can be considered, such as Solution 2. The solutions implies to trade-offs between two objective functions. These trade-offs can not reach the outstanding optimization in one direction, but provide a relatively comprehensive solution which does not sacrifice much on either objective function. (3) If the production is the priority objective, Solution 3 is the best maintenance strategy satisfying decision-maker's demand. In the situation, the decision-maker has the sufficient budget, so the cost expended on maintenance activities does not need strict control. Solution 3 can minimize the production losses and ensure the most efficient electricity production.

In Table 4.4, from cost priority solution to production loss priority solution, the maintenance thresholds ($A^{\max}$ and $A^{\min}$) both gradually decrease regardless of whether uncertainty is considered or not. The lower thresholds mean more frequent maintenance cycles, while repairing more components in each cycle, especially the number of aged components which are preventively replaced increases with the decrease of $A^{\max}$. This change can effectively keep the wind farm in good condition, and the occurrence of failure events and related high material cost and long downtime can be reduced. Meanwhile, increasing the frequency of maintenance cycle and the number of repaired components also induces more cost and longer repair time. Comprehensively, the maintenance cost tend to increase and the production loss tend to decrease.

When considering uncertainty, the reduction of $A^{\max}$ and $A^{\min}$ of production priority solution is more significant compared to cost priority and compromise solution. In addition, the value of 0.4% increases to 0.8% with the purpose of balancing the relationship between the frequency of maintenance cycles and the maintenance thresholds. The increase means it is more demanding to trigger the ageing-based opportunity. Furthermore, the uncertainty makes the maintenances threshold decrease for the solutions with the same interest. In the decision-making environment considering the unknown lifetime distribution, the inaccurate prediction of component condition, and the unstable maintenance consequences, maintenance conditions are relaxed to allow as many components as possible to be repaired and replaced in order to ensure the good condition of the wind turbine and avoid the potential failure events.

The decision-makers have different interests when playing different roles. If the decision-maker is an independent service provider, the objective can be related to production losses or availability, depending on the target of maintenance contracts. Meanwhile, the service provider also concerns about the reduction of maintenance costs. Considering this point, the solutions following different preferences can provide the instruction in different directions. If the decision-maker is the asset owner or operator who may also be responsible for maintenance management, the most significant objective is to ensure the maximum profits. In this case, the maintenance costs and production losses can be merged to a single objective used to evaluate the maintenance strategy. The price of electricity refers to the first half of 2021 for the Netherlands, about 128€/MWh [55]. As shown in Table 4.4, the compromise solutions show a lower loss of profit, which the asset owner will be more interested in.

For each solution, the simulation of maintenance model is run a large number of times to estimate the average results. The distribution of the simulation results is shown in Fig. 4.13(a). Each solution has two marginal probability density functions of maintenance cost and production loss, just as shown in Fig. 4.13(b). The probability density functions can inform the decision-makers how likely a specific value or range of model outputs can be observed.

The probability density functions of solutions is compared in Fig. 4.14, showing a clear representation of the variability of the solutions. Introducing uncertainty makes the solutions show greater dispersion, especially of the production loss in Fig. 4.14(b), because the solutions under uncertainty are observed in a larger range. In Fig. 4.14(a), the dispersion of solutions of different interests have a similar trend, that means the change of decision variables does not significantly influence the dispersion in the perspective of maintenance cost. In Fig. 4.14(b), the solutions with less production loss present less dispersion from Solution 1 to 3, indicating the solutions become more stable and robust when the decision-makers

Table 4.4: Characteristics of solutions of different interest

Solution	$A^{\max}$	$A^{\min}$	ζ	Cost (k€/year)	Production loss (MWh/year)	Loss of profit (k€/year)
Cost priority (certainty)	0.571	0.955	0.40%	3224.3	5781.5	3964.3
Compromise (certainty)	0.569	0.939	0.40%	3241.3	5538.3	3950.2
Production priority (certainty)	0.559	0.918	0.40%	3290.4	5456.3	3988.8
Cost priority (uncertainty)	0.538	0.979	0.40%	3828.2	8190.9	4876.6
Compromise (uncertainty)	0.511	0.955	0.40%	3868.9	7458.6	4823.6
Production priority (uncertainty)	0.433	0.894	0.80%	4047.9	7172.4	4966.0

focus more on production loss.

In Table 4.5, the worst scenario and risky scenarios of different solutions are shown. As explained above, the maintenance costs and production losses vary in each simulation because of the stochastic processes, indicating the severe scenarios probably occur where the results are higher than our expectation. The worst scenario means the occurrence of the highest maintenance costs and production losses. In the worst scenarios, the Solution 3 under uncertainty displays a weak capacity to control risk about maintenance cost which is as high as 4844.9 (k€/year). Meanwhile, the robustness of Solution 1 under uncertainty is not ideal, because the production loss is 10762 (MWh/year), higher than the other two solutions. The risky scenarios from 1 to 3 representing the 95%, 90% and 85% of results are lower than a specific value. These results provide decision-makers with recommendations on risk limitation to more comprehensively evaluate the selected maintenance strategies.

4.5.5 Discussion of the results

(1) Most of the existing maintenance model optimization assumes the parameters are deterministic, and sets the reduction of maintenance cost as the sole objective. This is an ideal situation, differing much from the context decision-makers are confronted with. The results have shown the presence of uncertainty greatly impacts the estimation of maintenance performance, thus the predetermined solutions are not optimal any more.

(2) The maintenance model heavily relies on the input lifetime distribution to represent real degradation process and generate discrete failure events. Under the same MTTF, the uncertain failure distribution and parameters result in different model outputs. The output tends to be less when the shape of distribution is more concentrated around MTTF. In order to eliminate the potential uncertainty as much as possible, a database with more sufficient and reliable failure data is required to support maintenance decisions.

(3) The RUL prediction technology which can accurately evaluate the condition of components can provide significant decision basis of the maintenance strategy. The error between real and predicted failure times may result in higher maintenance costs and production losses according to the results. One reason is the lifetime of component is underestimated,

Table 4.5: Worst scenario and risky scenarios of solutions

		Solution 1 (certainty)	Solution 2 (certainty)	Solution 3 (certainty)	Solution 1 (uncertainty)	Solution 2 (uncertainty)	Solution 3 (uncertainty)
Worst scenario (100%)	Cost (k€/year)	3941.2	4010.6	4091.9	4620.6	4727.3	4844.9
	Production loss (MWh/year)	7614.3	7282.5	7299.1	10762.0	9708.6	9171.5
Risky scenario 1 (95%)	Cost (k€/year)	3574.2	3587.3	3635.4	4208.8	4222.8	4374.0
	Production loss (MWh/year)	6616.9	6305.8	6173.1	9314.6	8418.8	8062.2
Risky scenario 2 (90%)	Cost (k€/year)	3501.5	3520.2	3562.7	4127.5	4141.4	4306.8
	Production loss (MWh/year)	6428.2	6131.6	6013.4	9053.3	8199.0	7834.1
Risky scenario 3 (85%)	Cost (k€/year)	3447.7	3471.2	3515.4	4066.7	4087.8	4258.4
	Production loss (MWh/year)	6280.9	6017.6	5901.5	8879.2	8031.1	7697.2
Expected value	Cost (k€/year)	3224.3	3241.3	3290.4	3828.2	3868.9	4047.9
	Production loss (MWh/year)	5781.5	5538.3	5456.3	8190.9	7458.6	7172.4

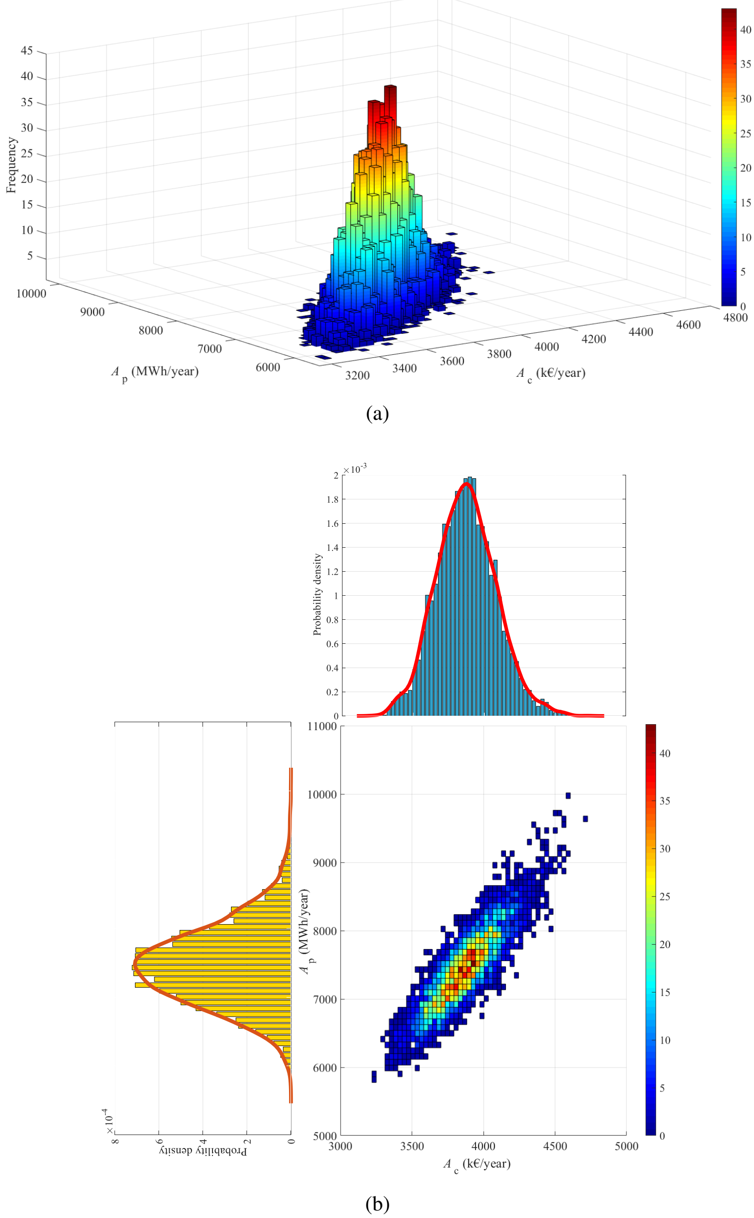
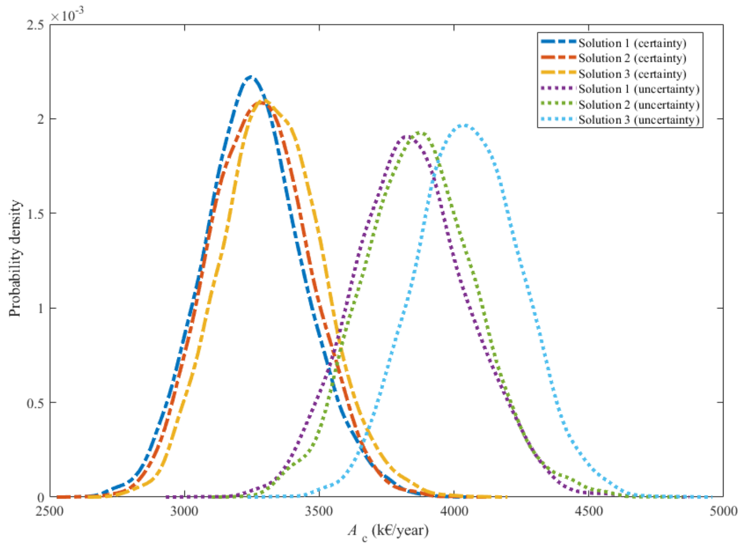
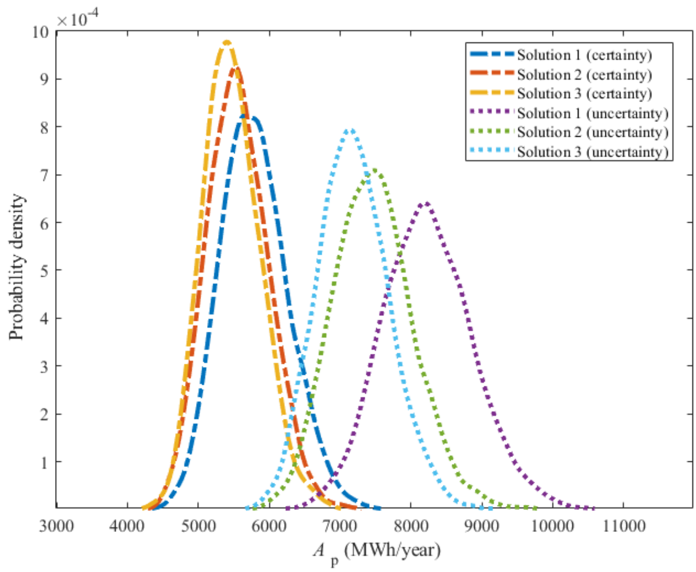


Figure 4.13: Distribution of the derived results: (a) Bivariate histogram plot. (b) Plot with marginal probability density function

thus the maintenance actions can not be performed in a timely manner. More failure events are then caused due to the underestimation. Another reason is the underestimated lifetime of components. Preventive repair and replacement is planned in a premature way, resulting in the cost associated with changing out components that have remaining useful life



(a)



(b)

Figure 4.14: Probability density functions: (a) Annual maintenance cost. (b) Annual production loss

and production loss. The improvement of prediction accuracy is significant to plan a sound maintenance strategy.

(4) The quality of maintenance actions is stochastic in the real maintenance situations,

depending on the factors, such as environmental conditions, human factors, etc. The results have revealed that the more unstable maintenance quality causes an increase of maintenance costs and production losses. Therefore, the maintenance provider should enhance the technician training and improve the maintenance conditions and environment, in order to carry out maintenance in a more stable manner. Moreover, if a database related to repair cost and time is developed with good quality, a more explicit relationship between maintenance activities and corresponding consumption can be clarified and made an input to the maintenance model. Such an unambiguous input can assist the decision-maker to evaluate the maintenance performance more accurately.

(5) The O&M costs include a variety of costs, i.e., material costs, labor costs, transportation costs. In maintenance optimization problems, "cost coefficients" refer to the numerical values assigned to various factors or variables that contribute to the overall maintenance cost. This research focuses on developing a comprehensive decision-making framework to provide maintenance strategies for decision-makers, thus the various costs are all considered in the model. In the future study, different cost factors for different decision makers can be considered. The impact of different factors on the total cost can be quantified and the optimal maintenance strategy is determined.

4.6 Conclusions

This chapter focuses on quantifying the influence of model parameter uncertainty on maintenance strategies and maintenance performance. To answer the Research Question 3, a multi-objective optimization framework for maintenance strategy planning with consideration of uncertainty is proposed. Firstly, the three types of uncertainties affecting the maintenance strategy are quantified in a probabilistic method. Their influence on the performance of different representative solutions is estimated. In addition, two sets of Pareto solutions are derived considering and disregarding uncertainties. These solutions represent reasonable trade-offs between conflicting maintenance objectives.

A case study of a generic offshore wind farm demonstrate that the performance of maintenance strategies worsen due to existence of uncertainty, and the solutions show greater dispersion. The maintenance costs are higher than the results in Chapter 3 due to the new added vessel and technician costs as well we uncertainty. The most influential uncertainty is uncertain performance of component lifetime prediction, followed by statistical uncertainty of component reliability and ambiguous estimation of maintenance consequences. Moreover, it is found that when confronting with an uncertain decision-making environment, it is more cost-effective to relax maintenance conditions to allow more components to be repaired and replaced in order to ensure the good condition of wind turbines and avoid potential failure events.

The proposed framework is a decision aid for for wind farm owners and operators, as well as maintenance providers. Considering the actual wind farm situation, the available database, and the maintenance objectives, more feasible and reliable suggestions are provided for the decision-maker who manages maintenance in an uncertain decision-making environment.

Chapter 3 and 4 study the development of maintenance strategies for offshore wind farm as well as influence of uncertainty. In the models, the spare parts for maintenance are assumed to be always available, and the inventory management is not concerned. Chapter 5 studies maintenance logistics from the perspective of spare parts inventory, and further optimizes the policies for maintenance and inventory. In addition, although the negative influence caused by uncertainty in model parameters is studied in this chapter, the feasibility of using new data to update uncertain or inaccurate parameters is ignored. This issue will be addressed in Chapter 7, where the influence of uncertainty will be gradually mitigated in a active manner by utilizing new data.

Chapter 5

A Multi-echelon and Multi-unit Inventory Maintenance Policy

In Chapter 3, a predictive opportunistic maintenance strategy is proposed to design a maintenance strategy to instruct the maintenance actions, but the inventory management, this significant factors in maintenance logistics, is not studied. This chapter follows Chapter 3 by developing a multi-unit and multi-echelon inventory network to support the implementation of maintenance activities. The maintenance strategy and inventory policy are joint optimized to achieve a cost-effective integrated maintenance and inventory management. Considering that this chapter mainly studies the maintenance logistics for offshore wind farms from the aspect of spare parts inventory, the uncertainties accounted in Chapter 4 are not considered.

This chapter is organized as follows: Section 5.1 introduces the research background. Section 5.2 describes offshore wind farm system and policy. Section 5.3 introduces the joint maintenance and spare parts inventory optimization model. Section 5.4 presents the case study to evaluate the proposed approach and shows the sensitivity analysis. Section 5.5 concludes the chapter.

Parts of this chapter have been published in [111][1], [109][2], and [110][3].

5.1 Introduction

Maintenance and inventory are interrelated O&M processes for offshore wind farms, and the cost is not only generated from maintenance activities, but also the spare part inventory management. Regular maintenance, repair and spare parts constitutes more than 40% of O&M costs [49]. Well organized maintenance strategy and spare parts inventory policy

[1]M. Li, X. Jiang, and R. R. Negenborn. Cost-driven multi-echelon inventory optimization for offshore wind farms. Submitted to a conference, 2023.

[2]M. Li, X. Jiang, J. Carroll, and R. R. Negenborn. Joint optimization of multi-echelon inventory and predictive opportunistic maintenance: A case study of an offshore wind farm in the north sea. Submitted to a journal, 2023.

[3]M. Li, X. Jiang, J. Carroll, and R. R. Negenborn. Joint optimization of multi-echelon inventory and predictive opportunistic maintenance for an offshore wind farm in the north sea. Submitted to a conference, 2023

are deemed essential to improve the O&M of the offshore wind energy and enhance its competitiveness within the renewable energy market.

The joint maintenance and inventory problem becomes particularly challenging if one considers multiple options for maintenance operations, transportation methods for the necessary spare parts and manpower, and management for spare parts being stocked in maintenance facilities. According to the literature review in Chapter 2, the past research focusing on maintenance strategies and spare part inventory policies usually studies these two problems separately without considering the interrelation between them. In practical cases, the stock level of spare parts is determined by the demand caused by the maintenance implementation. Meanwhile, the maintenance implementation depends on the availability of spare parts to reduce failure downtime and costs. Therefore, inventory and maintenance management should be considered simultaneously to improve an OEM or service provider's operations.

The limited papers studying joint inventory and maintenance optimization commonly only notice component-level spare parts, and adopt a single-echelon inventory warehouse. It is not adequate enough for offshore wind turbines, because offshore wind turbines is a typical complex system not only consisting of different component-level units, but also various subcomponent-level units. These units are usually stored in warehouses at different echelons considering differences in size, weight, and maintenance requirements, instead of a single warehouse.

In this chapter, a joint multi-echelon and multi-unit inventory and predictive opportunistic maintenance optimization model is proposed to address the above issues. As introduced in Chapter 2, a Min/Max policy is one of the most typical policies for wind industry inventory management. Such a Min/Max policy is adopted to manage inventory management here. The objective is to connect and integrate the inventory model and the maintenance model to achieve a holistic model and improve management policies from a global perspective.

5.2 Offshore wind farm system and policy description

5.2.1 Characteristics of the offshore wind farm system

An offshore wind farm is a system which is composed of a number of offshore wind turbines used to produce electricity in the same offshore location. From the perspective of hierarchical levels [144], each offshore wind turbine consists of a series of critical components (e.g., gearboxes), and each component is further decomposed into subcomponents (e.g., gears, gear bearings, auxiliary systems). This model mainly concerns about the units in the nacelle. A 'unit' can refer to a single component or part of the component.

According to the criticality of components and subcomponents in the offshore wind turbines [10, 17, 81, 139], 4 units at the component level and 15 units at the subcomponent level are selected to, as shown in Fig. 5.1. Different from the maintenance model in Chapter 3, the pitch system, is not considered because mechanical and electromechanical components are mainly considered in this chapter. The pitch system works as an electrical control system, consisting of many control units and sensors, and the storage of its components is different.

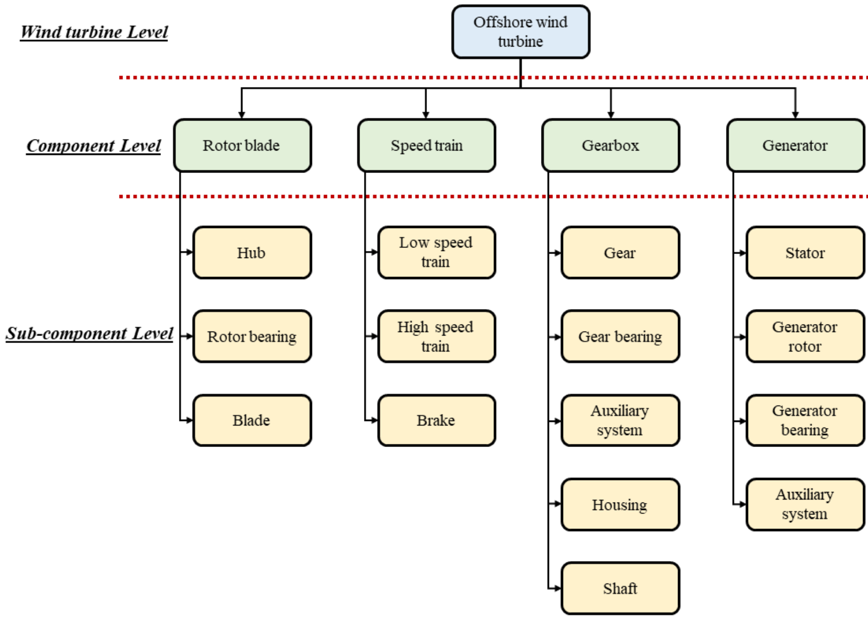


Figure 5.1: Hierarchical levels of offshore wind turbine

5.2.2 Description of the maintenance strategy

The predictive opportunistic maintenance strategy is established based on the model in Chapter 3 and Chapter 4. A brief introduction is made here to ensure the readability of the thesis. Owing to the development in the condition monitoring and RUL prediction technology in recent years, the failure time of the critical components can be predicted before failure events occur [94]. The overall offshore wind farm is inspected at a regular interval. The unobservability of the wind turbine component states and the inaccuracy of the RUL prediction are not considered in this model.

Two decision variables $A^{\min}$ and $A^{\max}$ are introduced as maintenance thresholds for component condition classification. The maintenance actions are determined as illustrated in Section 3.2.4. After identifying the health state of the offshore wind farm, the decision-maker, such as a maintenance service supplier responsible for both carrying out the maintenance tasks and storing the required spare parts, will decide whether to initiate a maintenance cycle.

5.2.3 Description of the inventory policy

With the maintenance strategy described in Section 5.2.2, the aim of the inventory policy is to satisfy the maintenance demands for spare parts as much as possible and, at the same time, to reduce the costs of spare parts inventory management. With the reference to the hierarchical levels in Fig. 5.1, an offshore wind turbine system is generally decomposed into component-level units and subcomponent units. A facility, termed as a warehouse, is

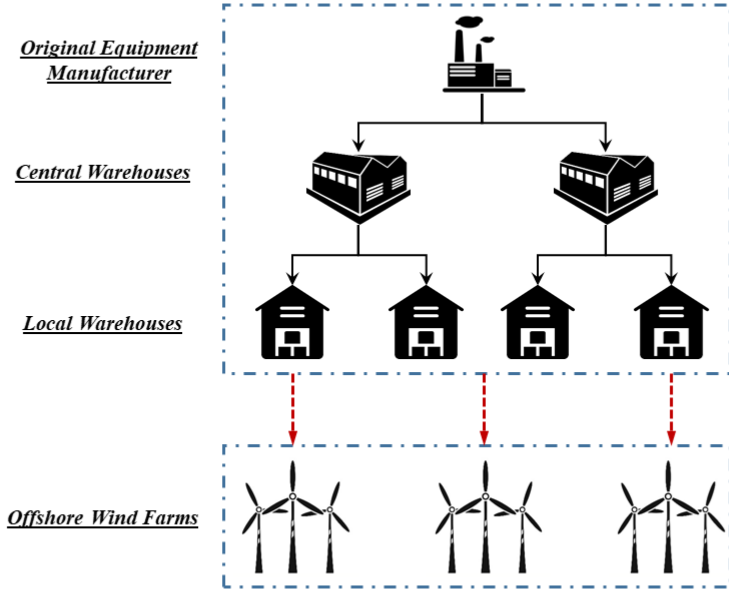


Figure 5.2: Hierarchy of an inventory network

where the spare parts are stored. Considering differences in size, weight, and maintenance requirements, these units are stored in different warehouses instead of storing all these in a single warehouse.

A inventory network in the wind industry is shown in Fig. 5.2. The OEM is located at the top of the hierarchy, manufacturing all the units necessary for maintenance implementation. Central warehouses are beneath the OEM, storing the units delivered directly from the OEM. Local warehouses are closer to offshore wind farms than central warehouses, and are usually located in the harbour used for the service work. The units such as blades are difficult to be stored in a local warehouse considering their large size. Such an inventory network supports the unit consumption for offshore wind farm maintenance. The inventory flow is in one way, from the top to the bottom of the inventory network.

A multi-echelon inventory network containing a central warehouse and a local warehouse is established to support the maintenance service for an offshore wind farm. The component-level units are stored in the central warehouse, while the subcomponent-level units are in the local warehouse. Both warehouses adopt Min/Max inventory policies.

A Min/Max inventory policy for central warehouses is illustrated in Fig. 5.3, where s^{C} and S^{C} are the minimum and maximum level. At the beginning, the stock level Q is kept at S^{C} until t_1, at which point a number of units are dispatched from the warehouse for maintenance. After that, the stock level is maintained until new maintenance requirement arrives at t_2. The level Q is reduced to the reorder point s^{C}. According to the Min/Max inventory policy, the stock level is replenished to order-up-to level S^{C} at t_3. The lead time between t_2 and t_3 is the amount of time between when a purchase order is placed to replenish units and when the order is received in the warehouse. The length of the lead time is influenced

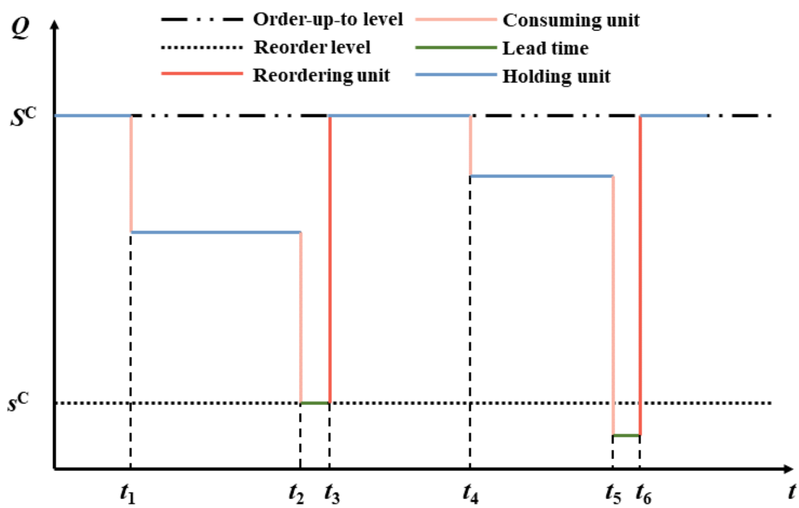


Figure 5.3: A Min/Max inventory policy

by factors including geographical location, local weather, and transportation modes. Similarly, the level Q decreases to be lower than s^{C} after dispatching units at t_4 and t_5, and consequently, a replenishment order is placed to recover the stock at t_6.

Once the quantity of the units in the warehouse cannot satisfy the requirement from the maintenance site, an emergency order is placed to deal with this emergency situation. For subcomponent-level units, the spare parts will be transshipped from the central warehouse to the site. While the quantity of component-level units are insufficient, the OEM will urgently provide the spare parts.

5.3 Joint maintenance and spare parts inventory optimization model

5.3.1 Inventory and maintenance model

The offshore wind farm contains K turbines, and the wind turbine consists of I components in series. According to Fig. 5.1, component i is further decomposed into J_i subcomponents. The specific type of the components/subcomponents of all wind turbines in the wind farm is assumed to be identical and equally critical. More details of the model can be found in Chapter 3 and a brief explanation is below.

At the beginning of the life cycle, the state of all the units in the offshore wind farm are brand new. The inspection and RUL prediction of all the turbines are performed at a regular interval, regardless of the time elapsed since the last maintenance of the individual components. It is assumed that inspections and RUL prediction are perfect and non-destructive, indicating that the true RUL is known accurately. The assumption is consistent with Chapter 3 while the potential RUL prediction error has been discussed in Chapter 4 but is not considered in this Chapter. Compared to the repair times and logistics times, the inspection time is ignored. The real lifetime is accurately forecast after inspecting the wind turbine and performing lifetime prediction. The influence of maintenance is to restore or recover the component condition.

In the maintenance model, decision vector $\left[A^{\min}, A^{\max}, \zeta\right]$ controls the frequency of maintenance cycles and the range of components qualified for various types of maintenance. Replacing a component after the failure occurs is more costly then a preventive replacement. The maintenance action of components has a priority than the order action of spare parts. It means when the spare parts are insufficient to support maintenance actions, the necessary spare parts are ordered urgently rather than cancelling the maintenance actions. Once the decision of a maintenance cycle is initiated, the service vessels and technicians are mobilized to carry out maintenance. The wind farm operator or maintenance service provider check whether the current vessels are available to complete all maintenance tasks within the time limit. The decisions of temporary leasing or sharing may be made to inflate the vessel fleet. Additionally, considering the weather constriction of different types of vessels, the vessels have to wait a random period of time for appropriate weathers, which is assumed to follow a Weibull distribution.

In the maintenance cycle s, a decision is made on whether or not to replace or repair a component. The binary variables X_{iks}^{FR}, X_{iks}^{PR}, $X_{ikj_is}^{\mathrm{MAR}}$, and X_{iks}^{MIR} represents the decision of failure replacement, preventive replacement, major repair, and basic repair. If the maintenance action is applied, the binary variable equals 1. Otherwise, it is equal to 0. When performing replacement for component-level units, a new corresponding component-level unit is required. If the the replacement is carried out before failure, the removed unit can be sent back to factory and overhauled or recast. In this case, the old unit can offset part of the cost of the new unit. Therefore, the cost of units required for preventive replacement is half.

A component is composed of multiple subcomponents. When performing a major repair, a defected component requires the replacement of one of its subcomponents. For example, a major repair for rotor blade requires one hub, or one rotor bearing, or one blade. These three subcomponent units have different failure rates. A higher failure rate indicates this unit has a higher probability to be needed in major repair

The implementation of maintenance actions replies on the service vessels, which are mobilized once a maintenance cycle is triggered. The spare parts, equipment, and technicians are loaded on board the available vessels. If the current vessels resource is unavailable to handle the maintenance workload, the O&M implementer has to seek for available vessels from the spot market. Then, the vessels have to await proper weather conditions including wave and wind before departing to the offshore wind farm location. The above time constitutes the length of lead time of vessels. It is assumed that the mobilization time of HLVs, FLVs, CTVs follows Weibull distribution (ε^{H}, σ^{H}), (ε^{F}, σ^{F}), and (ε^{C}, σ^{C}) respectively. The random mobilization time in s maintenance cycle m_s^{H}, m_s^{F}, and m_s^{C} are generated by sampling the Weibull distribution.

The total costs for maintenance activities C^{M}, is the sum of material costs for repair, vessel costs, technician costs, and mobilization costs.

The decision vector of inventory model is $\left[s^{\mathrm{C}}, S^{\mathrm{C}}, s^{\mathrm{L}}, S^{\mathrm{L}}\right]$. The central warehouse applies the inventory policy $\left(s^{\mathrm{C}}, S^{\mathrm{C}}\right)$ while the inventory policy used in the local warehouse is $\left(s^{\mathrm{L}}, S^{\mathrm{L}}\right)$. At the beginning, the warehouses are full, indicating that the quantity of component-level units is S^{C} and the quantity of subcomponent-level unit is S^{L}.

In the maintenance cycle s, while the vessels and technicians are organized after triggering a maintenance cycle, at the same time, the stock levels of spare parts are inspected and the required spare parts are delivered. According to the comparison between maintenance thresholds and component conditions, the requirement of various spare parts is determined. Suppose that the required number of component-level unit i in maintenance cycle s is γ_{is}, calculated as

$$\gamma_{is} = \sum_{k\in K} \left(X_{iks}^{\mathrm{FR}} + X_{iks}^{\mathrm{PR}}\right). \tag{5.1}$$

The number of subcomponent-level unit j_i located in component i in maintenance cycle s, κ_{ij_is}, is also obtained as

$$\kappa_{ijs} = \sum_{k\in K} x_{ikj_is}^{\mathrm{MAR}}. \tag{5.2}$$

The current quantity of component-level and subcomponent-level units are ${}^{-}\lambda_{is}^{\mathrm{C}}$ and ${}^{-}\lambda_{ij_is}^{\mathrm{S}}$. If the quantity of the current stock is sufficient enough to support the maintenance implementation, the needed spare parts are delivered to ports. The remaining quantity of spare parts in the central and local warehouse is $\left({}^{-}\lambda_{is}^{\mathrm{C}} - \gamma_{is}\right)$ and $\left({}^{-}\lambda_{ij_is}^{\mathrm{S}} - \kappa_{ij_is}\right)$ respectively. If the spare parts are insufficient, all the components in stock will be delivered out of the warehouse. In this case, an emergency order is placed to fill the missing quantity of spare parts, and binary variables y_{is}^{C} and $y_{ij_is}^{\mathrm{L}}$ represent whether an emergency order is place for component-level units and subcomponent-level units.

After delivering the necessary spare parts to the offshore wind farm, the stock levels in the warehouses ${}^{+}\lambda_{is}^{\mathrm{C}}$ and ${}^{+}\lambda_{ij_is}^{\mathrm{S}}$ are compared with the minimum storage limit. In the central warehouse, if ${}^{+}\lambda_{is}^{\mathrm{C}}$ is less than s^{C}, a new order is made to restore the quantity of units back to S^{C}. A binary variable z_s^{c} means a regular order is required. Otherwise, there is no need to place a new order. In a similar way, the quantity of spare parts is checked in the local warehouse. When z_s^{l} equals 1, a regular order is placed to replenish the subcomponent-level units.

The spare parts stored in the warehouses also incur cost to manage the inventory, i.e., holding cost. The holding cost is relevant to the cost of materials, the quantity of spare parts and the length of time the spare parts are stored in the warehouse. Suppose that T_s represents the time of maintenance cycle s. After completing the regular orders and emergency orders, the quantity of spare parts in the central and local warehouses are ${}^{+}\lambda_{in}^{\mathrm{C}}$ and ${}^{+}\lambda_{ij_is}^{\mathrm{S}}$ respectively.

The total cost for inventory C^{I} is the sum of ordering cost C^{O}, holding cost C^{H}, and emergency cost C^{E}:

$$\begin{aligned}
&C^{\mathrm{I}} = C^{\mathrm{O}} + C^{\mathrm{H}} + C^{\mathrm{E}} = \\
&\sum_{s\in S}\left\{\begin{aligned} & z_s^{\mathrm{c}}C_s^{\mathrm{c}} + z_s^{\mathrm{l}}C_s^{\mathrm{l}} + \sum_{i\in I} {}^{+}\lambda_{i(s-1)}^{\mathrm{C}}\delta_i\left(T_s - T_{s-1}\right) + \sum_{j_i\in J_i}\sum_{i\in I} {}^{+}\lambda_{ij_i(s-1)}^{\mathrm{S}}\delta_{ij_i}\left(T_s - T_{s-1}\right) \\ & + \sum_{i\in I} y_{is}^{\mathrm{C}}E_i\left(\gamma_{is} - {}^{-}\lambda_{is}^{\mathrm{C}}\right) + \sum_{j_i\in J_i}\sum_{i\in I} y_{ij_is}^{\mathrm{L}}E_{ij_i}\left(\kappa_{ij_is} - {}^{-}\lambda_{ij_is}^{\mathrm{S}}\right)\end{aligned}\right\} \\
&+ \sum_{i\in I} {}^{+}\lambda_{i(S-1)}^{\mathrm{C}}\delta_i\left(L - T_S\right) + \sum_{j_i\in J_i}\sum_{i\in I} {}^{+}\lambda_{ij_i(S-1)}^{\mathrm{S}}\delta_{ij_i}\left(L - T_S\right),
\end{aligned} \tag{5.3}$$

where C_s^{c} and C_s^{l} are the order cost for component-level and subcomponent-level units; E_i

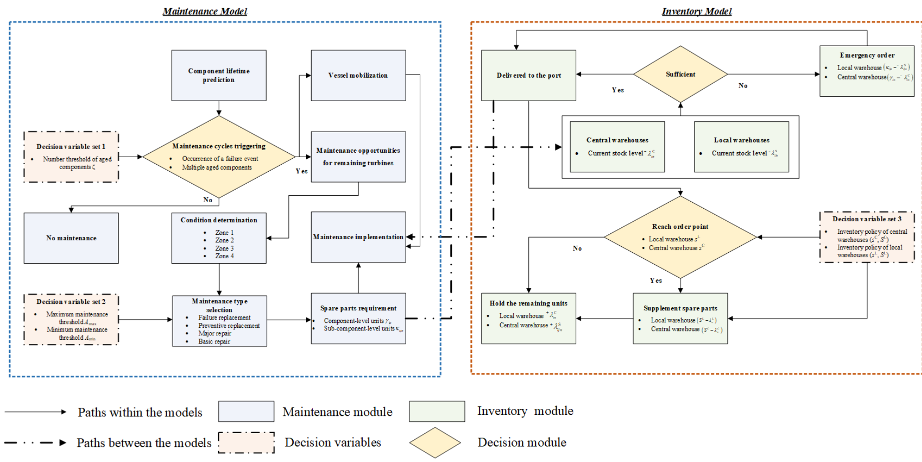


Figure 5.4: Illustration of the joint model

and E_{ij_i} are the emergency cost for component i and subcomponent j_i at component i.

5.3.2 Cost function and optimization method

The developed maintenance and inventory models are related, as illustrated in Fig. 5.4. The maintenance requirement of spare parts is delivered to the warehouses, and the spare parts are prepared at the port to implement the maintenance, which constitute the connection between the two models.

In addition to the maintenance and inventory cost, the production loss in the downtime which is caused by turbine failure and maintenance implementation will also generate revenue loss. The total cost of the lost production C^{P} is obtained by

$$C^{\mathrm{P}} = r\sum_{s\in S}\left\{\begin{array}{l} \sum\limits_{k\in K}\left(T_s - F^{\mathrm{T}}_{ks^-}\right) + \sum\limits_{i\in I}\sum\limits_{k\in K}\left(\begin{array}{l} X^{\mathrm{FR}}_{iks}N^{\mathrm{FR}}_{iks} + X^{\mathrm{PR}}_{iks}N^{\mathrm{PR}}_{iks} + X^{\mathrm{MIR}}_{iks}N^{\mathrm{MIR}}_{iks} + \\ \sum\limits_{j_i\in J_i} X^{\mathrm{MAR}}_{ikj_is}N^{\mathrm{MAR}}_{ikj_is} \end{array}\right) \\ +\max\left(\max\left(m^{\mathrm{H}}_s, m^{\mathrm{F}}_s, m^{\mathrm{C}}_s\right), \max\left(L^{\mathrm{l}}_{ij_is}, L^{\mathrm{c}}_{is}, \eta^{\mathrm{o}}_{is}, \eta^{\mathrm{c}}_{ij_is}\right)\right) \end{array}\right\}, \quad (5.4)$$

where r is the expected cost of the lost production per turbine per day; $F^{\mathrm{T}}_{ks^-}$ is the failure time of the turbine k; $L^{\mathrm{l}}_{ij_is}, L^{\mathrm{c}}_{is}$ are the lead time for regular orders from local and central warehouses respectively; $\eta^{\mathrm{o}}_{is}, \eta^{\mathrm{c}}_{ij_is}$ are the lead time for emergency orders for local and central warehouses.

The decision vector of the joint optimization problem is

$$\vec{x} = \left[A_{\min}, A_{\max}, \zeta, s^{\mathrm{C}}, S^{\mathrm{C}}, s^{\mathrm{L}}, S^{\mathrm{L}}\right] \quad (5.5)$$

where $s^{\mathrm{C}}, S^{\mathrm{C}}, s^{\mathrm{L}}, S^{\mathrm{L}}$ are integer variables.

The objective is to minimize the expected annual cost as

$$\begin{aligned} \min_{\mathbf{x}} \quad & A_{\mathrm{c}} = \tfrac{C^{\mathrm{P}}+C^{\mathrm{M}}+C^{\mathrm{I}}}{L} \\ \text{s.t} \quad & s^{\mathrm{C}} < S^{\mathrm{C}} \\ & s^{\mathrm{L}} < S^{\mathrm{L}} \\ & s^{\mathrm{C}}, S^{\mathrm{C}}, s^{\mathrm{L}}, S^{\mathrm{L}} \in \mathbb{Z}^{+} \end{aligned} \tag{5.6}$$

This problem is a non-linear single-objective optimization problem with mixed variables and constraints. A meta-heuristic algorithm, GA, is employed to solve this optimization problem with a large solution space. GA has the strengths of dealing with a multivariate and non-linear problem and has been applied in various engineering optimization problems [82]. A typical GA has five phases: Initialization, evaluation, selection, crossover, and mutation. More detailed description and explanation can be found in Section 3.2.4 and [169].

5.4 Case study

5.4.1 Scenario set-up

The developed model is applied to a 300-MW offshore wind farm, as shown in Fig. 5.5. Both the maintenance base and the local warehouse are located at this port. The production facility for this operational offshore wind farm is located in the central region of Denmark, which is also the central warehouse is situated. The reason for this is that the wind turbine provider is in Denmark and there is no manufacturing factory in the Netherlands. The number of wind turbines in the wind farm is 100. The technical parameter of the wind turbine can be found in Section 3.3.1. In Table 5.1, the parameters are derived and estimated from the literature [91, 105]. The parameters in Table 5.2 for subcomponents are estimated according to [10, 17, 40, 81, 139]. Table 5.3 lists the ordering parameters for components and subcomponents.

Table 5.1: Parameters for vessels

Vessel		HLV	FSV	CTV
Mobilization time	Scale parameter (weeks)	4	2	1
	Shape parameter	3.1	3.4	3.3
Cost (k€)	Mobilization	80	-	-
	Day rate	50	18	8
Technician	Number	8	4	2
	Day rate (k€)		0.6	
Working shift (hours)		24	12	12

Figure 5.5: Geographical location of the offshore wind farm and warehouses

5.4.2 Optimization results

The expected value of the objective function under a specific set of maintenance strategies and inventory policies is estimated by averaging a large number of repeated Monte Carlo simulations. The optimization procedure takes around 19 hours to find the optimal solution on a computer with the configuration of 4-CPU E5-1620 V3 3.5 GHz and 32 GB memory. The main configuration of GA is:(1) a population size of 40 individuals, (2) a maximum number of generations of 50, (3) mutation probability of 0.2,(4) crossover probability of 0.8.

The optimization process results are represented in Fig. 5.6. Each generation consist of a population of individuals and each individual represents a point in search space and possible solution. With the increase of the generation, the performance of the best individual gradually converges to a stable value. The optimization results and the values of the corresponding decision variables is shown in Table 5.4. Compared to the inventory policy of the local warehouse, it is obvious that the values of s^{C} and S^{C} of the central warehouse are both less. It can be explained that, on the one hand, the holding costs of the component-level units are higher considering the component-level units are more costly than subcomponent-level units. It is more economical to keep a low level of spare parts in the warehouse. On the other hand, the gap between $A^{\min}$ and $A^{\max}$ is larger than the gap between $A^{\max}$ and 1,

Table 5.2: Parameters for subcomponents

Component	Subcomponent	Replacement probability (%)	Cost (k€)
Rotor blade	Hub	60.6	35
	Rotor bearing	11.6	10
	Blade	27.8	140
Speed train	Low speed train	45.6	26
	High speed train	30.4	13
	Brake	24	6
Gearbox	Gear	1.1	74
	Gear bearing	69.2	70
	Auxiliary system	12.6	15
	Housing	3.1	7
	Shaft	14	64
Generator	Stator	12.7	28
	Gnerator rotot	8.5	18
	Generator bearing	36.4	7
	Auxiliary system	42.4	7

Table 5.3: Parameters for orders

Unit	Lead time (days)		Reorder	Holding cost	Emergency
	Regular	Emergency	cost (k€)	rate (per day)	order cost rate
Component	3	28	50	0.001	1
Subcomponent	1	7	25		

indicating the number of preventive replacements and failure replacements are lower than major repair. Consequently, the requirement of component-level units is lower. This also means the number of emergency order is less, leading to lower costs for emergency orders. Therefore, the policy for the central warehouse (4,2) is lower than (9,4).

5.4.3 Sensitivity analysis

The influence of the parameters relevant to the maintenance and inventory model on the maintenance costs under the optimal strategy is analyzed, in order to determine the significance of various parameters to the joint policies. Table 5.5 shows the results for sensitivity analysis. The benchmark using the parameters in Section 5.4.1. Scenario 1 reduces the value of the parameters to half, and Scenario 2 doubles the values. The results are further compared in terms of percentage in Fig. 5.7. Parameter from 1 to 6 is age reduction,

Table 5.4: Optimal strategies and minimum annual costs

	A_{min}	A_{max}	ζ	S_{L}	s_{L}	S_{C}	s_{C}	A_{T} (k€/year)
Value	0.728	0.884	3.75%	9	4	4	2	21275.7

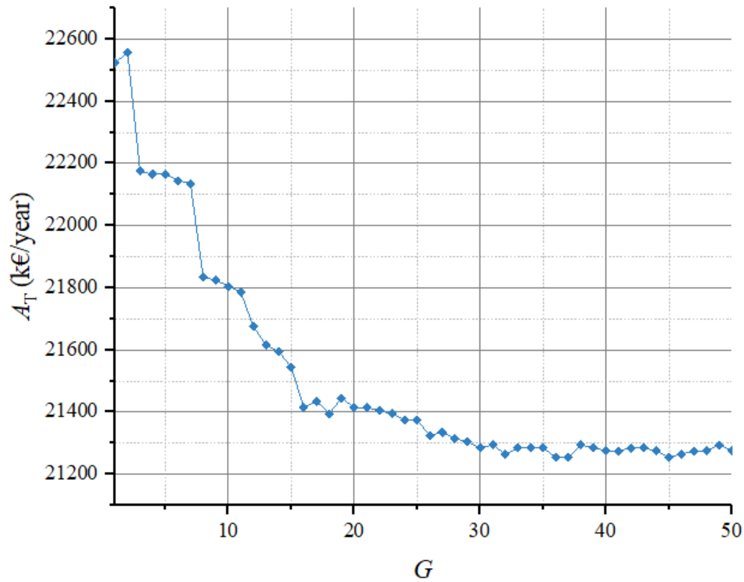


Figure 5.6: Convergence of the optimization results as the generation increases

Table 5.5: Results of sensitivity analysis

	Benchmark (k€/year)	Scenario 1 (k€/year)	Scenario 2 (k€/year)
Age reduction of major repair	21275.70	30203.60	18371.45
Emergency order cost rate		20285.96	23274.27
Holding cost rate		20139.04	23542.35
Unit cost		16236.26	31349.51
Vessel and technician cost		17245.40	29335.23
Leading time for orders		21256.34	21401.97

emergency order cost rate, holding cost rate, unit cost, vessel and technician cost, and lead time for orders respectively. These parameters are key factors in maintenance strategies and inventory policies, directly affecting maintenance effectiveness and cost estimates.

The detailed comparison and results are described below:

(1) Sensitivity to the age reduction of major repairs

Age reduction indicates the positive effect of a major repair on component condition. A higher value of age reduction means that with the same cost, the effect of the major repair is more obvious, otherwise the effect is reduced. It is noted that the value of age reduction has a heavy influence of the policy performance. The costs have a significant increase with the decrease of age reduction. How to ensure the quality of maintenance actions and the best possible recovery of the component condition is an important factor in pursuing for a cost-effective.

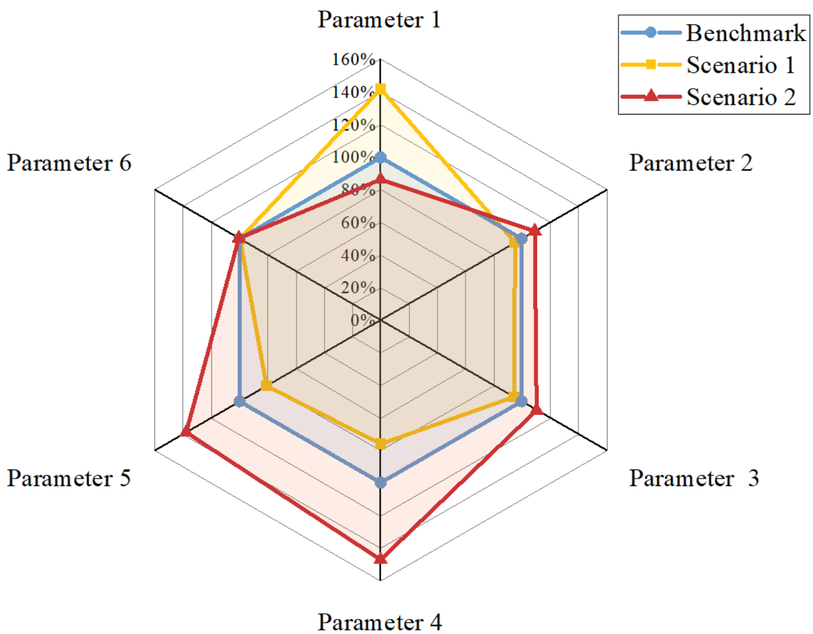


Figure 5.7: Comparison of influence of parameters on results

(2) Sensitivity to the emergency order cost rate

A more expensive emergency order will lead to higher costs without uncertainty. The cost for emergency order only accounts for a small portion of the total cost, which can explain the increase/decrease is not very obvious. Lowering emergency order costs will reduce relevant costs. At the same time, it means that the negative impact caused by insufficient stock level will be reduced, which will further facilitate the stock level to be kept at a low level and reduce holding costs. It is beneficial to improve the organization and delivering of an emergency order to lower the relevant costs.

(3) Sensitivity to the holding cost rate

Holding cost rate brings about a little greater influence than emergency order cost rate. Similar to the change in emergency order costs, a higher holding cost represents it is more economical to reduce the number of spare parts in the warehouses. In this context, it is more likely to happen that the spare parts are insufficient, leading to longer lead times for orders and more emergency orders. In this way, improving the storage of spare parts is very important for the overall process of O&M.

(4) Sensitivity to the unit costs

Unit costs are the most influential parameters in the model. On one hand, the change in unit costs affects the costs for maintenance actions including replacements and major repairs. On the other hand, the inventory costs are correspondingly influenced. It is more or less costly to hold and order spare parts. From the perspective of O&M, within an equivalent budget, reducing the manufacturing costs of the wind turbines is conducive to performing more maintenance actions and ensuring a higher level of inventory to support maintenance requirements.

(5) Sensitivity to the vessel and technician costs

Vessel and technician costs, these transportation costs, are the second influential factors. The harsh marine environment and the long distance of offshore wind farms away from the shore, are the key factors bringing challenges for offshore O&M. Rising the related costs will incur an obvious increase. In addition, the negative influence is that it is more costly to trigger a maintenance cycle, thus the frequency of maintenance activities will reduce to avoid expensive transportation costs. The offshore wind farm state will not be maintained effectively, resulting in more costs relevant to maintenance. It is important to facilitate the innovation to improve transportation equipment to reduce costs and lead times.

(6) Sensitivity to the lead times for orders

Although a longer lead time means the spare parts will be prepared more lately and the available service vessels have to suspend during this period, lead times have the least influence on the results. It can explained that initiating a maintenance cycle does not only await spare parts, but also available service vessels and suitable weathers. The lead times for orders coincide with these waiting times, and the maximum value is taken as the final lead time. As a result, the cost is not obviously sensitive to lead times for orders.

5.5 Conclusions

The offshore wind turbine, as a complicated equipment, consists of various components and subcomponents. The O&M of an offshore wind farm is usually supported by an inventory network containing multiple warehouses. In this context, the past single-unit and single-echelon spare parts inventory models is not appropriate.

This chapter introduces a multi-unit and multi-echelon inventory network and develops a joint optimization model for maintenance and inventory for offshore wind farms, addressing Research Question 4. The most cost-effective joint maintenance strategy and inventory policy is obtained based on the specific numerical example. It is found that the storage of spare parts also incurs significant costs, which are usually ignored in the past maintenance models. This leads to inaccurate calculation of maintenance logistics costs and consequently affects management policies, especially for the maintenance service providers who are responsible for both maintenance implementation and spare parts provision. Therefore, instead of separately studying maintenance and spare parts inventory, the two should be integrated for overall optimization.

In addition, compared with the results of Chapter 3 and Chapter 4, it can be found that there are significant differences in maintenance thresholds when considering spare parts or not, which can be explained by the interdependence between maintenance and spare parts inventory. Increasing the maintenance thresholds will reduce the frequency of maintenance and the demand for spare parts, and lower the management cost of spare parts, but it will worsen the health status of the wind farm. Decreasing the thresholds will maintain the wind farm in a better state, but require more spare parts, resulting in higher spare parts inventory costs. Therefore, an overall optimization is beneficial for improving the entire maintenance logistic for offshore wind farms. Moreover, the sensitivity analysis shows that the most influential factor in inventory management is unit costs, followed by transportation costs and maintenance effect. In comparison, lead times for orders, holding cost rates, and emergency order cost rates are less influential.

In the next chapter, another important maintenance resource for offshore wind farms is studied, i.e., maintenance vessels, which are organized to support the implementation of maintenance strategies in a cost-effective manner.

Chapter 6

Maintenance Vessel Fleet Configuration Management

In Chapter 3, a predictive opportunistic maintenance strategy is proposed to determine the maintenance tasks required in maintenance cycles. This chapter follows Chapter 3, studying how to configure the hybrid maintenance vessel fleet to support the implementation of theses maintenance tasks in a cost-effective manner, aiming to solve the fleet size and mix problem for O&M activities at offshore wind farms.

This chapter is organized as follows: Section 6.1 introduces the research background. Section 6.2 formalized the methodology for solving fleet size and mix problems. Section 6.3 presents the case study to evaluate the proposed approach and sensitivity analysis. Section 6.4 concludes the chapter.

Parts of this chapter have been published in [107][1].

6.1 Introduction

After a maintenance strategy is designed as in Chapter 3), the maintenance resources, e.g., service vessels, are organized to support the implementation of the maintenance activities under the instruction of the designed maintenance strategy. The cost of vessels accounts for a large portion, even more than 70%, of the total O&M costs for offshore wind turbines [30]. Minimizing the costs associated with the vessel fleet is essential to reduce the LCOE of offshore wind power, which is required to make offshore wind power commercially more attractive and boost the installed capacity of this renewable energy source.

Different types of vessels are needed to support maintenance activities. For example, CTVs can transport technicians to the site to conduct minor repair activities. When lifting activities are required, a HLV is needed to lift the heavy components to the height of the cabin. FSVs are designed to transport maintenance personnel, equipment, and supplies. They have a large deck area for carrying equipment and supplies, as well as accommodations for crew and personnel, which are employed to conduct major repair tasks. The

[1] M. Li, B. Bijvoet, K. Wu, X. Jiang, and R. R. Negenborn. Optimal size and composition of a hybrid maintenance vessel fleet for offshore wind farms. Submitted to a journal, 2023.

wind farm operator (or maintenance service provider) usually owns some vessels to conduct maintenance tasks, but these vessels may not be sufficient when a high number of maintenance tasks must be completed. In this case, vessels must be chartered which can be fairly expensive. Therefore, the determination of the optimal fleet size and mix to support maintenance activities for an offshore wind farm is crucial. This problem involves the daily operation of vessel organization. Compared to the strategic and tactical decisions, an important factor, metocean parameters including wave and wind, should be considered. The metocean parameters directly affect the coordination and dispatching of service vessels. In addition, more details relevant to vessels should be added to better evaluate the performance of the decisions when compared to the models in Chapters 3-5, such as fuel cost, penalty cost for late return, vessel transfer inside the wind farm, etc.

6.2 Methodology

In this section, the overall framework studying the vessel fleet mix and size problem is introduced. A simulation method is used to formalize the maintenance logistics activities in the maintenance cycles, and the input and output of the models are introduced. Then an optimization method, SA method, is employed to find the determine the optimal vessel fleet and make leasing decisions.

6.2.1 Overall framework

A vessel fleet management model is developed to support the offshore wind farm operators in the decision stage, and Fig. 6.1 shows the simulation flowchart illustrating the information flow between different parts. The black lines represent the information delivery in the framework, and the red lines represent the inner interaction among agents in the simulation. The inputs section is the part where all the information about each simulation is defined and the information is delivered to the specific agent simulations section. Afterwards, the development of the discrete event is simulated based on the input information and the analysis is performed, in order to output the results and evaluate the performance of the vessel fleet

6.2.2 Assumptions

In this section, the following assumptions are made when developing the model:

1. *Maintenance cycles and tasks.* A maintenance cycle is started when a wind turbine stops working or a specific number of components are aged. The maintenance cycles are ended when all maintenance tasks are completed. Maintenance tasks for different components of a turbine can be performed simultaneously. Once a maintenance task is started, the vessel can only be assigned to a new task after the task is finished. Once the maintenance task starts, the chartered vessel should always finish it even though its charter period has ended, and its late return will lead to the extra cost based on late-return days. After the end of a charter period, a vessel will never be assigned to a new maintenance task. Either a minor repair or a major repair cannot be performed twice on one component within the same maintenance cycle. The spare parts are always available and every vessel is equipped with sufficient spare parts for its maintenance tasks.

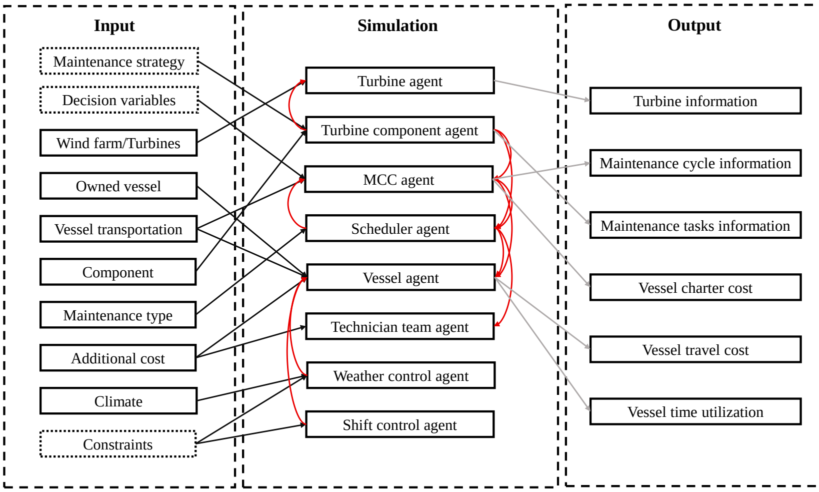


Figure 6.1: The framework for vessel fleet management

2. *Metocean condition*. The metocean conditions mainly considered are wave height and wind speed. Wind speed and wave height are assumed to be independent of each other. Referring to the wind speed at hub, the wind speed at different height at sea can be calculated. The current weather condition is independent from the previous weather condition.

3. *Repair and travelling time*. All the repair times are considered constant and independent of weather conditions. The travel speed of a vessel is assumed to be constant. The round trip travelling time between the base and the offshore wind farm is considered to be constant and independent of weather conditions. The inter-transit time between two turbines is assumed to be constant, where the detailed layout of the wind farm is ignored.

4. *Technicians*. Each vessel is equipped with technicians of the maximum number. The technicians are assumed to be sufficient when any vessel is chartered. The cost for technicians of an owned vessel is paid based on the entire duration of each maintenance cycle, and the cost for technicians of a chartered vessel counts from the start of a charter period until the day when the vessel is returned.

5. *Vessel charter and mobilization*. It is assumed that the charter rates are fixed and the charter period can be extended unlimited. Once a charter period starts, the entire charter period will be charged. The costs of non-maintenance personnel are assumed to be included in the charter rate. When mobilization is initiated, if one maintenance cycle ends before the mobilization is finished, the mobilization activity needs to be stopped and the full mobilization cost is charged.

6. *Charter extension*. During each maintenance cycle, the charter period of each vessel type may need to be extended due to a large number of remaining tasks. The decision logic to decide whether a charter period should be extended or not is to compare the number of available vessels in the fleet to the required number of vessels to perform the remaining tasks. If the vessels are sufficient, there is no need to extend the charter. On the contrary, it is necessary to extend the contract. Once a charter period is ended, the vessel always

returns to base, regardless of whether the charter period will be extended. Through this process, technicians on board need to be renewed and the vessel needs to be resupplied. If one vessel is decided to extend the charter period, after it arrives at the base, it will return back to the site after the shift start of the next day if weather permits.

7. *Maintenance priority*. For maintenance tasks that need the same vessel for maintenance, the component with a higher age is prioritized. For vessels, the on-site vessels are prioritized over the vessels staying at the base. If there are multiple available vessels on site, the vessels with more assigned teams are prioritized.

6.2.3 Decision variables

The vessel fleet is configured under the maintenance strategy in Chapter 3. Four types of maintenance, failure replacement, preventive replacement, major repair, and basic repair (minor repair), are considered in this model. The components' health is categorized into different zones according to its current age and failure age. Replacement requires HLVs, major repair requires FSVs, and basic repair requires CTVs. Performing these maintenance tasks requires a hybrid vessel fleet consisting of HLVs, FSVs, and CTVs. In the sth maintenance cycle, the numbers of tasks of each vessel type are represented by N_s^{HLVT}, N_s^{FSVT}, N_s^{CTVT} respectively.

In this model, the decision variables are the number of vessels to be chartered in each maintenance cycles. The number of chartered vessels is determined by the number of maintenance tasks per vessel type to be completed in the maintenance cycles and the number of each type of vessel owned. The three variables are N_s^{HLVC}, N_s^{FSVC}, N_s^{CTVC}, representing the number of the chartered vessel in sth maintenance type respectively. Th variables, $X_{\mathrm{T}}^{\mathrm{HLV}}$, $X_{\mathrm{T}}^{\mathrm{FSV}}$, and $X_{\mathrm{T}}^{\mathrm{CTV}}$, indicating the estimation of how many tasks one vessel is expected to execute during the maintenance cycles. The given number of owned vessels of each type are N_s^{HLVO}, N_s^{FSVO}, N_s^{CTVO}. The following equations used to decide how many vessels of each type to charter can be expressed as

$$N_s^{\mathrm{HLVC}} = \left\lceil \frac{N_s^{\mathrm{HLVT}}}{X_{\mathrm{T}}^{\mathrm{HLV}}} \right\rceil - N_s^{\mathrm{HLVO}}. \tag{6.1}$$

$$N_s^{\mathrm{FSVC}} = \left\lceil \frac{N_s^{\mathrm{FSVT}}}{X_{\mathrm{T}}^{\mathrm{FSV}}} \right\rceil - N_s^{\mathrm{FSVO}}. \tag{6.2}$$

$$N_s^{\mathrm{CTVC}} = \left\lceil \frac{N_s^{\mathrm{CTVT}}}{X_{\mathrm{T}}^{\mathrm{CTV}}} \right\rceil - N_s^{\mathrm{CTVO}}. \tag{6.3}$$

6.2.4 Simulation methods

Simulation inputs

The logistics planning for offshore wind farm operation and maintenance activities is a complicated process, involving the necessary input parameter which are introduced below.

1. *Wind farm and turbines inputs*. Table 6.1 and Table 3.1 show the inputs relevant to wind farm. The input [1] shows the number of turbines in the offshore wind farm. Input [2] displays the distance between the based onshore and the offshore wind farm. Input [3]

indicates the simulation time horizon. Inputs [4-5] are the shift start and shift end of the wind farm, and all the maintenance tasks can only be executed within this period. Input [6] is the soft time window for each maintenance cycle, once the number is exceeded, the daily penalty cost will be taken into account.

Table 6.1: Wind farm and turbine inputs

No	Name	Unit
1	Number of turbines	-
2	Distance from shore	km
3	Simulation time horizon	year
4	Shift start	hh:mm
5	Shift end	hh:mm
6	Soft time window	day

2. *Owned vessels inputs*. The number of owned vessels of each type is pre-defined as inputs in the simulation model, because the decision-makers have known how many vessels have been available at the beginning. On the basis of the number of owned vessels, the decision-maker can make leasing decisions.

3. *Vessel transportation inputs*. For three types of vessels, different transportation inputs are shown in Table 6.2. Input [1] is different travel speeds. Input [2] is the inter-transit time for different vessels to move between two turbines, where the time of a team entering the turbine is included. Inputs [1-2] are independent of the weather condition and assumed to be constant according to the prior assumption section. Input [3] is the minimum working window, which means that, the time window that at least must be available for a vessel or team to work on a maintenance task before it starts/resumes. Input [4] is the number of technicians on the vessel when the vessel travels to execute the maintenance task. As previously mentioned, it is assumed that every vessel is equipped with technicians of the maximum number. Input [5] is the maximum number of parallel teams and it indicates the number of teams on each vessel that can work on different maintenance tasks simultaneously. Inputs [6-8] are weather-related limitations of each vessel and vessels cannot work if the weather condition data exceeds any limitation. Inputs [9-10] are the Jack-up/Jack-down time, which is the time for stabilizing the HLV by stationing its legs on the seabed. Inputs [8-10] are only considered for HLVs because FSVs and CTVs are not required to lift heavy parts to the hub level of the turbine. Inputs [11-13] are related to chartering vessels. Input [11], the mobilization time, indicates the time needed by a chartered vessel to get ready before it starts maintenance tasks. Input [12] is the length of a charter period. Input [13] indicates the length of each extended charter period, and this happens when a charter period is ended but the maintenance tasks are not finished. At the beginning of each maintenance cycle, the chartered fleet size is decided, and during the cycle, it is periodically checked whether more vessels need to be chartered, and the interval is indicated as input [14] Input [15] specifies the daily penalty factor of the exceeded days for those chartered vessels that return after the charter period has ended. Input [16] is the fuel consumption while travelling, which is part of the total cost of the objective function. Input [17] is the required time for a team of technicians to leave the turbine and enter the vessel in terms of safety.

Table 6.2: Transportation inputs of vessels

No	Name	Unit
1	Travel speed	knot
2	Inter-transit time	min
3	Minimum working window	min
4	Technicians on-board	person
5	Maximum parallel teams	team
6	Limit wave height	m
7	Limit wind speed at sea	m/s
8	Limit wind speed at hub	m/s
9	Jack-up time	hour
10	Jack-down time	hour
11	Mobilization time	day
12	Charter length	day
13	Extend charter period length	day
14	Regular charter check	day
15	Penalty factor for late return	-
16	Fuel consumption	mt/h
17	Safety margin	min

4. *Failure and maintenance inputs*. Four components, rotors and blades, generators, gearboxes and bearings, are considered in the simulation model, and the lifetime of each component is generated by using the Weibull distribution with specific shape parameters and scale parameters. Maintenance type inputs contain the time and cost of different types of maintenance tasks on the different turbine components.

5. *Additional cost inputs*. Besides the parameters introduced above, more inputs are required for the total cost calculation, including electricity price, charter costs, mobilization costs, fuel costs, technician costs, and penalty costs.

6. *Climate inputs*. Wind speed and wave height are considered the climate inputs, and synthetic climate datasets can be generated by using the Weibull distribution. Referring to [27], the wind power law developed in [79], shown as (6.4), is used to calculate the wind speed values at sea level and hub level, based on the wind speed value at the reference level 21m.

$$\frac{v_2}{v_1} = (\frac{h_2}{h_1})^{\alpha}, \tag{6.4}$$

where v_2 is the wind speed at height h_2, v_1 is the wind speed at height h_1, and α is the constant coefficient for the wind power law equation.

Inputs [1-2] are the Weibull shape parameter and the Weibull scale parameter to generate the wind speed at the height of 21 m. Inputs [3-4] are the Weibull parameters to generate the wave height. Input [5] is the relevant height above sea level and is used to obtain the wind speed at sea level. Input [6] is the coefficient used in the Equation 6.4, to obtain wind speed of different altitudes.

Table 6.3: Climate inputs

No	Name	Unit
1	Weibull shape parameter of wind speed (at 21m)	-
2	Weibull scale parameter of wind speed (at 21m)	m/s
3	Weibull shape parameter of wave height	-
4	Weibull scale parameter of wave height	m
5	Relevant height above sea	m
6	Wind speed coefficient	-

Table 6.4: Maintenance zone

Maintenance type	Zone
No maintenance	Zone 1
Basic repair	Zone 2
Major repair	Zone 3
Preventive replacement	Zone 4
Failure replacement	Failed

Simulation process

The simulation model contains eight different agents, and each agent is responsible for a certain process. The current status of an agent is represented by its mode, for example, a turbine can have the modes ‘working’ or ‘not working’, and a vessel can have the modes ‘idle at base’, ‘travel to site’, etc. The three most important process interactions are ‘activate”, ‘passivate’, and ‘hold’. ‘Activate’ is used to continue an agent’s process at the current period. ‘Passivate’ is used to stop the agent’s process (the agent becomes passive). ‘Hold’ is used to delay the agent’s process, and the agent becomes active at the scheduled time. All agents will be described below.

1. *Turbine agent.* Each turbine in the offshore wind farm is represented by a turbine agent. One turbine consists of 4 critical components. The turbine starts producing electricity at the start of the simulation and stops working due to failure or maintenance implementation.

2. *Turbine component agent.* Each critical component is represented by a turbine component agent, with an individual lifetime. Referring to the component age and its lifetime, the components are categorized in zone 1, zone 2, zone 3, zone 4, or zone f (component failed), as shown in Table 6.4. More details about maintenance opportunities and actions can be found in Section 3.2.4. A difference should be explained that the model in Section 3.2.4 only considers replacement and major repair. In this chapter, the previous multi-level major repair is further categorized into major repair and basic repair. The element, employing CTVs to perform basic repair, is added in the model.

3. *Maintenance cycle trigger agent.* Maintenance activities can be performed within a certain period, which is referred to as the maintenance cycle in this research. A maintenance cycle can be initiated by any one of two triggers, one is when the number of components in zone 4 equals or exceeds a defined threshold, and another one is when the number of failed

components equals or exceeds a defined threshold.

4. *Maintenance cycle control agent.* The maintenance cycle control agent is used for the simulation environment. The maintenance cycle control agent is activated if any of the maintenance cycle triggers is reached. The maintenance cycle control agent is also responsible for chartering vessels. Once the maintenance cycle starts, vessels can be chartered at the start of a maintenance cycle or during the cycle if additional vessels should be chartered.

5. *Scheduler agent.* This agent is responsible for assigning maintenance tasks to teams of technicians as well as vessels. Every time the scheduler agent is activated, it determines the remaining maintenance tasks of each type and sorts the tasks according to the maintenance priority. Then, the agent assigns the maintenance tasks to teams of technicians and vessels based on the maintenance priority. If all maintenance tasks are completed and all the vessels are back at base, the maintenance cycle control agent will end the maintenance cycle.

6. *Vessel agent.* Each vessel in the fleet, either chartered or owned, is represented by a vessel agent. The processes vary for chartered and owned vessels. An owned vessel agent idle at the base if no maintenance cycle is active. If a decision is made to charter a new vessel, a chartered vessel agent is created and the vessel is added to the fleet. The chartered vessel is available after the mobilization is done.

In case the charter period of a chartered vessel has ended during a maintenance cycle, it is checked in advance whether the charter period should be extended before the charter expires. If the charter period is not extended, the chartered vessel is removed from the fleet.

The agent simulation vary for different vessel types due to the different characteristics. HLVs lift heavy parts to the hub level of turbines for preventive and failure replacement tasks. HLVs work continuously for 24 hours a day and can stay on-site for multiple days, but can only perform one maintenance task at a time. Jacking up/down is limited by wind speed and wave height. After jacking up, maintenance tasks can be performed when weather conditions allow. The HLV can only start a maintenance task if the wind speed at the hub level does not exceed the limit within a minimum working window plus a safety margin. Once a task is finished, the HLV jacks down and travels to the next turbine or stays jacked up to start a new task. If there are no tasks, the HLV returns to the base and stays idle until the end of the maintenance cycle/charter period.

FSVs are used for major repair maintenance tasks, lifting medium-weighted parts to the turbine's platform. FSVs can stay offshore for multiple days but are restricted by shift hours and can only work on one maintenance task at a time. Weather conditions of wave height and wind speed at sea constrain FSV operations, which can stay on-site or travel during rough weather. FSVs only start a maintenance task if the weather window is sufficient and have a safety margin for technicians to leave the turbine. If a maintenance operation is ceased due to rough weather or approaching shift end, it will resume the next day if the weather permits or if the remaining shift time meets the minimum working window. If no tasks are assigned, FSVs will travel back to base and stay idle until the end of the maintenance cycle/charter period, or until assigned to a new task.

CTVs are used for minor repairs and maintenance tasks, with strict weather and shift hour limitations. The vessel is smaller than previous types and can only transport technicians to the turbine. CTV activities are limited by weather conditions and must return to base before rough weather. Shift hours also limit CTV activities, with teams picked up at the end of the shift. If more than one team is assigned, the CTV delivers the team with the least repair time first. CTVs will wait at a turbine if a team is still working. Before traveling to the site, the CTV checks for sufficient weather windows and time for all teams to work. Unassigned teams are only assigned tasks if they can work for the minimum required time.

7. *Technician team agent*. When a maintenance task is assigned to a team of technicians, a technician team agent is temporarily created. The created technician team agent will terminate and be removed once the team has finished the maintenance task and is picked up by the vessel.

8. *Weather control agent*. Each vessel in the fleet has its own weather control agent and the agent has the function to check whether the weather window is sufficient for vessels to travel to the site for maintenance activities. The weather control agent is responsible for interrupting a vessel that is in operation and must respond to rough future weather conditions, and the vessel has to stop the maintenance activity, or even travel back to the base if the vessel type is CTV.

9. *Shift control Agent*. The shift control agent is the agent for the simulation environment that ensures the vessels constrained by shift hours are activated at shift start and start picking up teams at shift end. At the end of each day during a maintenance cycle, an overview of the location and activity of each vessel in the fleet is obtained.

Constraints for transportation systems

Different types of vessels have different characteristics and their maintenance and operations are affected by varying conditions. These characteristics are the constraints which shown are in Table 6.5. In input [1], it is assumed that HLVs and FSVs can stay offshore for multiple days, while the CTV has to return to the base every day. In input [2], in terms of shift hours, only HLVs can work 24 hours a day on a three-shift basis. While the FSVs and CTVs are constrained by shift hours, resulting that, FSVs and CTVs can only work within the shift hours. Once the shift ends, even if there is any maintenance task not finished, FSVs and CTVs have to stop the maintenance activity. FSVs have to stay on-site and CTVs need to return to base. Inputs [3-5] are weather constraints. It is assumed that all the vessel types are constrained by the wave height and the wind speed at sea level, and only HLVs are constrained by the wind speed at the hub level.

Table 6.5: Constraints for transportation systems

No	Name	HLV	FSV	CTV
1	Stay on-site for multiple days	✓	✓	
2	Constrained by shift hours		✓	✓
3	Constrained by wave height	✓	✓	✓
4	Constrained by wind speed at sea	✓	✓	✓
5	Constrained by wind speed at hub	✓		

Simulation outputs

During the simulation, the process of all maintenance activities in the wind farm will be checked and recorded every 20 minutes in the log, including turbine information, cycle information, component information, vessel charter information, vessel travel information, as well as vessel time information. These information is collected as simulation outputs. Based on the above-mentioned outputs, the total cost can be obtained and used for the objective function.

1. *Turbine information*. The operating status of every turbine is recorded. Based on this information, the total electricity production of the offshore wind farm can be calculated. To determine the wind farm's total electricity production, individual turbines' electricity production during the simulation horizon is calculated. The relationship between the wind speed at the hub level w_t and the generated power P_t^{w} at day t is given by (4.9).

2. *Maintenance cycle information*. The model tracks when maintenance cycles start and end, to calculate the length of maintenance cycles and penalty costs related to prolonged maintenance cycles.

3. *Maintenance tasks information*. When a maintenance task is completed, the information on the maintenance task is traced, including the turbine and component type, the maintenance type, the costs, and the time of completion, in order to calculate the number of each type of maintenance tasks and the corresponding costs.

4. *Vessel information*. The information include the start and end time of mobilization, the start and end time of a charter period, whether the charter period is ended by the end of a maintenance cycle or by the end of the charter period, whether the chartered vessels are returned on time or late (together with the number of late days), and whether mobilization is stopped by the end of a cycle. The technicians on chartered vessels are paid for the duration of the charter period while the technicians on an owned vessel are paid for the duration of the maintenance cycles. Then the costs of chartering vessels, mobilizations, and technicians can be calculated. In addition, based on the number of round trips from base to the site and the number of inter-transits, the fuel cost for travelling can be calculated.

6.2.5 Objective function and optimization method

The aim is to make leasing decisions to configure a vessel fleet, in order to conduct the required maintenance tasks cost-effectively, thus the optimization objective is minimizing the total costs in the planning horizon as

$$\begin{aligned} \min \quad & A_{\mathrm{c}}(N_s^{\mathrm{HLVC}}, N_s^{\mathrm{FSVC}}, N_s^{\mathrm{CTVC}}) = \frac{\sum_{s\in S}\left(C_s^{\mathrm{task}} + C_s^{\mathrm{penalty}} + C_s^{\mathrm{vessel}} + C_s^{\mathrm{loss}}\right)}{L_p} \\ \text{s.t.} \quad & N_s^{\mathrm{HLVC}}, N_s^{\mathrm{FSVC}}, N_s^{\mathrm{CTVC}} \in \mathbb{Z}^+ \end{aligned} \tag{6.5}$$

where $C_s^{\mathrm{task}}, C_s^{\mathrm{penalty}}, C_s^{\mathrm{vessel}}, C_s^{\mathrm{loss}}$ are costs for repair tasks, penalty, vessels, and production losses respectively; L_{P} is the length of planning horizon.

SA is a versatile and robust heuristic solution strategy which offers a good balance between exploration and exploitation, making it a valuable tool for solving a wide range of optimization problems, and an acceptable answer for typical problems can be obtained in a reasonable time [135]. We use this method to solve the problem in this Chapter. More discussion about the adoption of heuristic methods can be found in Chapter 7.

The algorithm is inspired by the physical process of annealing, which involves heating and then slowly cooling a material to reduce its defects and increase its stability. The algorithm starts with an initial solution to the optimization problem and then iteratively explores the search space by generating a new solution in each iteration. The new solution is generated by applying a random perturbation to the current solution, and the perturbation is controlled by a parameter known as the temperature. During the early iterations, the temperature is set high, allowing the algorithm to accept solutions that are worse than the current solution with some probability. This helps the algorithm to escape from local minima and explore a wider region of the search space. As the algorithm progresses, the temperature is gradually decreased, reducing the probability of accepting worse solutions and allowing the algorithm to converge towards the global minimum.

6.3 Case study

6.3.1 Scenario set-up

In this section, a case of an offshore wind farm is used to evaluate the performance of the developed model. The scenario is extended based on the wind farm in Chapter 3.3.1, and more details related to vessels and metocean is added. The inputs describing the maintenance strategy is summarized in Table 6.6. and Table 6.7. The two-level major repair is further categorized into major repair requiring FSVs and minor repari requiring CTVs.

Since the model in this chapter considers much more details of maintenance logistics than the previous models, the calculation time is also greatly increased. For each set of decision variables, 20 Monte-carlo simulations are generated to represent different situations, which are less than previous chapters. The length of the planning horizon is set as 15 years. The specified maintenance cycle length is set as 60 days.

Table 6.6: Description of the maintenance strategy

Maintenance type	Component age	Vessel type
No maintenance	[0, 50)	-
Minor repair	[50, 80)	CTV
Major repair	[80, 95)	FSV
Preventive replacement	[95, 100)	HLV
Failure replacement	≥ 100	HLV

Table 6.7: Threshold for starting a maintenance cycle

The trigger of starting a maintenance cycle	Threshold value
The number of zone 4 components	1
The number of failed components	1

The inputs of wind farm and turbine are listed in Table 6.8. The number of owned CTVs is one. The parameters related to vessels are listed in the Table 6.9, which estimated from [27]. The minimum working window for HLV is equal to the time required for its maintenance task. The safety margin of CTV is the total time of the maximum number of parallel teams times the inter-transit time, as well as the time required to travel back to base. The minor repair costs for rotor, bearing, gearbox, and generator, are 4k€, 1k€, 5k€, and 1.5k€ respectively. The additional cost inputs are displayed in the Table 6.10 [27]. Climate inputs are shown in the Table 6.11. The values are derived from [13, 79].

Table 6.8: The values of wind farm and turbine inputs

No	Name	Value	Unit
1	Number of turbines	50	turbine
2	Distance from shore	50	km
3	Simulation time horizon	15	year
4	Shift start	08:00	hh:mm
5	Shift end	20:00	hh:mm
6	Soft time window	60	day

Table 6.9: Values of vessel inputs

No	Name	Value			Unit
		HLV	FSV	CTV	
1	Travel speed	11	13.5	24	knot
2	Inter-transit time	40	40	20	min
3	Minimum working window	-	120	60	min
4	Technicians on-board	24	12	12	person
5	Maximum parallel teams	1	1	4	team
6	Limit wave height	2.8	2	1.7	m
7	Limit wind speed at sea	36.1	25	25	m/s
8	Limit wind speed at hub	15.3	–	–	m/s
9	Jack-up time	3	–	–	hour
10	Jack-down time	3	–	–	hour
11	Mobilization time	30	21	7	day
12	Charter length	30	30	30	day
13	Extend charter period length	15	15	15	day
14	Regular charter check	15	15	15	day
15	Penalty factor for late return	2	2	2	-
16	Fuel consumption	0.55	0.2	0.24	mt/h
17	Safety margin	20	20	-	min

The simulation is run in Python language and solved using Salabim. All simulations are run on an Intel Xeon 14-core-28-threads processor with 128G DDR4 memory. The configuration of the SA algorithm is: (1) Initial starting temperature is 100 and stopping temperature is 4. (2) Cooling rate is 0.5.(3) Number of moves at each temperature is 40.

Table 6.10: The values of additional cost inputs

No	Name	Value	Unit
1	Electricity price	150	€/MWh
2	HLV charter rate	110000	€/day
3	FSV charter rate	10000	€/day
4	CTV charter rate	2500	€/day
5	HLV mobilization cost	800000	€
6	FSV mobilization cost	200,000	€
7	CTV mobilization cost	50,000	€
8	HLV fuel cost	450	€/mt
9	FSV fuel cost	300	€/mt
10	CTV fuel cost	300	€/mt
11	HLV technician cost	100,000	€/year
12	FSV technician cost	100,000	€/year
13	CTV technician cost	60,000	€/year
14	Penalty cost	50,000	€/day

Table 6.11: The values of climate inputs

No	Name	Value	Unit
1	Weibull shape parameter of wind speed (at 21m)	2.43	-
2	Weibull scale parameter of wind speed (at 21m)	8.58	m/s
3	Weibull shape parameter of wave height	1.58	-
4	Weibull scale parameter of wave height	1.1	m
5	Relevant height above sea	5	m
6	Shear component	0.1	-

6.3.2 Results

The computational time for solving the optimization problem is about 30.3 hours. The obtained values of variables are $X_{\mathrm{T}}^{\mathrm{HLV}} = 6$, $X_{\mathrm{T}}^{\mathrm{FSV}} = 24$, $X_{\mathrm{T}}^{\mathrm{CTV}} = 150$. The number of HLVs, FSVs, and CTVs which are chartered in each maintenance cycle are listed in Table 6.12.

Each combination of three numbers illustrates the chartered number of each vessel type in each maintenance cycle in each scenario. For example, the result is (1,2,0) in 14th cycle in SET1 simulation, indicating 1 HLV and 2FSVs are charted. Given that 1 CTV has been owned, the vessel fleet in this maintenance cycle is composed of 1 HLV, 2FSVs, and 1 CTV.

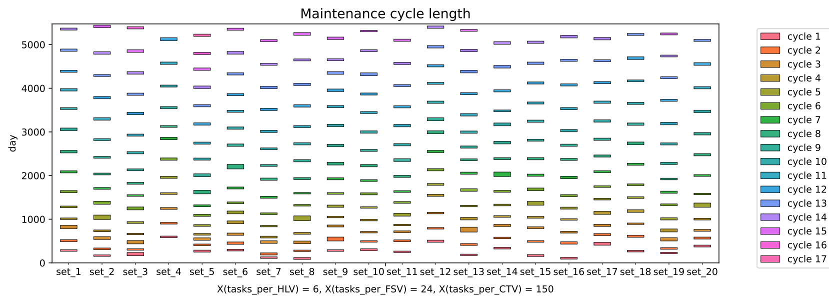
The maintenance cycle length are shown in Fig. 6.2. In the top part of the figure, from a down-up perspective to the Y-axis, the relative location of each maintenance cycle of each scenario to the whole time horizon is displayed, and the thickness of each bar illustrates the relative length of each maintenance cycle. The bottom part of the figure displays the details of each maintenance cycle. It can be seen that, for each scenario, the number of the maintenance cycle can be different. The reason leading to the difference is that, in different scenarios, the lifetime of each turbine component varies, and the component with a longer lifetime has a lower possibility for replacement, thus the maintenance cycle is not easily

Table 6.12: The number of chartered vessels in maintenance cycles

	SET1	SET2	SET3	SET4	SET5	SET6	SET7	SET8	SET9	SET10	SET11	SET12	SET13	SET14	SET15	SET16	SET17	SET18	SET19	SET20
Cycle 1	1, 0, 0	1, 0, 0	1, 0, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 0, 0	1, 0, 0	1, 0, 0	1, 1, 0	1, 0, 0	1, 0, 0	1, 0, 0	1, 0, 0	1, 0, 0	1, 0, 0	1, 1, 0	1, 0, 0	1, 0, 0	1, 1, 0
Cycle 2	1, 1, 0	1, 0, 0	1, 0, 0	1, 1, 0	1, 0, 0	1, 0, 0	1, 0, 0	1, 0, 0	1, 1, 0	1, 0, 0	1, 1, 0	1, 1, 0	1, 0, 0	1, 1, 0	1, 1, 0	1, 0, 0	1, 1, 0	1, 1, 0	1, 0, 0	1, 1, 0
Cycle 3	1, 1, 0	1, 1, 0	1, 0, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 0, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 2, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 0, 0	1, 1, 0
Cycle 4	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 0, 0	1, 1, 0	1, 0, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 0, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0
Cycle 5	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 0, 0	1, 0, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 0, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0
Cycle 6	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0
Cycle 7	1, 1, 0	1, 1, 0	1, 1, 0	1, 2, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 1	1, 1, 0	1, 1, 0
Cycle 8	1, 1, 0	1, 1, 0	1, 1, 0	1, 0, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 1	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0
Cycle 9	1, 2, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 1	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0
Cycle 10	1, 2, 0	1, 1, 0	1, 1, 0	1, 2, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 1	1, 1, 1	1, 2, 0
Cycle 11	1, 1, 0	1, 1, 1	1, 1, 0	1, 2, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 1	1, 1, 0	1, 1, 0	1, 1, 0	1, 2, 1	1, 1, 0	1, 2, 1	1, 1, 1	1, 2, 0
Cycle 12	1, 1, 0	1, 1, 0	1, 1, 1	1, 2, 0	1, 2, 0	1, 1, 0	1, 1, 1	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 1, 1	1, 1, 0	1, 1, 0	1, 2, 0	1, 1, 0	1, 1, 0	1, 2, 1	1, 1, 0
Cycle 13	1, 2, 0	1, 2, 0	1, 1, 0	-	1, 1, 0	1, 1, 0	1, 2, 0	1, 1, 0	1, 1, 0	1, 1, 0	1, 2, 0	1, 1, 0	1, 1, 0	1, 2, 1	1, 1, 0	1, 2, 1	1, 2, 0	1, 2, 0	1, 2, 0	1, 2, 0
Cycle 14	1, 2, 0	1, 1, 0	1, 1, 0	-	1, 1, 0	1, 1, 0	1, 2, 0	1, 2, 0	1, 1, 0	1, 2, 0	1, 1, 1	1, 1, 0	1, 1, 0	1, 1, 1	1, 1, 0	1, 2, 0	1, 1, 0	-	1, 1, 1	-
Cycle 15	-	1, 2, 0	1, 1, 0	-	1, 1, 0	1, 2, 0	1, 2, 0	1, 2, 0	1, 1, 1	1, 1, 1	1, 2, 0	-	1, 1, 1	-	-	-	-	-	1, 2, 1	-
Cycle 16	-	-	1, 2, 0	-	1, 1, 0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Cycle 17	-	-	-	-	1, 1, 0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

triggered.

For each maintenance cycle, the duration also varies. This can be affected by the weather condition and the workload within this period. If the weather condition is suitable for the task execution, then all the maintenance tasks can be finished faster than those of worse weather conditions. Also, the less number of maintenance tasks is, the less time required for each maintenance cycle is, therefore, its duration decreases accordingly.



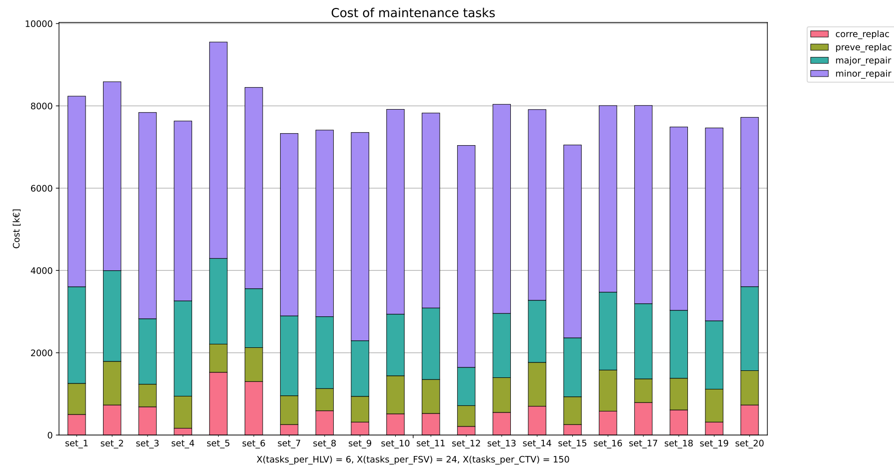
Unit: day	X(tasks_per_HLV) = 6, X(tasks_per_FSV) = 24, X(tasks_per_CTV) = 150																			
	set_1	set_2	set_3	set_4	set_5	set_6	set_7	set_8	set_9	set_10	set_11	set_12	set_13	set_14	set_15	set_16	set_17	set_18	set_19	set_20
cycle 1 length	37	34	75	38	45	38	37	45	38	46	34	48	33	39	45	39	64	37	33	43
cycle 2 length	47	39	33	38	38	55	48	33	89	34	43	35	44	35	37	54	48	48	37	45
cycle 3 length	75	66	77	43	55	52	60	61	44	34	40	36	112	50	41	41	51	34	75	42
cycle 4 length	37	41	33	40	37	64	42	42	37	38	35	49	58	39	40	34	70	60	68	39
cycle 5 length	40	103	42	50	42	65	33	109	52	33	64	42	35	39	85	45	39	39	50	96
cycle 6 length	49	68	67	52	50	39	39	36	38	46	41	51	59	42	63	49	37	39	44	34
cycle 7 length	48	42	37	55	42	45	45	33	47	42	40	50	49	104	49	56	44	46	48	41
cycle 8 length	57	42	42	42	82	104	51	47	61	54	48	68	43	47	52	47	48	64	38	52
cycle 9 length	60	41	44	52	66	55	44	52	56	46	64	69	49	60	44	50	52	53	54	56
cycle 10 length	44	45	51	45	47	51	44	51	56	52	53	52	51	66	50	54	52	48	48	56
cycle 11 length	55	56	46	55	47	45	52	48	50	47	56	44	56	42	47	51	51	43	59	51
cycle 12 length	47	54	56	67	52	51	54	55	59	47	50	51	49	50	48	49	51	62	46	60
cycle 13 length	52	46	50	-	52	50	57	54	60	66	47	56	60	60	54	49	46	45	47	46
cycle 14 length	46	55	56	-	59	61	47	45	43	48	51	53	57	59	51	59	56	-	42	-
cycle 15 length	-	60	59	-	55	47	48	62	57	33	50	-	43	-	-	-	-	-	44	-
cycle 16 length	-	-	49	-	51	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
cycle 17 length	-	-	-	-	53	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
total	694	792	817	577	873	822	701	773	787	666	716	704	798	732	706	677	709	618	733	661

Figure 6.2: The results of the maintenance cycle length

In general, most of the duration of each maintenance cycle is less than 60 days because of the constraint of the soft time window. Once the time is exceeded, the daily penalty cost and all vessel-related costs will be charged. While for the former cost, the result of the penalty cost related to prolonged maintenance cycles beyond the soft time window. The penalty cost is 0 for every maintenance cycle with a duration lower than 60 days, and for those with over 60 days, the penalty is the product of the number of exceeding days and the daily penalty. The costs of repair tasks are shown in Fig. 6.3. The cost distribution is consistent with Fig. 3.12. The difference related to the costs for major repair is because major repair tasks in Chapter 3 is further classified into major repair and minor repair in this model.

6.3.3 Sensitivity analysis

As the outputs of the simulation model are affected by many inputs, a sensitivity analysis on important inputs is performed to test different values for the verification as well as to evaluate how these inputs influence the results, which could be as a reference by wind



Unit: k€	X(tasks_per_HLV) = 6, X(tasks_per_FSV) = 24, X(tasks_per_CTV) = 150																			
	set_1	set_2	set_3	set_4	set_5	set_6	set_7	set_8	set_9	set_10	set_11	set_12	set_13	set_14	set_15	set_16	set_17	set_18	set_19	set_20
corre_replac	500.0	730.0	685.0	165.0	1525.0	1300.0	255.0	590.0	315.0	515.0	525.0	210.0	550.0	700.0	255.0	580.0	790.0	610.0	315.0	730.0
preve_replac	755.0	1060.0	550.0	780.0	685.0	825.0	700.0	540.0	625.0	925.0	825.0	505.0	845.0	1065.0	675.0	1000.0	575.0	770.0	800.0	835.0
major_repair	2348.75	2206.25	1591.25	2316.25	2082.5	1432.5	1941.25	1747.5	1352.5	1497.5	1738.75	930.0	1561.25	1510.0	1432.5	1892.5	1827.5	1651.25	1661.25	2041.25
minor_repair	4632.5	4590.5	5013.0	4370.5	5258.5	4891.0	4433.0	4534.0	5061.0	4978.0	4737.0	5393.0	5082.0	4636.0	4687.0	4534.5	4817.0	4455.5	4687.5	4115.5
total	8236.25	8586.75	7839.25	7631.75	9551.0	8448.5	7329.25	7411.5	7353.5	7915.5	7825.75	7038.0	8038.25	7911.0	7049.5	8007.0	8009.5	7486.75	7463.75	7721.75

Figure 6.3: The result of the cost of maintenance tasks

farm developers/researchers. The concerned input parameters are Weibull scale parameter of climate input, maximum parallel teams number on CTV, penalty cost, charter length, range of each component condition zone. These inputs are key parameters in the model, directly affecting the vessel organization and leasing decisions, thus we perform a sensitivity analysis on these input parameters. The values of the parameters increase by 50% and decrease by 50%.

The results of sensitivity analysis are shown in Table 6.13. In the developed model, under certain weather conditions, the balance between the number of chartering vessels and the lengths of maintenance cycles is significant to the total costs. The more vessels are chartered, the faster maintenance tasks are finished and the shorter the maintenance cycle lengths are. In this case, more vessels lead to more charter costs. On the other hand, if the vessel size is not enough for the maintenance tasks, the maintenance cycle needs to be prolonged, thus the penalty cost will be charged when the soft window is exceeded. It can be seen that the changes in penalty have no influence on the costs except for the annual penalty cost. Hence, the total O&M costs are very close.

In terms of the changes in the climate Weibull scale parameter, when the parameter decreases to be 0.5 times, there is a general decrease in every costs, and the cost of production loss decreases outstandingly. Nevertheless, when the scale parameter becomes larger, meaning that the weather conditions become worse, the influence is very significant. The costs of the vessel travelling, vessel chartering, penalty and production loss are extremely different from the original results. Under extreme weather conditions, the weather changes drastically, the minimum working window of HLV can never be satisfied and it keeps waiting for suitable weather conditions. Thus, once the maintenance cycle starts, no one maintenance cycle is completed and it lasts until the end of the wind farm time horizon. Minor repairs

Table 6.13: Results of sensitivity analysis

Description	Multiple	Annual cost (k€/year)					
		Vessel traveling	Vessel chartering	Repair tasks	Penalty	Production loss	Total
Benchmark	1	19.2	5052.8	522.8	88.0	671.6	6354.5
Climate parameter	1.5	6.8	15908.8	110.1	17205.2	89655.1	122886.0
	0.5	15.4	4670.8	513.4	40.8	49.2	5289.7
Component zone	1.5	27.0	4755.9	666.4	63.5	867.6	6380.4
	0.5	15.8	6543.8	517.4	429.0	712.1	8218.1
Charter length	1.5	19.2	6653.4	522.9	87.5	672.4	7955.4
	0.5	19.6	3879.1	525.0	106.0	673.9	5203.6
Penalty cost	1.5	19.2	5052.8	522.8	44.0	671.6	6310.5
	0.5	19.2	5052.8	522.8	132.0	671.6	6398.5
CTV teams	1.5	17.5	5094.0	520.9	93.7	699.0	6425.1
	0.5	24.9	5290.8	515.1	1020.0	682.6	7533.4

contribute the most to the cost of maintenance tasks while preventive replacement and failure replacement will never be performed.

The changes in the maximum parallel team result in fluctuations in the output results differently. The decrease in team number leads to insufficient resources for maintenance tasks, therefore, more time is needed and maintenance cycles need to be prolonged. More frequent activities are required and the travelling cost increases. On the other hand, the increment in the maximum parallel team does not mean a decrease in the total O&M cost. The number of maintenance cycles might increase due to the fact that maintenance tasks are completed faster and more triggers of starting a maintenance cycle can be reached. The reason is that the influence of maintenance activities on components, namely the value of age reduction, is more influential when the component is more aged. For example, at the beginning of a maintenance cycle, both components have a life of 1000 days. If the first component is quickly performed major repair on at day 1, its life is reduced to $1000 \cdot 0.5 = 500$ days. If the other component is repaired at day 40, its life is reduced to $1040 \cdot 0.5 = 520$ days. At this point, the life of the first component was $500 + 40 = 540$ days. In other words, it is not better to repair the parts earlier and faster. If maintenance are performed too quickly, the component will degrade sooner, potentially resulting in more failures and more maintenance cycles.

In the aspect of the charter length, the differences reveal important information. Compared with the benchmark, the cost of maintenance tasks when the charter length is longer is not significantly different. However, the longer charter length means that in the first several maintenance cycles with a low number of tasks, vessels quickly finish the tasks and have to wait until the end of the charter length, during which the charter cost is still charged. When meeting a similar number of tasks, the longer charter length will lead to the waste of vessel utilization and lead to an obvious increment of the total charter cost. Conversely, the short charter length goes in another direction where the charter is more flexible. Given a shorter initial charter length, the charter length can be extended when needed, and each charter can be made good use of, leading to the remarkable saving on the total charter cost.

The changes in the component zone range also result in different costs. When the length of each component zone becomes 1.5 times larger, it means more components are determined to repaired. What happens in this situation is that, components have fewer possibilities to fail because they can be fixed at an early age, thus, the number of the most expensive maintenance task, failure replacement, substantially decreases, and the cost can be saved a lot. However, the amount of minor repairs and major repairs climbs, leading to a sharp increment in their costs for maintenance tasks. Also, due to the frequent repair, more turbines need to stop running and the production loss cost climbs. In contrast, the shortening of the component zone results in the accumulation of maintenance tasks because each component could only be repaired/replaced when its situation is very bad. Therefore, more vessels need to be used and longer maintenance cycles are needed to address this situation of increased tasks.

6.4 Conclusions

Chapter 3 develops a maintenance strategy, and this chapter studies the vessel fleet organization under the determined maintenance strategy. The repair workload is determined in each maintenance cycles, and it is necessary to determine the mix and size of the hybrid vessel fleet. This chapter addresses Research Question 5, aiming to develop a simulation-based model that can be used to optimize fleet management decisions, providing decision-makers to make rational leasing decisions when triggering maintenance cycles.

Given an available number of owned vessels, the decisions involve determining the number of vessels of each type to be chartered at various moments throughout the wind farm lifetime. Uncertainties related to turbine component failures and weather conditions are considered in this model. Under a specific set of fleet configuration, the total costs are evaluated by using the developed model. Compared to the models in Chapters 3 and 4, more vessel parameters and minor changes in vessel dispatching for different maintenance tasks are introduced to make the model more complete and reasonable. A metaheuristic algorithm, SA method, is used to combine with the model to obtain the optimal solutions. The proposed methods can make the leasing decision to configure a hybrid maintenance vessel fleet to support the implementation of maintenance activities with minimum total costs including vessel costs, production losses, repair costs, and penalty cost. The results show that the cost of vessel chartering is higher than in previous chapters because of the refinement of the scheduling model for vessels. More elements are taken into account, which increases the cost of vessel charting. There is also a slight change in the division of maintenance tasks, so the estimate of maintenance costs has changed. The sensitivity analysis shows the offshore environment is crucial for maintenance implementation and directly affects the progress of conducting tasks. The followings are the setting of the maintenance strategy, the length of the charter contract, the team configuration of CTV, and and penalty costs.

Chapter 3-6 focuses on maintenance strategy and resource organization for offshore wind farms, while an open-loop approach is used for decision-making without considering the feasibility to update decisions. The next chapter studies the development of a closed-loop maintenance strategy, which uses new data and captures the dynamic wind farm states to update the maintenance decisions over the lifetime of wind farm, in order to further improve the current maintenance strategies.

Chapter 7

A Closed-loop Strategy Considering Data Updates and Wind Farm States

Chapter 4 has pointed out that the design of the maintenance strategy which is proposed in Chapter 3 suffers from the uncertainty or inaccuracy in model parameters, and has identified the potential types of uncertainties and quantified their influence. Following the research in Chapter 3 and 4, this chapter proposes a closed-loop maintenance strategy optimization framework to adjust maintenance strategies periodically according to the dynamic wind farm states and updated RAM database.

This chapter is organized as follows: Section 7.1 introduces the research background of the problem. Section 7.2 presents the proposed framework and introduces the individual models within it. In Section 7.3, a case study for a generic offshore wind farm is provided to illustrate the applicability. Moreover, a comparative study of five scenarios is performed to highlight the economic benefit of the proposed approach. Section 7.4 summarizes the main findings of the results, and discusses the practical implications. Section 7.5 concludes the chapter.

Parts of this chapter have been published in [106][1] and [108][2].

7.1 Introduction

When determining solutions to maintenance optimization problems, it is helpful to distinguish between open-loop, reactive, and closed-loop solutions. As discussed in Chapter 2, an open-loop strategy indicates to find the optimal maintenance strategy at the beginning of

[1]M. Li, X. Jiang, J. Carroll, and R. R. Negenborn. Rolling horizon based adjustable maintenance management: A case study of a 3-MW wind turbine. In *Proceedings of the 18th EAWE PhD Seminar on Wind Energy*, pages 1–4, Bruges, Belgium, 2022.

[2]M. Li, X. Jiang, J. Carroll, and R. R. Negenborn. A closed-loop uncertainty-aware strategy for offshore wind farm maintenance. Submitted to a journal, 2023.

operation and to implement it over the entire lifetime. This open-loop strategy is the most widely used in the past studies.

Compared to an open-loop strategy that is applied over the entire optimization horizon blindly, a reactive strategy is determined step by step. The current strategy is formulated on the basis of the current state, and it is implemented until the next step in which a new strategy is determined again. The reactive maintenance strategy has the capacity of making decisions based on the present situation. Compared to the open-loop strategies, the reactive strategies are able to capture the wind farm states to update decisions which are more suitable for the current wind farm state. However, reactive strategies lack the ability to utilize the feedback (i.e., new RAM data) generated from the wind farm. If the feedback is integrated into decision-making to update decisions, this approach is called as 'closed-loop', referring to a process from information collection and use, to decision-making, action taking, and back again to information collection.

Therefore, in order to improve the performance of maintenance strategies, it is necessary to develop such a closed-loop strategy to improve the current open-loop maintenance strategy. In this chapter, we proposes a closed-loop maintenance strategy optimization framework to connect the decision-maker's maintenance model and the target offshore wind farm. New data is accumulated with the operation of the offshore wind farm to update inaccurate parameters in the maintenance model. At each decision-making step, the maintenance strategy is adapted to the current health state of the wind farm while making use of the updated parameters.

7.2 Method

In this section, we formally introduce the closed-loop maintenance strategy optimization framework over the wind farm service life in detail, as illustrated in Fig. 7.1. The decision-maker formulating the maintenance strategy is the wind farm owner and operators. As a crucial strategic decision in the maintenance management, the maintenance strategy consists of several thresholds. These thresholds act like maintenance criteria, which determine the triggering of maintenance cycles and the maintenance actions required for components in different health states in maintenance cycles. Before the operation of the wind farm, the decision-maker employs a maintenance model and an optimizer to determine the optimal maintenance strategy in view of the preferred objective. The resource for values of input model parameters can be from vendor guidelines, maintenance records, historic failure data, or even expert survey. Although uncertainty and inadequacy in the data is a serious problem for decision makers, the development of the current maintenance strategy still has to rely on these available data.

The sensors installed on the operating wind turbines record the various kinds of signals including vibration, temperature, and acoustic emission, depending on the type of the component that is monitored. Then the signals are transferred to a remote monitoring and control center where the experts perform fault prognosis for wind turbine RUL estimation. The health state of components is assessed according to the estimated RUL, and the decision-maker decides on whether to initiate a cycle of maintenance or not according to the current maintenance strategy. In the maintenance cycle, the spare parts, maintenance vessels, and technicians are organized to perform the maintenance actions.

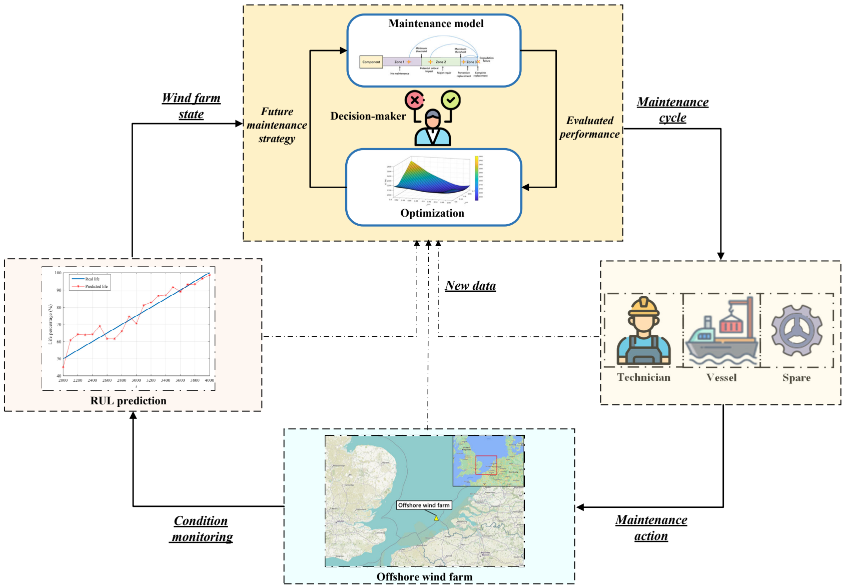


Figure 7.1: Schematic diagram of the closed-loop maintenance decision-making process

With the accumulation of failure data and maintenance records over the lifespan, new data can be delivered to the decision-maker's databases. The previous uncertain input parameters of the maintenance model are updated using the new data. The decision-maker periodically adjusts the pre-determined maintenance strategy, and then the new strategy is delivered to guide the maintenance in the following periods. The entire process introduced above is regarded as the closed-loop maintenance strategy optimization framework.

7.2.1 Offshore wind farm states

In this section, a mathematical model is developed to represent the dynamics of the offshore wind farm system. We suppose there is an offshore wind farm consisting of K turbines of the same type. Each turbine is simplified as a series system consisting of I components. More details about the maintenance model can be found in Chapter 3 and 4. The length of the offshore wind farm lifetime is represented by L. We use a discrete manner to represent this process, where the information of the wind farm state is updated every time period of Δs. The number of the wind farm states, represented by N, is obtained by $N = L/\Delta s$

For the state n, where $n \in \{1, \ldots, N\}$, the wind farm state $\boldsymbol{R}(n)$ has a set of variables representing the start state $\boldsymbol{\xi}(n)$, the end state $\boldsymbol{\omega}(n)$, and the interior state $\boldsymbol{\kappa}(n)$, as:

$$\boldsymbol{R}(n) = \begin{bmatrix} \boldsymbol{\xi}(n) & \boldsymbol{\kappa}(n) & \boldsymbol{\omega}(n) \end{bmatrix}. \tag{7.1}$$

The interior state is neither start state nor end state, but performs as a transition. The start state $\boldsymbol{\xi}(n)$ and the end state $\boldsymbol{\omega}(n)$ connect the current time period and the previous or subsequent time period as:

$$\boldsymbol{\xi}(n+1) = \boldsymbol{\omega}(n). \tag{7.2}$$

The state $\boldsymbol{R}(u)$ incorporates the effects of the failures and repairs that the wind farm system experiences during the length of period Δs. It is necessary to model this process in order to demonstrate how the system state transforms successively with the time going. The state $\boldsymbol{\xi}(n)$ is represented by:

$$\boldsymbol{\xi}(n) = \begin{bmatrix} \boldsymbol{w}(n) & \boldsymbol{u}(n) & \boldsymbol{v}(n) & \widetilde{\boldsymbol{v}}(n) & \boldsymbol{a}(n) & \boldsymbol{g}(n) \end{bmatrix}, \tag{7.3}$$

where $\boldsymbol{w}(n) = [w_{ik}(n)]_{I\times K}$ contains the variables representing the cumulative time of component i at turbine k at state n; $\boldsymbol{u}(n) = [u_{ik}(n)]_{I\times K}$ represents the current age of components; $\boldsymbol{v}(n) = [v_{ik}(n)]_{I\times K}$ represents the real lifetime of components; $\widetilde{v}(n) = [\widetilde{v}_{ik}(n)]_{I\times K}$ represents the predicted lifetime of components; $\boldsymbol{a}(n) = [a_{ik}(n)]_{I\times K}$ are the binary variables implying whether the component is in a failure state; $\boldsymbol{g}(n) = [g_{ik}(n)]_{I\times K}$ represents the failure moment of the turbine component if it is in the failure state.

The end state n is given by:

$$\boldsymbol{\omega}(n) = \begin{bmatrix} \bar{\boldsymbol{w}}(n) & \bar{\boldsymbol{u}}(n) & \bar{\boldsymbol{v}}(n) & \bar{\widetilde{\boldsymbol{v}}}(n) & \bar{\boldsymbol{a}}(n) & \bar{\boldsymbol{g}}(n) \end{bmatrix}, \tag{7.4}$$

where $\bar{\boldsymbol{w}}(n) = [\bar{w}_{ik}(n)]_{I\times K}$, $\bar{\boldsymbol{u}}(n) = [\bar{u}_{ik}(n)]_{I\times K}$, $\bar{\boldsymbol{v}}(n) = [\bar{v}_{ik}(n)]_{I\times K}$, $\bar{\widetilde{\boldsymbol{v}}}(n) = \left[\bar{\widetilde{v}}_{ik}(n)\right]_{I\times K}$, $\bar{\boldsymbol{a}}(n) = [\bar{a}_{ik}(n)]_{I\times K}$, $\bar{\boldsymbol{g}}(n) = [\bar{g}_{ik}(n)]_{I\times K}$ are the state matrix in the end states.

The updating of variables between the start state and the end state relies on the interior state $\boldsymbol{\kappa}(n)$, represented by:

$$\boldsymbol{\kappa}(n) = \begin{bmatrix} {}^{1}\boldsymbol{O}(n) & {}^{2}\boldsymbol{O}(n) & {}^{3}\boldsymbol{O}(n) & \boldsymbol{\theta}(n) & \boldsymbol{q}(n) & \boldsymbol{b}(n) \end{bmatrix}, \tag{7.5}$$

where ${}^{1}\boldsymbol{O}(n) = \left[{}^{1}O_{ik}(n)\right]_{I\times K}$contains the binary variables meaning whether a repair action is needed for the degradation failure of component i at turbine k; ${}^{2}\boldsymbol{O}(n) = \left[{}^{2}O_{ik}(n)\right]_{I\times K}$ contains the binary variables meaning whether a repair action is needed for the incident failure; ${}^{3}\boldsymbol{O}(n) = \left[{}^{3}O_{ik}(n)\right]_{I\times K}$ contains the binary variables meaning whether the component i at turbine k is at the ageing stage; $\boldsymbol{\theta}(n) = [\theta_{ikm}(n)]_{I\times K}$ contains the variables representing the quality of potential maintenance actions performed; $\boldsymbol{q}(n) = [q_{ik}(n)]_{I\times K}$ contains the variables representing the occurrence time of environmental impact; $\boldsymbol{b}(n) = [b_{ik}(n)]_{I\times K}$ contains the variables representing the influence of environmental impact.

We use ${}^{1}\boldsymbol{O}(n)$, ${}^{2}\boldsymbol{O}(n)$, ${}^{3}\boldsymbol{O}(n)$ to count the number of aged and failed components in the wind farm. A binary variable $d(n)$ in (7.6) is used to decide whether a maintenance cycle should be initiated. In the case that a critical incident arises, or a degradation failure occurs, or a sufficient number of components are aged, a maintenance cycle is determined to be triggered, and the available maintenance resources are organized to support the implementation of the determined maintenance strategy (see Fig. 7.1). The transfer among states $\boldsymbol{\xi}(n)$, $\boldsymbol{\kappa}(n)$, $\boldsymbol{\omega}(n)$ can be referred to Section 3.2.4.

$$d(n) = \begin{cases} 1 & \text{if} \sum_{i=1}^{I}\sum_{k=1}^{K} {}^{1}O_{ik}(n) \geq 1 \,\text{or} \sum_{i=1}^{I}\sum_{k=1}^{K} {}^{2}O_{ik}(n) \geq 1 \,\text{or} \sum_{i=1}^{I}\sum_{k=1}^{K} {}^{3}O_{ik}(n) \geq KI\zeta \\ 0 & \text{otherwise} \end{cases} \tag{7.6}$$

The total revenue losses during period n, represented by $\ell(n)$, composed of material cost, vessel cost, technician cost, and cost of production loss, are defined as

$$\ell(n) = d(n)\left\{ \begin{array}{l} M^{\mathrm{MOB}}(n)+ \\ \sum\limits_{k\in K}\left\{ \begin{array}{l} \left(T(n)-F_k^{\mathrm{T}}(n)\right) r+ \\ \sum\limits_{i\in I}\left\{ \begin{array}{l} \left[R_{ik}^{\mathrm{FR}} + N_{ik}^{\mathrm{FR}}\left(Q^{\mathrm{J}} + W^{\mathrm{FR}}T^{\mathrm{C}} + r\right)\right] X_{ik}^{\mathrm{FR}}(n)+ \\ \left[R_{ik}^{\mathrm{PR}} + N_{ik}^{\mathrm{PR}}\left(Q^{\mathrm{J}} + W^{\mathrm{PR}}T^{\mathrm{C}} + r\right)\right] X_{ik}^{\mathrm{PR}}(n)+ \\ \left[R_{ik}^{\mathrm{MIR}} + N_{ik}^{\mathrm{MIR}}\left(Q^{\mathrm{C}} + W^{\mathrm{MIR}}T^{\mathrm{C}} + r\right)\right] \\ X_{ik}^{\mathrm{MIR}}(n)+ \\ \sum\limits_{m=2}^{M-1}\left[\begin{array}{l} R_{ik}^{\mathrm{MAR}}(n)+ \\ N_{ikm}^{\mathrm{MAR}}(n) \\ \left(Q^{\mathrm{S}} + W^{\mathrm{MAR}}T^{\mathrm{C}} + r\right) \end{array}\right] \\ X_{ikm}^{\mathrm{MAR}}(n) \end{array}\right\} \end{array}\right\} \end{array}\right\}. \tag{7.7}$$

7.2.2 Decision-maker's virtual maintenance model

The state transition of the actual offshore wind farm and the execution of the maintenance cycles are modelled, which can be considered as the real O&M situation of the wind farm under a specific maintenance strategy. The strategy is a kind of control action that is decided on by the decision-maker. In order to design a sound maintenance strategy, the decision-maker relies on a virtual maintenance model to simulate the O&M in the real offshore wind farm and predict the expected annual revenue losses $\dot{A}_{\mathrm{r}}$ under the specific maintenance strategy.

Running such a maintenance model definitely requires input parameters. These parameters are derived from the database available to the decision-maker. In the decision-maker's maintenance model, the wind farm states are represented as:

$$\dot{\boldsymbol{R}}(u) = \left[\begin{array}{ccc} \dot{\boldsymbol{\xi}}(n) & \dot{\boldsymbol{\omega}}(n) & \dot{\boldsymbol{\kappa}}(n) \end{array}\right]. \tag{7.8}$$

The state $\dot{\boldsymbol{R}}(u)$ is different from $\boldsymbol{R}(u)$ due to the uncertainty in the parameters. These uncertainties induce an incorrect estimation of the system state. In this model, we suppose that the uncertain parameters include component lifetime parameters, RUL prediction error parameters, and maintenance consequence parameters, as introduced in Chapter 4. In the maintenance model, the component lifetime is also modelled following a two-parameter Weibull distribution as:

$$\dot{v_{ik}} = \dot{\sigma_{ik}}[-\ln(1-\gamma)]^{\frac{1}{\dot{\varepsilon_{ik}}}} \tag{7.9}$$

where the shape and scale parameters $\dot{\sigma_{ik}}$ and $\dot{\varepsilon_{ik}}$ are unequal to the parameters in (3.4), which represent the actual component failure information is still not fully recognizable by the decision-maker.

The decision-maker has realized the possible error between the predicted and real component age when developing the maintenance model. The prediction error modelling is based on the past performance of the adopted RUL prediction technology. However, once the RUL technique is applied in practice, it is very likely that the real prediction accuracy is far from our expected result given the negative influences from the actual operating environment. In this situation, the prediction error in the maintenance model is modelled as:

$$\dot{e}_{ik}(n) \sim N(\dot{\mu}_{ik}(n), \dot{\delta}_{ik}(n)^2). \tag{7.10}$$

The modelling of the maintenance consequences represents the decision-maker's estimation of maintenance effect, cost, and time, that result from the execution of the maintenance action. This estimation is dependent on the historic maintenance database. As discussed before, the historic database may be inaccurate and incomplete to derive the explicit estimation. Therefore, the coefficients input to the maintenance model is $\dot{\eta}_{\mathrm{c}}(n) \sim N(\dot{\mu}_{\mathrm{c}}, \dot{\delta}_{\mathrm{c}}^2)$ and $\dot{\eta}_{\mathrm{t}}(n) \sim N(\dot{\mu}_{\mathrm{t}}, \dot{\delta}_{\mathrm{t}}^2)$. The maintenance quality is $\dot{\theta}_{ikm}(n)$ with the parameters $\dot{\alpha}_m$ and $\dot{\beta}_m$. The expected value and the variance is $\dot{\mu}_{\theta_{ikm}(n)}$ and $\dot{\sigma}_{\theta_{ikm}(n)}$, respectively.

7.2.3 Rolling horizon and information updating

The earlier wind energy maintenance models mostly adopt a kind of open-loop method for decision-making. For a large time horizon, such a fixed strategy is likely to be inappropriate due to the ignorance of periodic properties and accumulated data. A decomposition based approach is needed to exploit the temporal structure and decompose the entire optimization problem into multiple optimization problems.

The decision-maker is assumed to employ a time interval $\triangle T$ for decision making, where $\triangle T = \rho \Delta s$. On the basis of the maintenance model proposed in Section 7.2.2, the decision-maker here uses a so-called shrinking-horizon approach [54] and decomposes the optimization problem into finite sub-problems $\{P^1, ..., P^Z\}$, as illustrated in Fig. 7.2. Each optimization problem belongs to a step of decision-making z, where $z \in \{1, ..., Z\}$, and is only dependent on the maintenance strategy and the present monitoring state of the wind farm. The maintenance strategy is designed for future T_{H}^z steps at zth decision-making step.

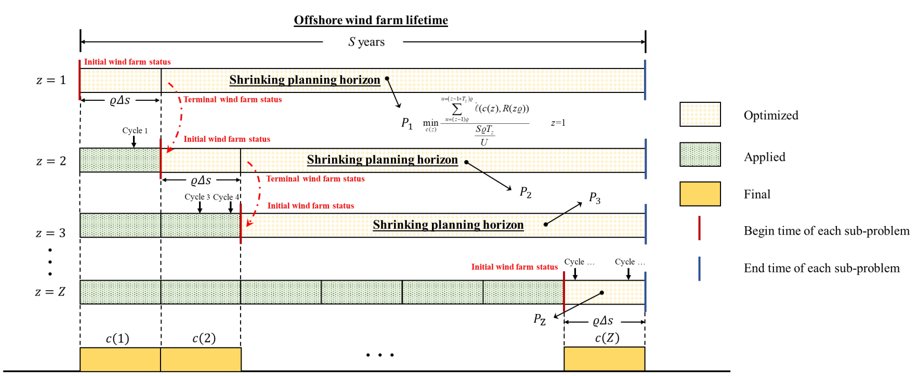
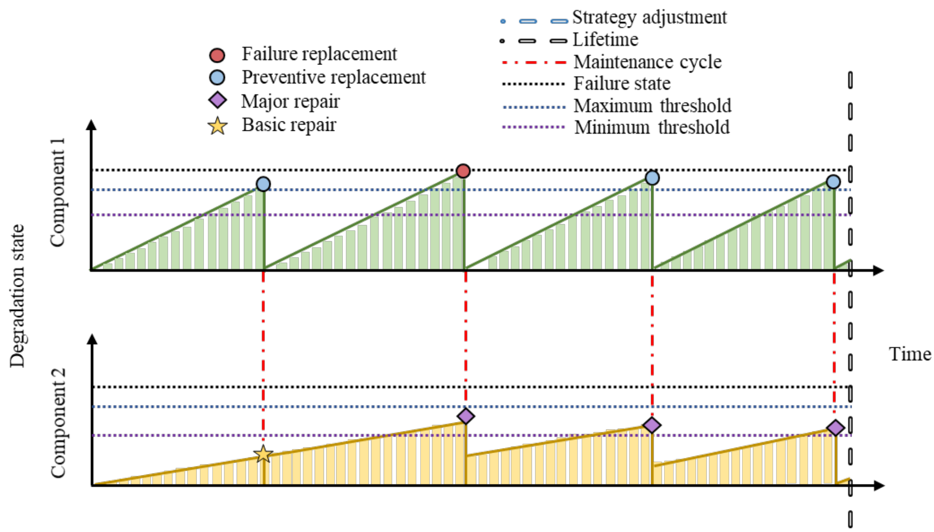


Figure 7.2: Schematic representation of the shrinking planning horizon over the wind farm lifetime

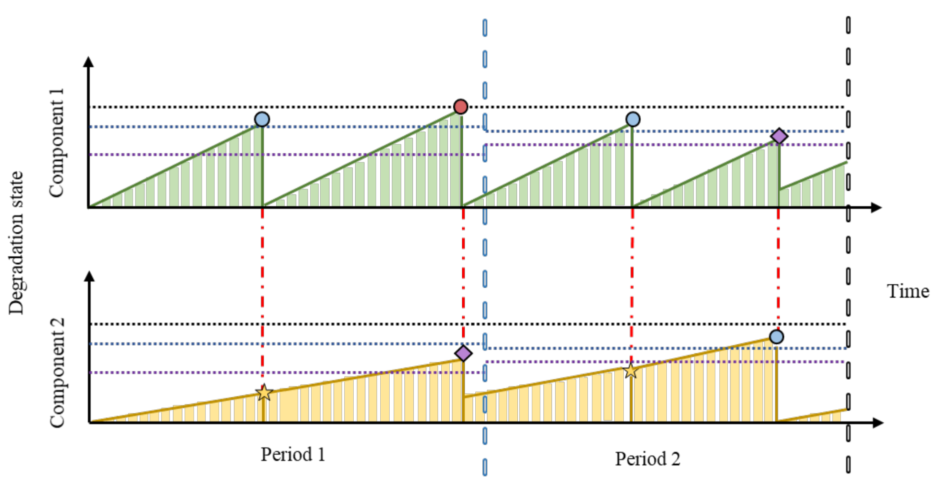
At the step z, the maintenance strategy that controls the maintenance management is implemented, and the process starts over when the step is at $(z+1)$. The strategy c^z is represented as:

$$c^z = \left[A_{\max}^z, A_{\min}^z, \zeta^z\right]. \tag{7.11}$$

A series of consequent strategies $\boldsymbol{c} = \mathrm{col}(c^1, \dots, c^2, \dots, c^Z)$ constitute the overall maintenance strategy during the wind farm lifetime, controlling maintenance timing and actions. We use a strategy consisting of two phases as an example, as shown in Fig. 7.3. Compared to Fig. 7.3(a), the maintenance thresholds are separated into two phases in Fig. 7.3(b), where the thresholds keep the same in period 1 and change in period 2. The moments of maintenance cycle 3 and 4, as well as the determined maintenance actions on component 1 and 2, are consequently different from Fig. 7.3(a).



(a) A conventional maintenance strategy



(b) A maintenance strategy separated in two periods

Figure 7.3: An illustration of changes in maintenance thresholds

The problem, P^z, defined to start at step z and cover the future horizon from z to $(z+T_{\mathrm{H}}^z)$, can be formulated as (7.12) to find the optimal solution c^z. In (7.12), the optimization objective, the annual revenue loss in the horizon, is calculated by dividing the sum of losses over by the horizon length. The final result, that is also the performance of the developed maintenance strategy, is the annual revenue losses A_{r} in reality when the maintenance strategy $\boldsymbol{c} = \mathrm{col}(c^1, ..., c^z, ..., c^Z)$ is implemented.

$$\min_{c(z)} \frac{\sum_{n=(z-1)\rho}^{n=(z-1+T_{\mathrm{H}}^z)\rho} \dot{\ell}(n, c^z, R(z\rho))}{\frac{L\rho T_{\mathrm{H}}^z}{N}}. \tag{7.12}$$

The input parameters for the optimization problem are estimated using the existing wind farm failure and maintenance databases. The decision-making is inevitably influenced by the lack of data, especially in the early operational phase of the wind farm. The design of the maintenance strategy is based on limited useful information, including the life test data from the original equipment manufacturer and subjective judgement of maintenance experts. In addition to the incompleteness of data, as [143] pointed out, much of the available field data may be inaccurate, undetailed, or redundant, leading to a negative effect on the estimation of maintenance model parameters.

The amount of wind turbine failure and maintenance data gradually increases as the offshore wind farm operates. Although the raw data gathered from the wind farm is not always ready and useful, We assume it has been well-prepared to identify the relations among the data variables. At the beginning of operation, the original database the decision-maker has known is $\boldsymbol{X} = [{}^1\boldsymbol{X}, {}^2\boldsymbol{X}, {}^3\boldsymbol{X}]$. The sub-dataset ${}^1\boldsymbol{X} = \{{}^1x_1, {}^1x_2, ..., {}^1x_{\varepsilon_1}\}$, ${}^2\boldsymbol{X} = \{{}^2x_1, {}^2x_2, ..., {}^2x_{\varepsilon_2}\}$, ${}^3\boldsymbol{X} = \{{}^3x_1, {}^3x_2, ..., {}^3x_{\varepsilon_3}\}$ contains component lifetime data, RUL prediction performance data, and maintenance implementation data respectively.

The initial lifetime parameters input into the maintenance model are derived from the database ${}^1\boldsymbol{X}$. The new lifetime sample consists of n_1 observations before decision-making step z is ${}^1\boldsymbol{X}^{z,D_1} = \{{}^1x_1^{z,D_1}, {}^1x_2^{z,D_1}, ..., {}^1x_{n_1}^{z,D_1}\}$. Hence the updated database is:

$$\begin{aligned} {}^1\hat{\boldsymbol{X}}^{z,D_1} &= \{{}^1\boldsymbol{X}, {}^1\boldsymbol{X}^{z,D_1}\} = \left\{{}^1x_1, ..., {}^1x_{\iota}, {}^1x_1^{z,D_1}, ..., {}^1x_{n_1}^{z,D_1}\right\} \\ &= \left\{{}^1\hat{x}_1^{z,D_1}, {}^1\hat{x}_2^{z,D_1}, ..., {}^1\hat{x}_{1+n_1}^{z,D_1}\right\}. \end{aligned} \tag{7.13}$$

The probability distribution D_1 is associated with a vector $\boldsymbol{\theta}^{D_1} = \left[\theta_1^{D_1}, \theta_2^{D_1}\right]$ of parameters. The probability that the sample can be observed is:

$$P({}^1\hat{\boldsymbol{X}}^{z,D_1}; \boldsymbol{\theta}^{D_1}) = f_{D_1}({}^1\hat{x}_1^{z,D_1}, {}^1\hat{x}_2^{z,D_1}, ..., {}^1\hat{x}_{\varepsilon_1+n_1}^{z,D_1} \Big| \theta_1^{D_1}, \theta_2^{D_1}). \tag{7.14}$$

We use the maximum likelihood estimation to update the parameters used in the maintenance model. The likelihood function is obtained as:

$$L({}^1\hat{\boldsymbol{X}}^{z,D_1}; \boldsymbol{\theta}^{D_1}) = \prod_{\tau=1}^{\varepsilon_1+n_1} f_{D_1}({}^1\hat{x}_\tau^{z,D_1}; \boldsymbol{\theta}^{D_1}). \tag{7.15}$$

The maximum likelihood estimation aims to find the values of the model parameters which can maximize the likelihood function, namely:

$$\hat{\theta} = \arg\max L({}^{1}\hat{\boldsymbol{X}}^{z,D_1}; \boldsymbol{\theta}^{D_1}). \tag{7.16}$$

The lifetime of components is modelled as a Weibull distribution with shape parameter $\dot{\varepsilon}$ and scale parameter $\dot{\sigma}$. The probability density function is:

$$f({}^{1}\hat{x}_{\tau}^{z,D_1}) = \frac{\dot{\varepsilon}}{\dot{\sigma}} \left(\frac{{}^{1}\hat{x}_{\tau}^{z,D_1}}{\sigma} \right)^{\varepsilon - 1} e^{-\left(\frac{{}^{1}\hat{x}_{\tau}^{z,D_1}}{\sigma} \right)^{\varepsilon}}. \tag{7.17}$$

Then, the likelihood function of the sample is:

$$L({}^{1}\hat{\boldsymbol{X}}^{z,D_1}; \boldsymbol{\theta}^{D_1}) = \prod_{\tau=1}^{\varepsilon_1 + n_1} \frac{\varepsilon}{\dot{\sigma}} \left(\frac{{}^{1}\hat{x}_{\tau}^{z,D_1}}{\sigma} \right)^{\dot{\varepsilon} - 1} e^{-\left(\frac{{}^{1}\hat{x}_{\tau}^{z,D_1}}{\dot{\sigma}} \right)^{\dot{\varepsilon}}}. \tag{7.18}$$

It is usually more convenience to use the natural logarithm of the likelihood function [22], which is called the log-likelihood:

$$\begin{aligned} &\ln(L({}^{1}\hat{\boldsymbol{X}}^{z,D_1}; \dot{\varepsilon}, \dot{\sigma})) = (\varepsilon_1 + n_1)\ln(\dot{\varepsilon}) - (\varepsilon_1 + n_1)\dot{\varepsilon}\ln(\dot{\sigma}) + (\dot{\varepsilon} - 1)\sum_{\tau=1}^{\varepsilon_1 + n_1} \ln(x_{\tau}^{z}) \\ &- \sum_{\tau=1}^{\varepsilon_1 + n_1} \left(\frac{{}^{1}\hat{x}_{\tau}^{z,D_1}}{\dot{\sigma}}\right)^{\dot{\varepsilon}}. \end{aligned} \tag{7.19}$$

The score equations are:

$$\frac{\partial \ln L}{\partial \dot{\sigma}} = -\frac{(\varepsilon_1 + n_1)\dot{\varepsilon}}{\sigma} + \frac{\dot{\varepsilon}}{\dot{\sigma}^{\dot{\varepsilon}+1}} \sum_{\tau=1}^{\varepsilon_1 + n_1} ({}^{1}\hat{x}_{\tau}^{z,D_1})^{\dot{\varepsilon}} = 0, \tag{7.20}$$

$$\begin{aligned} &\frac{\partial \ln L}{\partial \dot{\varepsilon}} = -\frac{\varepsilon_1 + n_1}{\dot{\varepsilon}} - (\varepsilon_1 + n_1)\ln\dot{\sigma} + \sum_{\tau=1}^{\varepsilon_1 + n_1} \ln({}^{1}\hat{x}_{\tau}^{z,D_1}) + \frac{\ln\dot{\sigma}}{\dot{\sigma}^{\dot{\varepsilon}}} \sum_{\tau=1}^{\varepsilon_1 + n_1} ({}^{1}\hat{x}_{\tau}^{z,D_1})^{\dot{\varepsilon}} \\ &- \frac{1}{\dot{\sigma}^{\dot{\varepsilon}}} \sum_{\tau=1}^{\varepsilon_1 + n_1} ({}^{1}\hat{x}_{\tau}^{z,D_1})^{\dot{\varepsilon}} \ln({}^{1}\hat{x}_{\tau}^{z,D_1}) = 0. \end{aligned} \tag{7.21}$$

Thereby, the parameters of lifetime of components are estimated at step z through calculating Equation (7.20) and (7.21). In the similar way, the updated databases for RUL prediction performance and maintenance implementation are:

$${}^{2}\hat{\boldsymbol{X}}^{z,D_2} = \{{}^{2}\boldsymbol{X}, {}^{2}\boldsymbol{X}^{z,D_2}\} = \left\{ {}^{2}\hat{x}_{1}^{z,D_2}, {}^{2}\hat{x}_{2}^{z,D_2}, \ldots, {}^{2}\hat{x}_{\varepsilon_2 + n_2}^{z,D_1} \right\}, \tag{7.22}$$

$${}^{3}\hat{\boldsymbol{X}}^{z,D_3} = \{{}^{3}\boldsymbol{X}, {}^{3}\boldsymbol{X}^{z,D_3}\} = \left\{ {}^{1}\hat{x}_{1}^{z,D_3}, {}^{1}\hat{x}_{2}^{z,D_3}, \ldots, {}^{1}\hat{x}_{\varepsilon_3 + n_3}^{z,D_3} \right\}. \tag{7.23}$$

The parameters in the Normal distribution of the prediction error or repair cost/time coefficient are updated as:

$$L({}^{2}\hat{\boldsymbol{X}}^{z,D_2}; \boldsymbol{\theta}^{D_2}) = \left(\frac{1}{\sqrt{2\pi\dot{\sigma}}} \right)^{\varepsilon_2 + n_2} \exp\left(-\sum_{\tau=1}^{\varepsilon_2 + n_2} \frac{({}^{2}\hat{x}_{\tau}^{z,D_2} - \dot{\mu})^2}{2\dot{\sigma}^2} \right), \tag{7.24}$$

$$\frac{\partial \ln L}{\partial \dot{\mu}} = \frac{1}{\dot{\sigma}^2} \sum_{\tau=1}^{\varepsilon_2+n_2} \left({}^2\hat{x}_{\tau}^{z,D_2} - \dot{\mu} \right) = 0, \tag{7.25}$$

$$\frac{\partial \ln L}{\partial \dot{\sigma}} = -\frac{\varepsilon_2+n_2}{2\dot{\sigma}^2} + \frac{\varepsilon_2+n_2}{2\dot{\sigma}^4} \sum_{\tau=1}^{\varepsilon_2+n_2} \left({}^2\hat{x}_{\tau}^{z,D_2} - \dot{\mu} \right)^2 = 0. \tag{7.26}$$

The parameters modelling the maintenance quality, which follows a Beta distribution, is estimated as:

$$L({}^3\hat{\boldsymbol{X}}^{z,D_3}; \boldsymbol{\theta}^{D_3}) = \left(\frac{\Gamma(\dot{\alpha}+\dot{\beta})}{\Gamma(\dot{\alpha})\Gamma(\dot{\beta})} \right)^{\varepsilon_3+n_3} \prod_{\tau=1}^{\varepsilon_3+n_3} {}^3\hat{x}_{\tau}^{z,D_3\,\dot{\alpha}-1} \prod_{\tau=1}^{\varepsilon_3+n_3} (1 - {}^3\hat{x}_{\tau}^{z,D_3})^{\dot{\beta}-1}, \tag{7.27}$$

$$\frac{\partial \ln L}{\partial \dot{\alpha}} = \frac{(\varepsilon_3+n_3)\Gamma'(\dot{\alpha}+\dot{\beta})}{\Gamma(\dot{\alpha}+\dot{\beta})} - \frac{(\varepsilon_3+n_3)\Gamma'(\dot{\alpha})}{\Gamma(\dot{\alpha})} + \sum_{\tau=1}^{\varepsilon_3+n_3} \ln({}^3\hat{x}_{\tau}^{z,D_3}) = 0, \tag{7.28}$$

$$\frac{\partial \ln L}{\partial \dot{\beta}} = \frac{(\varepsilon_3+n_3)\Gamma'(\dot{\alpha}+\dot{\beta})}{\Gamma(\dot{\alpha}+\dot{\beta})} - \frac{(\varepsilon_3+n_3)\Gamma'(\dot{\beta})}{\Gamma(\dot{\beta})} + \sum_{\tau=1}^{\varepsilon_3+n_3} \ln(1 - {}^3\hat{x}_{\tau}^{z,D_3}) = 0. \tag{7.29}$$

7.2.4 Optimization method

The maintenance optimization problem here is complicated, involving nonlinearities, combinatorial relationships, and uncertainties, and it is more efficient and feasible to use a heuristic algorithm to solve it. The optimization method used to find the optimal solution is the PSO algorithm with constriction coefficient. PSO algorithm was first proposed in [86], with the advantages including simple concept, easy implementation, robustness to control parameters, and computational efficiency [92]. The PSO algorithm has been widely used in solving maintenance optimization problems [6, 12]. The algorithm was originally inspired by the regularity of flocking activity of birds, which led to a simplified model using swarm intelligence. After that, new elements are introduced to improve its performance, such as constriction coefficient [48]. Compared to the original PSO algorithm, the particle converges over time due to a constriction coefficient. The amplitude of a particle's oscillation decreases as it concentrates on the local and neighbourhood previous optimal points. The convergence of the algorithm can be insured by using the constriction factor.

PSO has two primary operators: velocity update and position update. At the beginning, initial random positions and velocities are possessed to all the particles in the space. During each generation, every particle moves towards its previous best position and the best position found so far by the whole swarm. In iteration ϖ, the position of λth particle is changed as:

$$x_{\lambda}(\varpi) = x_{\lambda}(\varpi-1) + y_{\lambda}(\varpi), \tag{7.30}$$

while the velocity of λth particle is updated as:

$$y_{\lambda}(\varpi) = \eta^{o} \left[y_{\lambda}(\varpi-1) + \beta_1^{o}\upsilon_1^{o} \left(x_{\lambda}^{\mathrm{IB}} - x_{\lambda}(\varpi-1) \right) + \beta_2^{o}\upsilon_2^{o} \left(x_{\lambda}^{\mathrm{GB}} - x_{\lambda}(\varpi-1) \right) \right], \tag{7.31}$$

$$\eta^{o} = \frac{2}{\left| 2 - (\beta_1^{o}+\beta_2^{o}) - \sqrt{(\beta_1^{o}+\beta_2^{o})^2 - 4(\beta_1^{o}+\beta_2^{o})} \right|}, \tag{7.32}$$

where β_1^o and β_2^o are two acceleration coefficients, η^o is constriction coefficient, υ_1^o and υ_2^o are two positive random numbers uniformly sampled from [0,1], x_λ^{GB} is the neighborhood best state found so far, and x_λ^{IB} is the individual best state found so far.

The velocity and position of each particle is updated in iterations where the position of each particle is evaluated by the Equation (7.30) and (7.31). This process repeats until the maximum iteration number to capture the optimum solution.

7.3 Case study

7.3.1 Scenario set-up

The developed O&M framework is applied to the cased expanded based on Chapter 4. The farm consists of a group of five 3-MW wind turbines individually containing five critical components. Compared to the models in Chapter 3 and 4, this model requires more times of optimization times, and the workload of calculation is also greatly increased, thus the numerical example is reduced to a 5-turbine wind farm. The accuracy of the RUL technique is about 87.2 % under the error parameter μ_a and δ_a are both 0.01, and the value of a_s and a_p are 0.02. The variance of maintenance quality is 0.01. The value of μ_c and μ_t is 2, and δ_c and δ_t is 0.5.

The parameter setting of the PSO optimizer is: (1) maximum number of iterations is 40, the swarm size is 30 (2) acceleration coefficients β_1^o and β_2^o are 2.05, constriction coefficient η^o is 0.73. The fitness value of each particle is estimated with a Monte Carlo simulation with 400 repetitions.

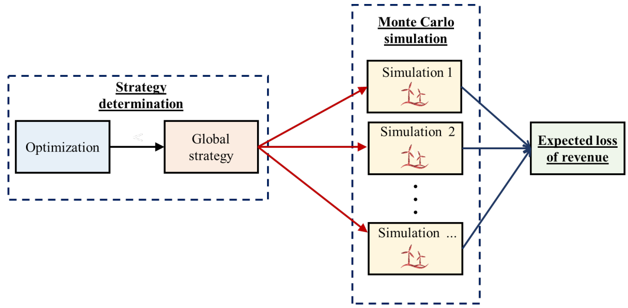
Table 7.1: Maintenance vessel parameters

Vessel	Mobilization cost (k€)	Daily cost (k€)	Technician number	Daily technician cost (k€)
HLV	57	50	8	
FSV	-	18	4	0.6
CTV	-	8	2	

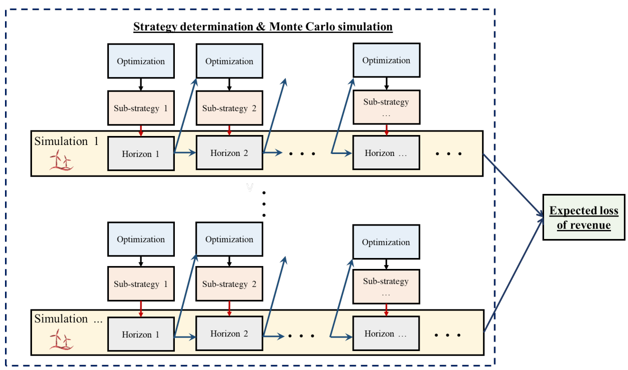
7.3.2 Computational results and comparative study

In this section, we present five scenarios in which different assumptions, conditions, and decision-making processes are introduced. The simulation is implemented in Matlab®, using one node with 48 cores, 2x Intel XEON E5-6248R 24C 3.0GHz, and 192 GB memory at DelftBlue (TU Delft supercomputer) [39]. The simulation time for the scenarios using an open-loop approach is about 0.2 hours. The time for each other scenario is about 150 hours, much higher than open-loop approach. The reason is that the optimizer is conducted once in the open-loop approach while the optimizer is performed much more times in the other scenarios, as illustrated in Fig. 7.4.

Below is a list of the different scenarios where the maintenance strategy is optimized:



(a) An open-loop maintenance strategy optimization process



(b) A reactive or closed-loop maintenance strategy optimization process

Figure 7.4: An illustration of differences between optimization processes

- O-K scenario: An open-loop maintenance strategy disregarding uncertainty

  This scenario demonstrates an ideal situation where the model parameters listed in Section 7.3.1 are accurately known by the decision-maker, which is an assumption commonly used in the existing maintenance models. Once the maintenance strategy is optimized at the beginning phase, it will be implemented over the entire lifetime.

- O-U scenario: An open-loop maintenance strategy considering uncertainty

  A common situation in actual O&M is that the decision maker's information is deviated from the actual information. The inaccurate parameters input into the model are: RUL accuracy is about 93.1 %, under the value of a_{s} and a_{p} is 0.01; the variance of maintenance quality is 0.001; the value of δ_{c} and δ_{t} is 0.3. The determined strategy is also employed over the entire lifetime without any adjustment.

- R-K scenario: A reactive maintenance strategy disregarding uncertainty

  A scenario similar to O-K scenario, supposes the model parameters are known. The difference is that the decision-maker periodically updates the maintenance strategy. The number of decision-making step is set as $Z = 4$. In other words, the maintenance strategy is adjusted every 5 years according to the current monitoring state of the wind farm. The prediction horizon for decision-making steps gradually shrinks from 20 years to 5 years.

- R-U scenario: A reactive maintenance strategy considering uncertainty

  Instead of the open-loop optimization method, the maintenance strategy is also redesigned every 5 years. The decision-maker ignores the potential parameter uncertainties, only considering the monitoring state of the wind farm and using the initial parameters to optimize the maintenance strategy.

- C-U-A scenario: A closed-loop uncertainty-aware maintenance strategy

  The decision-maker has been aware of the model parameter uncertainty and consciously change the strategy based on an updated database containing historic O&M data and new cumulative data. Until a sufficient amount of new data is collected, the decision-maker cannot update the decisions as there is no basis to support the update. The volume of data in the database expands at a rate of 5% per year, and the strategy is updated every five years in line with the expanded database.

The expected annual revenue losses in O-K scenario, as a function of the maintenance thresholds and the number threshold of aged components, are given in Fig. 7.5. The surface has convexity, indicating there exists an optimal solution. By using the optimizer to solve the optimization problem, the optimal combination of the decision variables is given by (0.451, 0.962, 4%). In O-K scenario, the parameters in the model are accurate, thus the model output is the corresponding optimal result 806.4 k€/year.

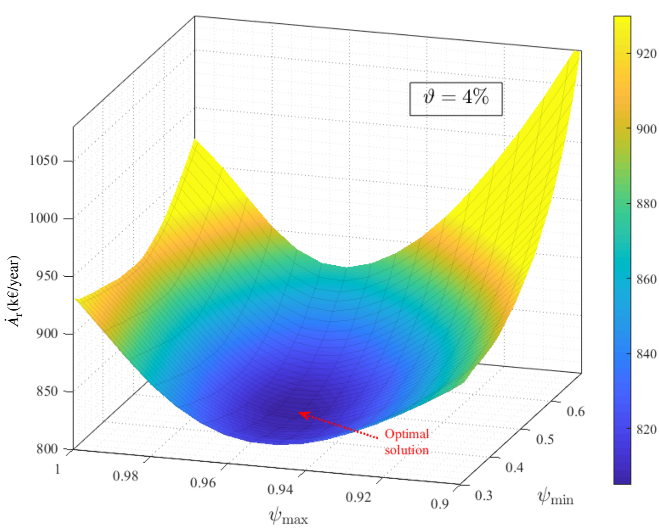


Figure 7.5: Annual revenue losses versus decision variables in O-K scenario

Fig. 7.6 shows the estimated annual revenue losses in O-U scenario. In comparison with Fig. 7.5, the expectation of the revenue losses is lower due to the inaccuracy of the model parameters. The optimal solution (0.409, 0.925, 4%) corresponds to the minimum annual revenue losses in the maintenance model. The actual performance of the solution is estimated by inputting the solution into the wind farm system with accurate parameters, given by 826.4 k€/year.

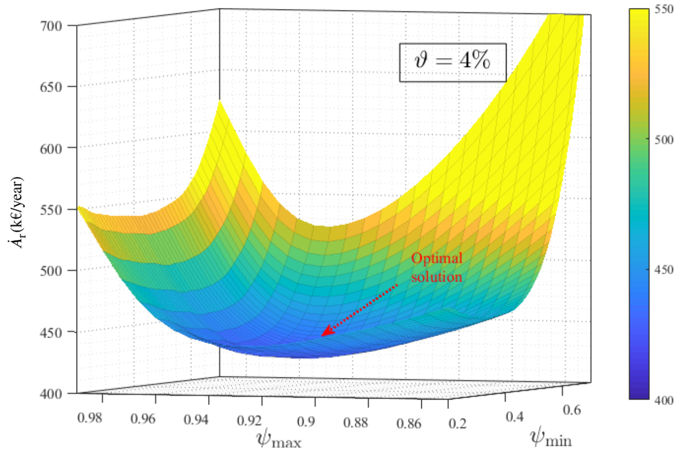
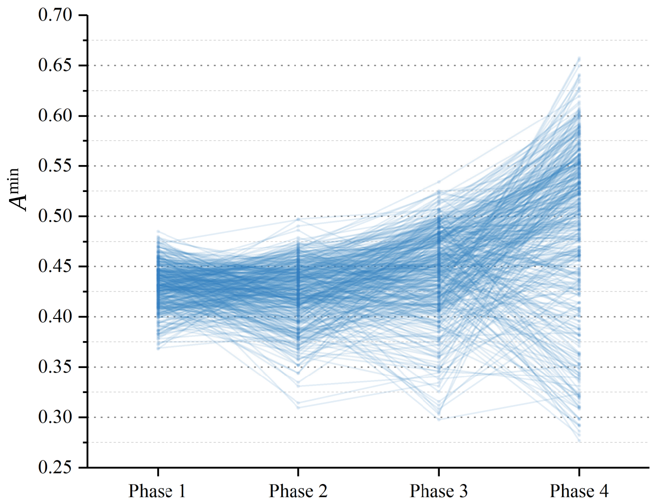


Figure 7.6: Annual revenue losses versus decision variables in the maintenance model in O-U scenario

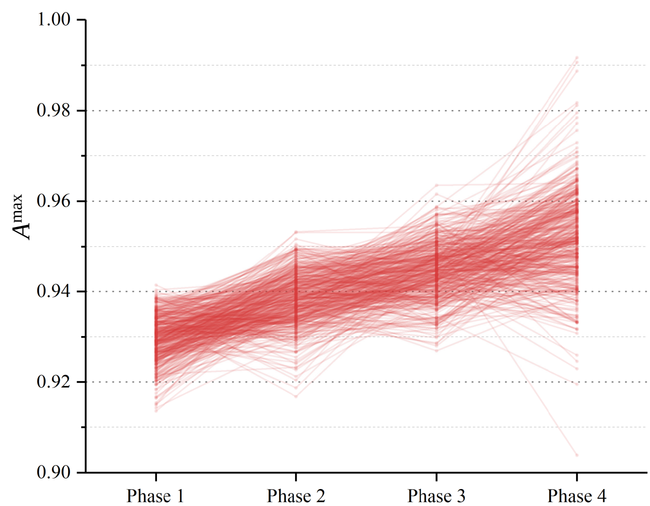
The O-K and O-U scenarios adopt an open loop where the optimizer is run once, so that only one optimal solution is obtained. In R-K, R-U, and C-U-A scenarios, the number of decision-making step is set as 4, indicating the global maintenance strategy consists of 4 sub-strategies in one simulation. Hence a total of 4×400 optimizations are performed in each scenario, as the number of Monte Carlo simulation is 400.

We use Fig. 7.7 to illustrate the variety of the maintenance thresholds in C-U-A scenario. The number of the optimal combination of decision variables derived is 1600, belonging to four different phases, and the duration of each phase is 5 years. In Fig. 7.7(a), the thresholds mostly concentrate in the range 0.38 to 0.48. The reason for the various thresholds at first phase is that the PSO is a heuristic algorithm, so the near-optimal solutions with close performance are obtained. Then the range of fluctuation increases over time in the following phases. In phase 4, the minimum thresholds even fluctuate from about 0.28 to 0.65. In addition, in the region composed of light blue dots at different phases, the shade of blue represents the concentration of the thresholds. The graph shows that the thresholds become more diverse as the operational time increase, because the state of the wind farm is more various, and the thresholds are determined according to the state.

Fig. 7.7(b) reveals a similar trend: the maximum thresholds become more fluctuating. Compared to the minimum thresholds, the range of maximum thresholds is smaller, around 0.92-0.98 in phase 4. That can be explained by the different feature of these two thresholds. Minimum threshold $\psi_{\min}$ is more relevant to the determination of major repairs, while maximum threshold $\psi_{\max}$ controls the component replacement. For different wind farm states, it is more cost-effective to adjust the scope of application of the major repair rather than extending the scope of replacement. It should be explained here that the value of the third decision variable ϑ is always equal to 4%, because the case is a small-scale offshore wind farm and the change of ϑ is not influential.



(a) Variety of minimum health threshold $A^{\min}$



(b) Variety of maximum health threshold $A^{\max}$

Figure 7.7: Health thresholds in C-U-A scenario

The comparison of annual revenue losses over the lifespan and different phases is shown in Table 7.2 and Fig. 7.8. The utilization of reactive approach is able to reduce the cost in O-K scenario and O-U scenario from 806.4 k€/year and 836.4 k€/year to 798.0 k€/year and 823.3 k€/year in R-K and R-U scenario respectively. If the parameters are updated in the process, the annual revenue losses further decreases from 823.3 k€/year in R-U scenario to 808.1 k€/year in C-U-A scenario.

Table 7.2: Comparison of different scenarios in different phases of the wind farm

	O-K scenario	O-U scenario	R-K scenario	R-U scenario	C-U-A scenario
Annual revenue losses in phase 1 (k€/year)	723.0	732.4	722.2	733.8	731.2
Annual revenue losses in phase 1 (k€/year)	886.1	914.7	881.4	906.4	900.3
Annual revenue losses in phase 1 (k€/year)	824.1	856.2	815.9	840.4	824.8
Annual revenue losses in phase 1 (k€/year)	792.4	842.1	772.4	812.4	776.1
Annual revenue losses in the lifespan (k€/year)	806.4	836.4	798.0	823.3	808.1

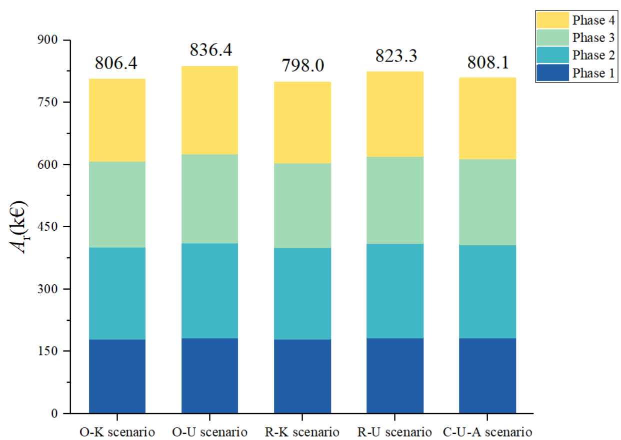


Figure 7.8: Comparison of annual revenue losses in different scenarios

A more detailed comparison is shown in Fig. 7.9. The annual revenue losses in the scenarios under unknown parameters are greater than the scenarios where the parameters are known accurately. This is easily understood, since the inaccurate parameters induce negative influence on decision-making, leading to a non-optimal solution and corresponding worse performance. The benefits of reactive approach are mainly reflected in two aspects. Firstly, the revenue loss decrease by 1.0% and 1.6%, regardless of whether the parameters are known or not, and the performance is better under unknown parameters. Moreover, compared with the open-loop method, the negative impact of parameter uncertainty on revenue losses is smaller, approximately 3.2% which is less than 3.7%.

R-K, R-U, and C-U-A scenarios represent the best, the worst, and the intermediate consequences if the maintenance strategy is periodically adjusted. When decision-makers are aware of the potential uncertainty in the model parameters, they will attempt to remove this uncertainty in pursuit of the optimal consequence, which is represented by R-K scenario. As shown in Fig. 7.9, a reduction around 1.8% has been realized owning to the new collected data. A further reduction about 1.2% is hopefully be achieved if more data are available to realize the ideal case. As discussed before, O-U scenario is the situation the decision maker is most likely to face in reality. In comparison to it, the C-U-A scenario proposed in this study makes a 3.4% reduction.

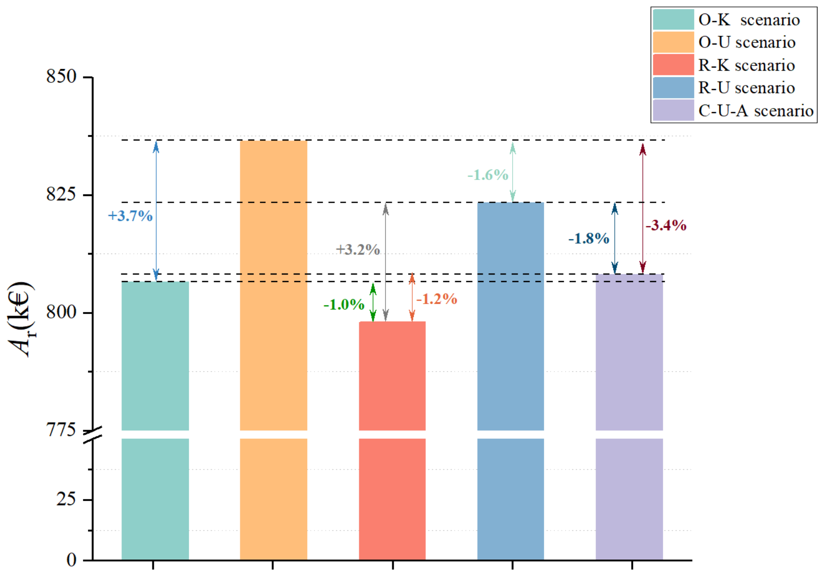


Figure 7.9: Comparison of annual revenue losses

Fig. 7.10 illustrates the annual revenue losses in different phases of the wind farm. No matter the wind farm operates in which scenario, the highest revenue losses always arise in the phase 2, followed by phase 3 and phase 4, and the losses are always lowest in the first phase. The reason for this situation is related to component failure modelling. In this paper, Weibull distribution is used to randomly generate the component lifetime, and the failure parameters determine the rough time to failure. In the early phase of the wind farm, the components are mostly in a healthy state. The impact of deterioration and failure is therefore small, and the revenue losses are lowest. In the later phases, especially the phase 2, the ageing of the wind farm leads to a peak in maintenance, so the revenue losses are higher. Then after that, the state of the wind farm improved and therefore the losses in phase 4 are relatively low.

From the beginning to the end, O-U scenario always lead to the highest revenue losses, and R-K scenario gives the best performance. In phase 1, the performance of O-K, R-K is similar, and the results in O-U, R-U, and C-U-A are close. The slight deviations in the calculation results are due to the randomness in the simulation. In this phase, the implemented strategy is determined at the beginning, and the uncertain parameters induce a higher revenue losses. In phase 2, C-U-A scenario is located in the midstream. With the continuous revision of the parameters, its performance gradually surpasses R-U scenario and finally approaches R-K scenario.

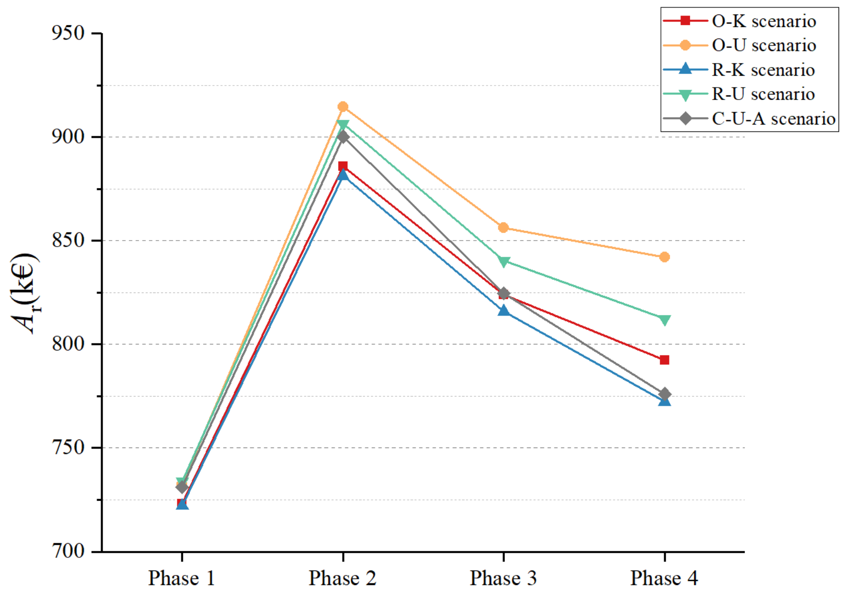


Figure 7.10: Change of annual revenue losses in different phases

7.4 Discussion

It is known to us all that the availability of RAM data has been the biggest challenge bringing about obstacles in O&M studies of wind energy. The O-K and O-U scenario assume that the model parameters are known to the decision-maker, which is an ideal situation cannot be realized up to now. However, this is the decision-making environment we are pursuing, where the prior knowledge is sufficient to support the estimation of the parameters. On the contrary, the other scenarios where the original model parameters differ from the practical information are more real O&M situations. Until more new data is added to the database, it is difficult to make a judgement on how to adjust the strategy. Once the enough amount of reliable data is accumulated, the new decisions based on the updated parameters are able to achieve a further cost reduction.

The results are relevant and beneficial for decision-makers and practitioners in wind energy industry. The developed maintenance strategy can provide decision-makers with health management criteria as a basis for determining when maintenance cycles are triggered and which component requires what kind of maintenance. A closed-loop approach can help the wind farm owners or operators to reduce revenue loss and gain more profit. The value of information and the significance of a reliable RAM database is revealed. Without accurate and precise information, maintenance decisions are determined on the basis of unreliable data, which may lead to sub-optimal or even inadequate strategies. The introduction of advanced condition monitoring, fault prediction, and health management technologies has the capability to provide high quality data at the right time to assist the decision-maker to make the best maintenance decisions.

This study shows that a sound maintenance strategy should not be determined at one blow. Whether or not there is sufficient new data to update the model parameters, it is worth looking forward to periodically adjusting the maintenance strategy according to the monitoring state of the wind farm. Instead of a static and fixed one, the maintenance strategy should be more flexible and dynamic. With the support of the condition monitoring technique, the maintenance strategy can be re-optimized and adapted to better manage the future wind farm states.

In addition, we can notice that the negative influence which non-optimal solutions bring about is not so notable. It can be attributed to the benefits of the applied preventive opportunistic maintenance strategy, where most of the maintenance actions are performed before the component failure. Variations in thresholds control the range of maintenance. Higher thresholds lower the number of the components subject of maintenance, indicating that the corresponding maintenance costs are lower. However, less maintenance is not beneficial to the wind farm state, perhaps result in more failure in the future. The results are the opposite when the thresholds are lower. In other words, changing thresholds is a double-edged sword. That can explain the revenue losses are not very sensitive when slightly changing the combinations of thresholds. In other words, the application of the maintenance strategy using the failure prognosis of component as the decision basis is robust and reliable from the perspective of economics.

Finally, the future offshore wind farm will be large-scale. Due to the limitation of the computing capacity, the case study in this paper is set as a five-turbine wind farm. The improvement in small wind farms is relatively insignificant, as the overall state is not very various and the dependence on parameters is not strong enough. Considering the offshore wind farm is tend to be much bigger in the future, the potential of the proposed model in terms of reducing revenue loss is expected to be more significant.

7.5 Conclusions

This chapter proposes a closed-loop maintenance strategy optimization framework to adjust maintenance strategies periodically, addressing the Research Question 6. A mathematical model is developed to use a series of matrices to represent the discrete wind farm states under a predictive opportunistic maintenance strategy. Moreover, the information about the component condition received by the decision-maker and the maintenance actions performed are modelled, and the potential uncertainties therein are identified. Then, the maintenance model on which the decision-maker relies is formalized. This model serves as a tool to predict the maintenance performance, namely revenue losses, when a specific maintenance strategy is conducted. Compared to the real wind farm, the prediction produced by this maintenance model is inaccurate as there is a discrepancy between the model parameters derived from the database and the actual parameters. New data is accumulated with the operation of the offshore wind farm to update inaccurate parameters in the maintenance model. Finally, the underlying optimization problem is modelled repeatedly for a certain period of time, then solved, and then moved forward for a period of time. The entire problem is decomposed into a series of multi-period sub-optimization problems. At each decision-making step, the maintenance strategy is adapted to the current health state of the wind farm while making use of the updated parameters.

The proposed model is applied on a generic offshore wind farm to test its performance in terms of revenue losses. Compared to the revenue losses in Chapter 4, a higher degree of uncertainty is taken into account, so the estimated revenue losses is larger. The five scenarios in the comparative study have revealed that the closed-loop maintenance strategy exploiting feedback from offshore wind farm system and capturing wind farm states is able to reduce about 3.4% of revenue loss in comparison to conventional open-loop strategies. The research provides a new approach for designing long-term maintenance strategies for offshore wind farms.

Chapter 8

Conclusions and Future Research

In this thesis, we have developed approaches to improve effectiveness of maintenance strategies and resource organization for offshore wind farms. The effectiveness refers to organizing maintenance logistics in a cost-effective manner. The maintenance logistics is developed to move towards closed-loop decision-making to utilize new data and capture dynamics of the wind farms. This last chapter concludes the thesis. Firstly the key questions and the main research question are answered. Subsequently, directions for future research are provided.

8.1 Conclusions

Over the past decades, there has been a significant increase in offshore wind power capacity. Maintenance logistics plays a crucial role in the offshore wind energy industry, as it directly affects the profitability of wind projects and is a key factor in maintaining a competitive advantage for offshore wind energy. The goal of this thesis is to improve maintenance logistics for offshore wind farms. More specifically, maintenance strategies and resource organization are developed to be more effective and efficient, and a closed-loop approach is introduced to improve maintenance logistics.

This research goal can be partially achieved through the last four years of research. The determination of maintenance strategies is improved by: (1) considering predictive analytics and maintenance opportunities; (2) analyzing influence of model parameter uncertainty; and (3) adopting a closed-loop approach to mitigate model parameter uncertainty. The organization of maintenance resources is improved by: (1) developing a multi-echelon and multi-unit inventory network; and (2) developing a vessel fleet configuration model. The research can serve decision-makers (offshore wind farm owners/operator, maintenance service providers) to arrange sound maintenance logistics to enhance profitability of offshore wind energy. The performance of the proposed approaches is evaluated on a generic offshore wind farm. This generic case is gradually developed and expanded, where more details and parameters are added depending on the research focus. However, there are still limitations of the research, which will be discussed in Section 8.2.

The main research question and key research questions are addressed as below.

8.1.1 Main research question

The main question addressed in this thesis is: *How to improve effectiveness of maintenance strategies and resource organization for offshore wind farms and move towards a closed-loop decision-making approach?*

Strategic and tactical maintenance logistics decisions have long-lasting impacts on wind farm O&M. Maintenance logistics is composed of multiple links, from designing a maintenance strategy to implement maintenance activities. In order to develop an effective and efficient maintenance logistics plan to address this main research question, the first step is to use the life prediction of the wind turbine components and potential maintenance opportunities to design the optimal maintenance criteria over the lifetime of offshore wind farms. The maintenance criteria can assist decision-makers to make decisions about when to perform which types of maintenance on which component. Then, the implementation of maintenance decisions requires assurance of available maintenance resources. Maintenance resources, including maintenance spare parts and maintenance vessels, need to be adequately prepared in advance, but controlled to a reasonable amount. The final step is to utilize the data accumulated over time to dynamically adjust the maintenance criteria over the offshore wind farm lifetime. Negative effects caused by model parameter uncertainty are gradually mitigated to reduce revenue losses over the life cycle.

8.1.2 Key research questions

More specifically, the key research questions that are related to the main research question are answered as follows.

1. *What is the state of the art in the area of wind energy maintenance logistics, especially in the maintenance strategy and resource organization?*

   Through Chapter 2, we generally overview the classification scheme of offshore wind energy maintenance logistics, then give a detailed review on state-of-the-art in maintenance strategy optimization and maintenance resource organization. Maintenance logistics for offshore wind farms is categorized into strategic, tactical, and operational levels from the perspective of the planning horizon. The decisions at the strategic level determine the maintenance logistics over the lifetime, indicating that improvements to strategic decisions may lead to life cycle effect on offshore wind farm O&M, followed by tactical decisions.

   In the maintenance strategy optimization studies, there are several research gaps to be filled. First, it is necessary to develop a predictive opportunistic maintenance strategy considering predictive analytics and maintenance opportunities. Multiple-component age-based preventive dispatch and environmental impact can be taken into account to improve triggers of maintenance cycles and models of wind turbine failures. Second, it is important to study and quantify the influence of uncertainty on maintenance strategies and corresponding performance in an uncertain decision-making environment. Third, the maintenance strategy should be improved to realize a closed-loop decision-making manner, integrating new data to assist in updating the maintenance strategy.

In the maintenance resource organization, the problems include spare parts management and vessel fleet configuration. A joint multi-unit and multi-echelon inventory and predictive opportunistic maintenance optimization problem is a significant issue deserving attention. When configuring mix and size of vessel fleet, combining the simulation modelling methods with heuristic solving methods under novel maintenance strategies needs our attention.

2. *How to develop a maintenance strategy for an offshore wind farm that uses predicted component failure times and captures various types of maintenance opportunities?*

   In Chapter 3, a predictive opportunistic maintenance strategy is developed for offshore wind farms. The offshore wind turbines are subject to degradation and impact from the environment simultaneously. Three types of maintenance opportunities are considered. Failures due to ultimate degradation and critical impact will create maintenance opportunities, namely failure-based opportunity and incident-based opportunity. Another maintenance opportunity considering the number of aged components, age-based opportunity, is also considered to balance costly failure replacement and over-frequent maintenance cycles. Decisions determining the maintenance actions on components are decided based on component predicted failure times. The case study shows that introducing age-based opportunity is able to decrease up to 11.9% maintenance costs compared to past predictive opportunistic maintenance strategies, balancing the maintenance frequency to avoid over- and under-maintenance.

3. *How to quantify the influence of model parameter uncertainty on maintenance strategies and corresponding performance?*

   Based on the predictive opportunistic maintenance strategy model in Chapter 3, Chapter 4 focuses on quantifying the influence of model parameter uncertainty on maintenance strategy and performance. Three types of uncertainties, i.e., statistical uncertainty of component reliability, uncertain performance of component lifetime prediction, and ambiguous estimation of maintenance consequences, affecting the maintenance strategy are identified and quantified in a probabilistic method. A case study is used to estimate their influence on the performance of different representative solutions. The most influential uncertainty is uncertain performance of component lifetime prediction, followed by statistical uncertainty of component reliability and ambiguous estimation of maintenance consequences. In addition, two Pareto fronts disregarding and considering uncertainties are compared to show the influence of uncertainties on determined maintenance strategies. In the specific case study, the uncertainties result in negative influence, about 21.5% - 25.5% and 32.4% - 37.9% increase in maintenance costs and production losses respectively. In an uncertain decision-making environment, we find it is more effective to relax maintenance conditions to allow more components to be repaired and replaced in order to ensure the good condition of wind turbines and avoid potential failure events. The negative influence on maintenance costs and production losses are reduced to as low as 18.7% and 31.5% respectively.

4. *How to manage the maintenance inventory to support the implementation of the maintenance actions?*

   In Chapter 5, an integrated framework containing an inventory model and a predictive opportunistic model based on Chapter 3 is proposed. The inventory model considers 4 critical units at the component level and 15 units at the subcomponent level. A multi-echelon inventory network containing local warehouses and central warehouses is developed for storing the necessary spare parts for maintenance implementation. A case study is used to evaluate the performance of the joint policies. Sensitivity analysis shows that item costs is the most influential factors on total cost, as high as 47.3%, followed by maintenance effect (up to 42.0%), vessel and technician costs (about 37.9%), emergency order costs (about 9.4%), holding costs (about 5.3%), and lead time for orders (about 0.6%).

5. *How to make suitable leasing decisions to configure the maintenance vessel fleet?*

   In Chapter 6, a model to investigate the most cost-effective allocation of hybrid maintenance vessels is proposed. A time-domain simulation method is used to simulate the scenarios where the maintenance activities are performed under the specific configuration of the maintenance vessel fleet. The decisions about the leasing decisions are made during the maintenance cycles to adjust the configuration of the vessel fleet. In the case study, the maintenance vessel fleets are configured in a cost-effective manner to support the implementation of the maintenance activities. The sensitivity analysis shows that the most influential factors affecting vessel mix and fix is metaocean conditions, followed by maintenance strategies, chartering length, number of maintenance teams and penalty costs.

6. *How to periodically update the maintenance strategy based on new data and wind farm state to realize closed-loop decision making?*

   In Chapter 7, a closed-loop maintenance strategy optimization framework over the wind farm service life is proposed for decision-makers to identify a more profitable manner of wind farm maintenance management. In this framework, the life-cycle maintenance optimization problem is decomposed into a series of sub-optimization problems covering multiple time periods by using a rolling-horizon approach. Each sub-optimization problem is intentionally designed based on the monitored farm condition and the current RAM database. Meanwhile, parameter uncertainty in the maintenance model is gradually mitigated by updating the current database. The proposed approach was applied in simulation experiments, a generic small-scale offshore wind farm, to assess its performance. Computational results show that capturing dynamic wind farm states can reduce about 1.6% revenue losses in comparison to conventional strategies, which is value of wind farm condition monitoring. If the updates of the RAM database is considered, the economic benefit of the maintenance strategy is further reducing 1.8% of revenue loss, representing a high value of new RAM data.

8.2 Future research

With respect to the proposed methodological framework and its applications addressed in this thesis, challenging issues that require future research are:

Limitation of the research

- *Utilizing real data to make decisions for specific real wind farms and verify models*

  Data availability is still one of the biggest challenge in RAM studies of offshore wind farms. Although this issue has been highlighted in many conferences, presentations and papers, much more efforts are still needed to address this issue. A good maintenance logistics plan should be aimed at a specific wind farm, using its historical data or data from similar wind farms in similar marine environments. In this thesis, due to the limited availability of RAM data, the model parameters are obtained from several papers and reports rather than real historical data obtained for a specific actual wind farm.

  In addition, due to incompleteness in data and practical limitations, it is very difficult to verify the developed maintenance logistics model by comparing to actual offshore wind farms. Instead, we have to compare the results with the past studies and perform sensitivity analysis to verify the models. This problem is not only encountered in this paper, but is also a common obstacle in current maintenance logistics studies. In fact, maintenance logistics models involve some uncertain concepts and details of maintenance implementation. For instance, the concepts of major and minor repairs are distinguished in this thesis based on the maintenance effect, but in some literature, they are classified according to expenditures. This leads to an unclear relationship between maintenance consequences (such as money) and maintenance effects (improvement in the health of components). This relationship can only be evaluated relying on a large amount of real RAM data.

  These details vary in maintenance models in different studies, and it is difficult to find results from actual cases to clarify them. Different settings for these parameters or models can potentially bring significant changes to the results and decisions. For example, in the model of Chapter 3, we assume that maintenance is not necessary for very young (healthy) components. This assumption is very common in current models on system reliability and maintenance. However, considering that the maintenance frequency of wind turbines is based on years, a more reasonable setting is to perform some basic maintenance on these components. We gradually add this detail to the following chapters, which will inevitably affect the results. For one more example, the concept of multi-level maintenance is mentioned in this thesis. Based on the model in Chapter 3, we subdivide the required maintenance vessels for different levels of maintenance in Chapter 6. Low-level major repairs require CTVs, and high-level major repairs require FSVs. In Chapters 4, 5, and 7, we further refined the model, assuming that minor repairs require CTVs, major repairs require FSVs, and replacements require HLVs. In actual situations, vessel dispatch is determined based on task requirements. However, when actual task situations do not fully correspond to the theoretical maintenance model's concepts, it can cause confusion and lead to changes in the results due to changing some settings.

To solve this problem, the only way to get more reasonable and reliable results is to use real data to prove the setting of some parameters in the theoretical maintenance model when a large amount of data is available.This thesis mainly focuses on developing generic models to improve maintenance logistics. If more data can be added and details can be clarified, the model will be more reliable after modification. In the future, it is necessary to utilize more real data to clarify and verify the concepts and parameters in the model, and organize maintenance logistics decisions for specific wind farms and test its effectiveness in real wind farms.

- *Fully coordinated closed-loop maintenance logistics architecture.*

  Maintenance logistics are categorized into strategic, tactical, and operational levels. This thesis addresses the maintenance logistics problems from a strategic and tactical perspective and attempts to integrate the strategic and tactical decisions, providing a pathway to manage offshore wind farm O&M in a long planning horizon. However, maintenance logistics is a complicated process where details at an operational level are also important but out of consideration in this thesis. In addition, the strategic model and tactical model have not been fully integrated in this thesis. For instance, in the maintenance strategy optimization model in Chapters 3, 4, and 7, the spare parts organization and vessel fleet configuration are considered roughly, but the specific details are only modelled in Chapters 5 and 6. The reason is that the details in the lower level models introduces a significant computational burden in the higher level models, thus rough consideration is more feasible. However, this may result in inaccurate estimation of outcome (cost/power production), leading to non-optimal solutions from a global view. Future research should fully explore the coordination among decisions at three levels and integrate the models at different levels. A fully closed-loop maintenance logistics architecture is realized, in which lower-level decisions are made under the guidance of higher-level decisions, while higher-level decisions take into account the feedback of lower-level decisions. The entire architecture is able to continuously update decisions based on new data and real-time situations.

- *Considering specific failure modes and maintenance action for various types of components*

  The thesis designs maintenance strategies for entire offshore wind farms. The condition of critical components is assessed in terms of their expected lifetime and operational states. The types of repair are divided into replacement, major repair, and basic repair. In this process, no specific computational model is built for each component, and the specific failure modes of different components and the corresponding repair behaviour are not considered. For example, the failure mode of a wind turbine blade may include surface and delamination cracks, for which injection repair can be used. In future research, it is necessary to model the state of the component more specifically, perform more targeted repair actions, and evaluate the maintenance results more accurately.

Addressing new related topics

- *Autonomous offshore wind inspection and repair*

This thesis mainly focuses on maintenance logistics decision-making after inspection, thus remote and on-site inspection are not considered when developing the models. The challenging sea conditions pose safety risks, potential delays, cancellations, and prolonged turbine downtime for human-only missions, making it difficult to operate and inspect the large offshore wind farms that will be located in deep waters far away from the shore. For instance, inspection and repair missions on wind turbine blades are typically performed by rope-access technicians, working in extreme marine conditions and during restricted weather windows. If the missions can be conducted by autonomous vessels, aerial vehicles, and crawling robots, offshore operation and maintenance will be more efficient. Future research will address how to consider autonomous inspection and repair in the models to evaluate its impact on offshore wind farm operation and maintenance.

- *Utilizing digital twins and developing prescriptive maintenance.*

  A digital twin can provide a detailed representation of the physical and functional characteristics of wind turbines throughout their lifespan, and facilitate the exchange of information between physical and virtual models. It has the capability to anticipate how the wind turbine will react to unforeseen events before they occur and can forecast the performance of wind turbines in various situations, while considering the impact of different factors. In order to enable technicians to understand the effect of specific maintenance actions on the wind turbine, various maintenance scenarios can be simulated by using digital twins.

  Predictive maintenance involves collecting data on the condition of the wind turbine and identifying potential failures, but requires human analysis and decision-making to create a work order. Prescriptive maintenance goes beyond predictive maintenance by automatically generating work orders and managing maintenance tasks through artificial intelligence, with minimal human intervention. Prescriptive maintenance can even use historical data to identify patterns and provide recommendations, such as reducing wind turbine efficiency to prolong its lifespan if necessary parts are not readily available. In summary, predictive maintenance predicts potential issues, while prescriptive maintenance goes one step further by recommending specific actions to prevent problems from occurring in the first place. Future research will consider digital twins in the current models and develop prescriptive maintenance, facilitating the connection between digital twins and maintenance decisions and finally enabling higher productivity and more profitability in the wind industry.

- *Cooperation and conflicts among stakeholders.*

  Various stakeholders are involved in offshore wind farm O&M as mentioned in Fig. 2.1. Their interests may align or conflict with each other in different scenarios. For example, the maintenance tasks can be conducted by wind farm owner or maintenance service provider. In this process, their interests may conflict. Wind farm owners' purpose is to hire a service provider for less money and keep the wind farm in a satisfactory operating state. Service providers want to get higher quotes and meet the wind farm owner's mission targets with less money. When more than one service providers are hired to maintain offshore wind farms, they should determine whether to select maintenance services and when to execute services for the wind turbines.

In this process, stakeholders playing as different player may cooperate or compete with each other. This thesis focuses on generic maintenance logistics models, where cooperation and conflicts among stakeholders are not considered. Future research will address how to design maintenance strategies for multiple plays to balance their profits.

- *Operational decisions and improving heuristics algorithm*

  Decisions at an operational level are important as they involve detailed planning for maintenance implementation. This research is out of consideration in this thesis but will be left for future work. Different from strategic and tactical decisions, the operational decisions have much shorter time horizon for planning, from hourly to daily. When dealing with the problems requiring solutions in a short time, improving performance of selected heuristics algorithms is significant.

  The selection of heuristics algorithms and the setting of parameters consider two main aspects. Firstly, the algorithm shall ensure sufficiently broad range searching to find the approximate optimal solutions. Secondly, the computation shall be efficient - simulation would converge in a time-effective manner. In this thesis, the models involves a small number of decision variables. For example, in Chapter 3, the maintenance optimization problem only involve three decisions variables which do not have much space for variation. The number of constraints is also small. The solution space does not involve local optimum, indicating that it is easy to avoid getting stuck in a solution that is optimal within a local neighborhood, which will be shown in Section 3.3.2. In this context, the complexity and specificity of this optimization problem is small and does not create a lot of difficulties when using heuristic algorithms. Moreover, the strategic decisions do not have a requirement for solution time, indicting the efficiency of the algorithm is unnecessary to be concerned. We have also done several preliminary tests with different heuristic algorithms before and found that this model is not very sensitive to the selection of heuristic algorithms. Considering this is not the focus of the maintenance model, these results are not shown in the thesis. However, operational (day-to-day) decisions have a strict requirement on performance of heuristics algorithm, aiming to obtain the acceptable solutions within a limited time horizon. Future research will address how to use improved heuristics algorithm to organize operational activities.

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Glossary

List of symbols and notations

Below follows a list of the most frequently used symbols and notations in this thesis.

$^{-}(\cdot)$	Parameter at the beginning of maintenance cycle
$^{+}(\cdot)$	Parameter at the end of maintenance cycle
$\dot{(\cdot)}$	Parameter in the virtual maintenance model
$(\cdot)_i$	Parameter of component i
$(\cdot)_j$	Parameter of subcomponent j
$(\cdot)_k$	Parameter of turbine k
$(\cdot)_m$	Parameter of maintenance level m
$(\cdot)(n)$	Parameter at wind farm state n
$(\cdot)_s$	Parameter at maintenance cycle s
$(\cdot)_{s^-}$	Parameter before s maintenance cycle
$(\cdot)_t$	Parameter at time t
$(\cdot)_y$	Parameter at inspection y
$(\cdot)^z$	Parameter at decision-making step z
$\triangle s$	Length of time periods for wind farm state
$\triangle T$	Time interval for decision making
A	Health indicator
$\widetilde{A}$	Health state indicator based on predicted failure times
A_{c}	Annual maintenance cost
A^{max}	Maximum age percentage threshold
A^{min}	Minimum age percentage threshold
A_{p}	Annual production loss
A_{r}	Annual revenue loss in the wind farm system
A_{T}	Expected annual cost for maintenance and inventory
a_{p}	Proportional parameter of mean of prediction error
a_{s}	Proportional parameter of standard deviation of prediction error
$\boldsymbol{a}$	Failure state matrix in end state
$\bar{\boldsymbol{a}}$	Failure state matrix in start state
B	Number of aged components
$\boldsymbol{b}$	Influence matrix for impact
b	Age increase of component due to influential impact
C^{E}	Emergency cost

C^{H}	Holding cost
C^{I}	Total cost for inventory
C^{M}	Total maintenance costs
C^{MAT}	Total cost of material for repair
C^{MOB}	Total mobilization cost
C^{O}	Ordering cost
C^{P}	Cost of lost production
C^{c}	Order cost for component-level units
C^{l}	Order cost for subcomponent-level units
C^{T}	Total costs related to maintenance effort
C^{TEC}	Total technician cost
C^{VES}	Total vessel cost
C^{task}	Repair task related costs
C^{penalty}	Penalty related costs
C^{vessel}	Vessel related costs
C^{loss}	Production losses related costs
$\boldsymbol{c}$	A series of maintenance strategy during lifetime
c	Maintenance strategy
d	Binary variable determining whether a maintenance cycle is trigged
E	Emergency cost for component
$\bar{e}$	Average Prediction Error
e	Prediction error
F	Failure time of component
F^{T}	Failure time of turbine
$f^{\mathrm{p}}()$	Probability density function
$\bar{\boldsymbol{g}}$	Failure moment matrix in end state
$\boldsymbol{g}$	Failure moment matrix in start state
I	Set of components at one wind turbine
i	Index of component
J_i	Set for subcomponents at component i
j	Index for j subcomponent
K	Set of offshore wind turbines
k	Index of offshore wind turbine
L	Offshore wind farm lifetime
L^{c}	Lead time for regular orders from central warehouses
L^{l}	Lead time for regular orders from local warehouses
L_{p}	Length of the planning horizon
ℓ	Revenue loss in the wind farm system
l	maintenance level
M	Set of maintenance levels
M^{FR}	Total cost of failure replacement
M^{f}	Total fixed cost
M^{MAR}	Total cost of major repair
M^{MOB}	Mobilization cost
M^{PR}	Total cost of preventive replacement
M^{TR}	Total transportation cost

m	Index for m maintenance level
m^{C}	Mobilization time for CTVs
m^{F}	Mobilization time for FSVs
m^{H}	Mobilization time for HLVs
N	Set of time period
N^{FR}	Repair time of failure replacement
N^{MAR}	Repair time of major repair
N^{MIR}	Repair time of basic repair
N^{PR}	Repair time of preventive replacement
N^{T}	Total downtime
N^{HLVC}	The number of chartered HLV
N^{FSVC}	The number of chartered FSV
N^{CTVC}	The number of chartered CTV
N^{HLVO}	The number of owned HLV
N^{FSVO}	The number of owned FSV
N^{CTVO}	The number of owned CTV
N^{HLVT}	The number of tasks requiring HLV
N^{FSVT}	The number of tasks requiring FSV
N^{CTVT}	The number of tasks requiring CTV
n	Index for offshore wind farm states
${}^{1}\boldsymbol{O}$	Binary variable matrix for degradation failure
${}^{2}\boldsymbol{O}$	Binary variable matrix for incident failure
${}^{3}\boldsymbol{O}$	Binary variable matrix for ageing stage
$\tilde{P}$	Predicted remaining useful life percentage
P	Real remaining useful life percentage
P^{C}	Occurrence probability of critical impact
P^{I}	Occurrence probability of influential impact
P^{M}	Occurrence probability of minor impact
P_{rated}	Rated capacity of wind turbine
P^{T}	Total production losses
P^{w}	Power production
P	Sub-optimization problem
Q^{C}	Daily cost of CTVs
Q^{J}	Daily cost of heavy-lift vessels
Q^{S}	Daily cost of field support vessels
$\boldsymbol{q}$	Occurrence moment matrix for impact
$\boldsymbol{R}$	State of wind farm system
R^{FR}	Material cost of failure replacement
R^{f}	Fixed cost to trigger a cycle of maintenance
R^{MAR}	Material cost of major repair
R^{MIR}	Material cost of basic repair
R^{PR}	Material cost of preventive replacement
R^{TR}	Transportation cost to turbine
r	Expected cost of the lost production per turbine per day
S	Set of maintenance cycles
S^{C}	High limit of inventory in central warehouses

S^{L}	High limit of inventory in local warehouses
s	Index of maintenance cycle
s^{C}	Low limit of inventory in central warehouses
s^{L}	Low limit of inventory in local warehouses
T	Arrival time of maintenance cycle
T^{C}	Daily personnel cost
T^{period}	time period in wind farm lifetime
T_{H}	Future horizon at decision-making step
$\boldsymbol{u}$	Current age matrix in start state
$\bar{\boldsymbol{u}}$	Current age matrix in end state
u	Age of component
$\boldsymbol{v}$	Real lifetime matrix in start state
$\bar{\boldsymbol{v}}$	Real lifetime matrix in end state
$\widetilde{v}$	Predicted lifetime matrix in start state
$\bar{\widetilde{\boldsymbol{v}}}$	Predicted lifetime matrix in end state
v	Failure age of component
$\widetilde{v}$	Predicted lifetime of component
W^{MAR}	Number of required technicians for major repair
W^{MIR}	Number of required technicians for basic repair
W^{FR}	Number of required technicians for failure replacement
W^{PR}	Number of required technicians for preventive replacement
$\boldsymbol{w}$	Cumulative time matrix in start state
$\bar{\boldsymbol{w}}$	Cumulative time matrix in end state
w	Wind speed
w_{in}	Cut-in wind speed
w_{out}	Cut-out wind speed
w_{rated}	Rated wind speed
${}^{1}\hat{\boldsymbol{X}}^{D_1}$	Updated database for parameters D_1
${}^{1}\boldsymbol{X}$	Original component lifetime database
${}^{1}\boldsymbol{X}^{D_1}$	New component lifetime data sample for parameters D_1
${}^{2}\hat{\boldsymbol{X}}^{D_1}$	Updated database for parameters D_1
${}^{2}\boldsymbol{X}$	Original RUL prediction performance database
${}^{2}\boldsymbol{X}^{D_1}$	New RUL prediction performance data sample for parameters D_1
${}^{3}\hat{\boldsymbol{X}}^{D_1}$	Updated database for parameters D_1
${}^{3}\boldsymbol{X}$	Original maintenance implementation database
${}^{3}\boldsymbol{X}^{D_1}$	New maintenance implementation data sample for parameters D_1
X^{a}	Binary variable for age-based opportunity
X^{c}	Binary variable for critical impact
X^{EI}	Binary variable for environmental impact
X^{FR}	Binary variable for failure replacement
X^{f}	Binary variable for failure-based opportunity
X^{i}	Binary variable for incident-based opportunity
X^{MAR}	Binary variable for major repair
X^{MIR}	Binary variable determining basic repair
X^{PR}	Binary variable for preventive replacement

X^{TR}	Binary variable determining turbine is visited.
$X_{\mathrm{T}}^{\mathrm{HLV}}$	Decision variable determining chartering HLVs
$X_{\mathrm{T}}^{\mathrm{FSV}}$	Decision variable determining chartering FSVs
$X_{\mathrm{T}}^{\mathrm{CTV}}$	Decision variable determining chartering CTVs
Y	Total number of inspection
y	Index for y inspection
y^{C}	Binary variable for emergency component-level unit orders
y^{L}	Binary variable for emergency subcomponent-level unit orders
Z	Set for decision-making steps
z	Index for z decision-making step
z^{c}	Binary variable for regular component-level unit orders
z^{l}	Binary variable for regular subcomponent-level unit orders
α^{r}	Shape parameter of maintenance quality
β^{r}	Shape parameter of maintenance quality
γ	Required number of component
δ	Holding cost rate
δ_{a}	Fixed parameter of standard deviation of prediction error
δ_{c}	Standard deviation of coefficient determining maintenance cost
δ^{R}	Standard deviation of prediction error of component
δ_{t}	Standard deviation of coefficient determining repair time
ε	Shape parameter of component failure distribution
ζ	Percentage threshold of number of aged components
η^{c}	Lead time for emergency orders for central warehouses
η_{c}	Coefficient determining maintenance cost
η^{o}	Lead time for emergency orders for local warehouses
η_{t}	Coefficient determining repair time
$\boldsymbol{\theta}^{D_1}$	Probability parameters D_1 in maximum likelihood estimation
$\boldsymbol{\theta}^{D_2}$	Probability parameters D_2 in maximum likelihood estimation
$\boldsymbol{\theta}^{D_3}$	Probability parameters D_3 in maximum likelihood estimation
$\boldsymbol{\theta}$	Maintenance quality matrix
θ	Maintenance quality
$\boldsymbol{\kappa}$	Interior state of wind farm system
κ	Required number of subcomponent
λ^{C}	Current quantity of component
λ^{S}	Current quantity of subcomponent
λ	Intensity function of environmental impact
μ^{R}	Mean of prediction error of component
μ_{a}	Fixed parameter of mean of prediction error
μ_{c}	Mean of coefficient determining maintenance cost
$\mu_{\theta}^{\mathrm{r}}$	Expected value of maintenance quality
μ_{t}	Mean of coefficient determining repair time
$\boldsymbol{\xi}$	Start state of wind farm system
$\sigma_{\theta_l}^{\mathrm{r}}$	Standard deviation of maintenance quality
σ	Scale parameter of component failure distribution
ρ	Number of covered wind farm state in a decision-making step
$\boldsymbol{\omega}$	End state of wind farm system

List of symbols and notations

The following abbreviations are used in this thesis.

ANN	Artificial Neural Network
CTV	Crew Transfer Vessel
FMEA	Failure Mode and Effects Analysis
FMECA	Failure Mode Effects and Criticality Analysis
FSV	Field Support Vessel
FTA	Fault Tree Analysis
GA	Genetic Algorithm
GRASP	Greedy Randomized Adaptive Search Procedure
HLV	Heavy Life Vessel
IPCC	Intergovernmental Panel on Climate Change
LCOE	Levelized Cost of Energy
MABO	Multiple Age based Opportunity
MILP	Mixed-Integer Linear Programming
MIP	Mixed-Integer Programming
MTTF	Mean Time To Failure
NABO	None Age based Opportunity
$NSGA-II$	Non-dominated Sorting Genetic Algorithm II
OAV	Offshore Assistance Vessel
OEM	Original Equipment Manufacturer
O&M	Operation and Maintenance
PSO	Particle Swarm Optimization
RAM	Reliability, Availability and Maintainability.
RUL	Remaining Useful Life
SA	Simulated Annealing
SAA	Sample Average Approximation
SABO	Single Age based Opportunity
SCADA	Supervisory Control and Data Dcquisition
SOV	Service Operation vessels
SP	Stochastic Programming
SV	Supply Vessel

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Samenvatting

De offshore windcapaciteit van Europa zal naar verwachting in 2050 450 GW bereiken, wat 30% van de elektriciteitsvraag van Europa zal dekken. Met de toename van de geïnstalleerde capaciteit zullen de kosten voor O&M ook aanzienlijk toenemen, aangezien de O&M-kosten een van de grootste bijdragers zijn aan de levenscycluskosten. De verbetering van het O&M-management voor offshore windparken, met name onderhoudslogistiek, vertegenwoordigt een aanzienlijke kostenverlagingsmogelijkheid en zal blijven zorgen voor de belangrijkste factor bij het vormgeven van de toekomstige ontwikkeling van de offshore windsector.

Recent onderzoek biedt duidelijke inzichten in het beheer van onderhoudslogistiek, waarbij beslissingen worden gecategoriseerd in drie niveaus: strategisch, tactisch en operationeel. Onderhoudsstrategieën en resource-organisatie zijn respectievelijk strategische en tactische beslissingen met een langdurige invloed op offshore windparken. Met sensoren en communicatietechnologieën kunnen eigenaren en exploitanten van windparken en serviceproviders de gezondheidsinformatie van windparken gebruiken om onderhoudsstrategieën te ontwerpen en onderhoudsresources te organiseren, en nieuwe gegevens gebruiken om beslissingen bij te werken om zo in een gesloten lus te realiseren. Daarom luidt de onderzoeksvraag van deze scriptie: *hoe kan de effectiviteit van onderhoudsstrategie en resource-organisatie voor offshore windparken worden verbeterd en hoe kan er worden overgegaan naar een besluitvormingsbenadering in gesloten lus*?

In deze scriptie wordt eerst een open-lus voorspellende opportunische onderhoudsstrategie ontwikkeld die gebruik maakt van voorspelde componentfouten en onderhoudsmogelijkheden. Vervolgens wordt de invloed van onnauwkeurigheid of onzekerheid in modelparameters gekwantificeerd op onderhoudsprestaties en -strategieën. De significantie van verschillende onzekerheden wordt gerangschikt en er worden suggesties gedaan om om te gaan met de onzekere besluitvormingsomgeving. Vervolgens worden benaderingen voorgesteld om de belangrijkste onderhoudsbronnen, namelijk reserveonderdelen en servicevaartuigen, te organiseren om de implementatie van de open-lus onderhoudsstrategie op een kosteneffectieve manier te ondersteunen. Ten slotte ontwikkelt de open-lus onderhoudsstrategie zich tot een gesloten-lus onderhoudsstrategie die in staat is om dynamische windmolenparkstaten vast te leggen en de invloed van onzekerheden in modelparameters te verminderen, waardoor meer inkomstenverlies wordt voorkomen dan bij open-lus benaderingen.

Over het geheel genomen biedt deze scriptie een reeks benaderingen voor eigenaren en exploitanten van offshore windmolenparken en onderhoudsdienstverleners om strategische en tactische onderhoudslogistiek voor offshore windmolenparken te instrueren, waarbij het potentieel wordt aangetoond om de effectiviteit te verbeteren en over te gaan naar een gesloten kringloop.

Summary

Europe's offshore wind capacity is expected to reach 450 GW by 2050, meeting 30% of Europe's electricity demand. With the increase of installed capacity, the costs invested in O&M will also increase significantly considering O&M cost is one of the biggest contributors to life cycle costs. The improvement of O&M management for offshore wind farms, especially maintenance logistics, represents a significant cost-reduction opportunity and will continue to be a primary factor in shaping the future development of the offshore wind sector.

Recent research provides clear insights into maintenance logistics management, categorizing decisions into three levels, strategic, tactical, and operational. Maintenance strategies and resource organization are strategic and tactical decisions respectively, with a long-lasting influence on offshore wind farms. With sensors and communication technologies, wind farm owners/operators and service providers can use the health information of wind farms to design maintenance strategies and organize maintenance resources, and utilize new data to update decisions to realize a closed-loop manner. Thus the research question of this thesis is *how to improve the effectiveness of maintenance strategy and resource organization for offshore wind farms and move towards a closed-loop decision-making approach*?

In this thesis, an open-loop predictive opportunistic maintenance strategy utilizing predicted component failures and maintenance opportunities is developed first. Then, the influence of inaccuracy or uncertainty in model parameters is quantified on maintenance performance and strategies. The significance of different uncertainties is ranked, and suggestions are provided to cope with the uncertain decision-making environment. Next, the approaches are proposed to organize the primary maintenance resources, i.e., spare parts and service vessels, to support the implementation of the open-loop maintenance strategy in a cost-effective manner. Finally, the open-loop maintenance strategy develops towards a closed-loop maintenance strategy that is able to capture dynamic wind farm states and mitigate the influence of model parameter uncertainties, reducing more revenue losses than open-loop approaches.

Overall, this thesis provides a series of approaches for offshore wind farm owners and operators and maintenance service providers to instruct the strategic and tactical maintenance logistics for offshore wind farms, showing the potential for improving the effectiveness and moving towards a closed-loop manner.

Curriculum vitae

Mingxin Li was born on July 30, 1994 in Harbin, China. In 2012, Mingxin Li started his undergraduate study in Naval Architecture and Ocean Engineering at Harbin Engineering University. After receiving his Bachelor's degree in 2016, he continued his Master study under supervision of Prof. Liping Sun.

Upon acquiring his Master's degree in 2019 as the outstanding graduate student (summa cum laude), Mingxin Li decided to pursue his PhD degree at Delft University of Technology. Under the supervision of Prof. Rudy R. Negenborn and Dr. Xiaoli Jiang, he worked on the operation and maintenance for offshore wind farms. His research interests include renewable energy, asset management, operation and maintenance, risk and reliability analysis.

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