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Optimal Scheduling of Maintenance Tasks and Routing of a Joint Vessel Fleet for Multiple Offshore Wind Farms

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Submission date: June 2015
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Problem Description

The purpose of this thesis is to study the routing and scheduling of a given, joint vessel fleet that is used when performing maintenance operations at multiple offshore wind farms. A tactical problem with a short, finite planning period is formulated using mathematical programming models. Analysis and simulations are used to evaluate the performance of the models and the effect of changing different parameters of the models.

Preface

This master thesis is the concluding part of our Master of Science at the Norwegian University of Science and Technology (NTNU). The degree specialization is Managerial Economics and Operation Research at the Department of Industrial Economics and Technology Management. The thesis examines cost efficient schedules for performing operation and maintenance tasks at multiple offshore wind farms with a joint vessel fleet, and is a continuation of our work for the specialization project, conducted during the fall semester 2014.

We would like to thank our supervisors Professor Lars Magnus Hvattum (Department of Industrial Economics and Technology Management, NTNU), and Postdoctoral Fellow Magnus Stålhane (Department of Industrial Economics and Technology Management, NTNU), for their helpful and valuable discussions and feedback throughout the semester.

Trondheim, June 11, 2015

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Abstract

Wind energy is among the fastest growing electricity generation systems in the world. However, the offshore wind industry is challenged with still being far more costly than conventional energy sources. Operation and maintenance (O&M) can account for up to a third of the overall lifetime costs for an offshore wind farm. A reduction of these costs is therefore crucial in order for electricity production from offshore wind to be competitive in the market. This creates a demand for effective scheduling of the maintenance activities.

This thesis presents a static, deterministic model that utilizes weather forecasts to create schedules for multiple wind farms with a joint vessel fleet in order to minimize O&M costs. These schedules contain information on which vessel that should visit which wind farm and which tasks the vessels should perform and at what time.

Due to the complexity of the problem, exact methods struggles to solve larger problems with a planning period of more than one shift within a reasonable time. Two different rolling horizon heuristics are therefore proposed. The heuristics solve the problem by iteratively LP-relaxing some parts of the planning period of the problem, and fixing the solutions for some of the variables that are not LP-relaxed. The performance of the two heuristics were evaluated by comparing solution time and solution quality with the solutions obtained from an exact model.

The exact model and the best performing heuristic were further tested in a dynamic setting by simulating the problem over a longer time horizon. The results showed that the exact model solved for a planning period of one shift performed better, both in terms of solution time and solution quality, than the heuristic solved for a planning period of two and three shifts. Simulations of the problem can provide valuable information when making strategic decisions for offshore wind farms. This is illustrated for two different strategic issues; deciding a vessel fleet size and mix by comparing comparing different vessel fleets, and analyzing the synergy effects of a joint vessel fleet for two wind farms compared to two separate vessel fleets.

Sammendrag

Vindkraft er blant de raskest voksende energikildene i verden. Offshore vind er fremdeles langt mer kostbart enn konvensjonelle energikilder. Drift- og vedlikeholdskostnader utgjør nærmere en tredjedel av de totale livssykluskostnadene, og en reduksjon av disse kostnadene er derfor avgjørende for om elektrisitetsproduksjon fra offshore vind kan bli konkurransedyktig. Dette skaper et behov for tidsplaner som minimerer kostnadene knyttet til utførelse av drift- og vedlikeholdsoppgaver.

Denne avhandlingen presenterer en statisk, deterministisk modell som utnytter værmeldinger til å generere kostnadseffektive skiftsplaner for utførelse av drift- og vedlikeholdsoppgaver for flere vindparker med en felles skipsflåte. Disse skiftplanene inneholder informasjon om hvilke vindparker som skal besøkes av hvilke skip, hvilke oppgaver i de besøkte parkene som skal gjøres og når disse oppgavene skal jobbes med.

Problemets kompleksitet gjør at eksakte løsningsmetoder har problemer med å løse større problemer for en planleggingsperiode lengre enn ett skift. To ulike *rolling horizon*-heuristikker er derfor presentert. Disse heuristikkene løser problemet ved å iterativt LP-relaksere deler av problemets planleggingsperiode, for så å fiksere løsninger til noen av variablene som ikke LP-relakseres. Heuristikkene evalueres mot en eksakt modell ved å sammenligne løsningstid og løsningskvalitet.

Den eksakte modellen og den mest effektive heuristikken er videre testet i dynamiske omgivelser ved å simulere problemet over en lengre tidshorisont. Resulatatene viser at den eksakte modellen løst for en planleggingsperiode på ett skift er bedre, både med hensyn på løsningstid og løsningskvalitet, enn heuristikken løst for en planleggingsperiode på to og tre skift. Simuleringer av problemet kan bidra med verdifull informasjon ved strategiske beslutninger for offshore vindparker. Dette illustreres for to strategiske beslutninger; for bestemmelse av skipsflåte og for analysering av synergieffekter ved å ha en felles skipsflåte for to vindparker, sammenlignet med å ha to separate skipsflåter.

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List of Abbreviations

ATB – Aggregate Time Block of a Rolling Horizon Heuristic

AV – Accommodation Vessel

CTV – Crew Transfer Vessel

DTB – Detailed Time Block of a Rolling Horizon Heuristic

FTB – Frozen Time Block of a Rolling Horizon Heuristic

O&M – Operation and Maintenance

PPD – Pick-Up and Delivery Problem

RHH-1 – Rolling Horizon Heuristic 1

RHH-2 – Rolling Horizon Heuristic 2

SES – Surface Effect Ship

VRP – Vehicle Routing Problem

1 Introduction

Global electricity demand is increasing rapidly. Between 1990 and 2010 the electricity consumption increased with more than 80 %, and the International Energy Agency, IEA, estimates a further growth of almost 80 % towards 2040 [49, 50], as illustrated in Figure 1.

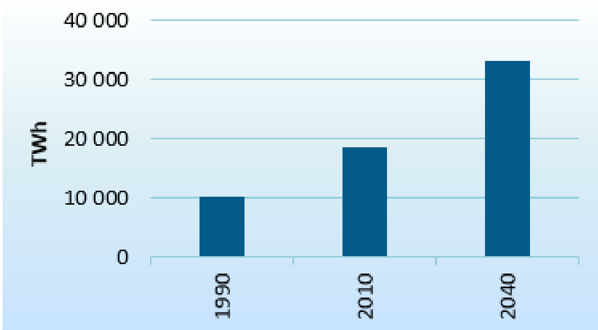


Figure 1: Global electricity demand 1990 - 2040. The figure is based on data from the International Energy Agency, IEA [49, 50].

Fossil fuels dominate the power sector and had a share of 68 % of the electricity generation in 2012 [50]. The rise in electricity demand will, in combination with the need to reduce greenhouse gas emissions, require greater investments in renewable energy sources. The European Union has committed to an energy target on reducing the greenhouse gas emissions by at least 40 % and meet 27 % of its energy consumption through renewable energy sources by 2030 [30]. On a global basis, the share of renewables are expected to increase towards 2040, from a share of 21 % in 2012 to a share of 33 % in 2040 [50].

Wind power is among the fastest growing electrical generation systems in the world [70] and is expected to contribute substantially to the future energy consumption [77]. Figure 2 shows the growth in cumulative installed wind power capacity from 1997 to 2014. In 2014 onshore wind turbines accounted for more than 97 % of the electricity generated from wind, however, as Figure 3 shows, the offshore wind industry is growing fast. Between 2011 and 2014 the installed capacity of offshore wind more than doubled.

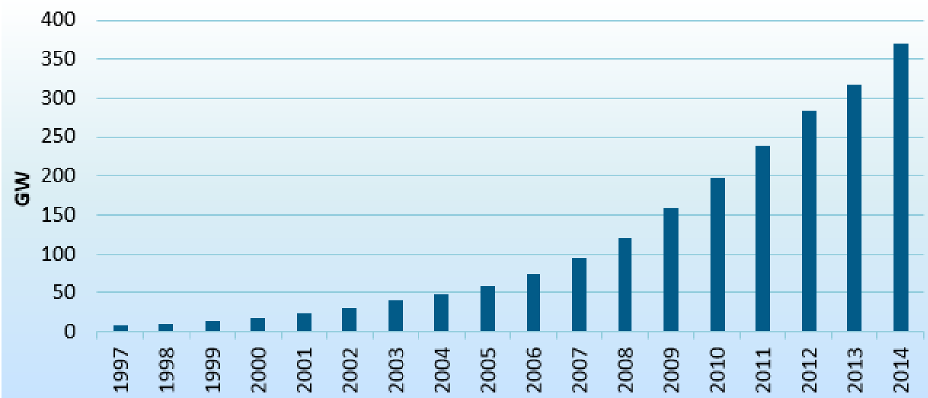


Figure 2: Global cumulative installed wind capacity 1997-2014. The figure is based on numbers from Global Wind Energy Council, GWEC [39].

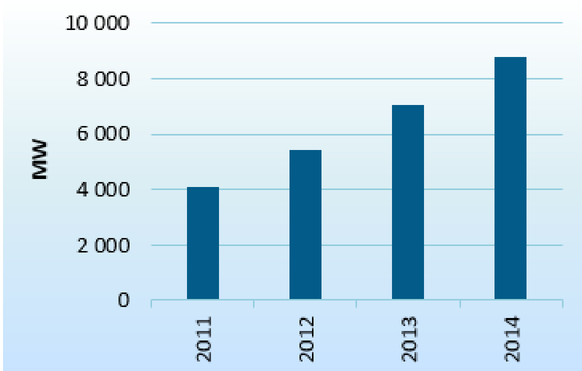


Figure 3: Global cumulative installed offshore wind capacity 2011-2014. The figure is based on numbers from Global Wind Energy Council, GWEC [39].

Wind power generation is driven offshore by several factors. One of the most important factors is space, as space is quickly becoming scarce for the installation of onshore wind turbines. Moving offshore gives the benefit of greater areas available for the installation of wind farms, it also allows for larger wind farms and for installation close to major urban cities. Installing wind turbines far from shore reduces the noise and visual impact. This will, in combination with less space restrictions, make it possible to use other designs for the turbine to improve efficiency [15]. There are generally higher wind speeds offshore than onshore which results in a greater energy potential for offshore turbines. An onshore turbine normally has around 2000-2300 full load hours per year while an offshore turbine normally reaches more than 3000 full load hours [76, 82]. It is expected that future wind farms will be located even further offshore than wind farms operating today, and that they will increase in wind turbine capacity and be located further offshore than current wind farms [55].

The potential of offshore wind is enormous, it could meet Europe's energy demand seven times over and the United States' energy demand four times over [36]. The offshore wind industry is expected to grow. It is expected that within 2020 offshore wind power capacity in Europe will grow to about 25 GW. China has an offshore wind development target of 30 GW by 2030 and the offshore wind sector in the United States is also starting to prosper [38]. Figure 4 illustrates an estimated development in the offshore wind sector towards 2022.

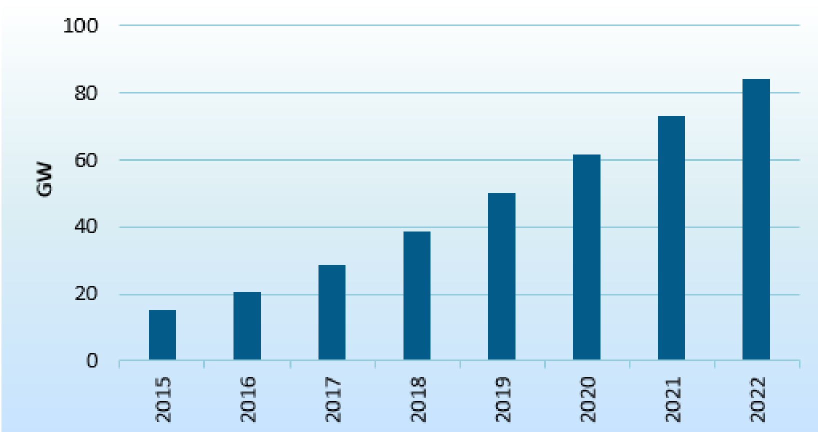


Figure 4: Forecast of global cumulative installed offshore wind capacity 2015-2022. The figure is based on numbers from Navigant Research [16].

Unlike onshore wind energy, which is starting to become competitive with fossil fuels, offshore wind energy is still far more costly than conventional energy sources [77]. Offshore wind energy is approximately 50 % more expensive than onshore wind energy, and is dependent on governmental subsidies [76, 82]. This is to a large extent due to higher installation costs, but also due to higher operation and maintenance (O&M) costs. O&M can account for up to a third of the overall lifetime costs for an offshore wind farm [69]. O&M costs include transportation costs, technician salaries and costs of repair actions and spare parts. They also include loss of revenue caused by production stop when a turbine is shut down during failures and maintenance operations. The high O&M costs of offshore wind are caused by rougher conditions than for onshore turbines. Rougher weather and salty water make offshore wind turbines more exposed to breakdowns. Rough weather and greater distances from shore also makes the turbines more difficult and expensive to access, and performance of maintenance is dependent on periods of good weather [15]. Difficulties of accessing turbines to repair failures may lead to long periods of downtime for the turbines and this can cause large financial losses.

The costs of offshore wind must be reduced in order to achieve a competitive price in the market. As O&M costs account for a substantial part of the total costs for offshore wind, a reduction of these costs is crucial to bring down the total costs. This is even more important for future wind farms, where installation further offshore decreases turbine accessibility and increases O&M costs. Efficient use of the maintenance vessel fleet and maximum utilization of periods of good weather is important to minimize the O&M costs. This creates a demand for effective scheduling of the maintenance activities.

A mathematical model that generates maintenance schedules for multiple wind farms with a joint vessel fleet is presented in this thesis to address the reduction of O&M costs for offshore wind energy. The mathematical model presented is a deterministic, static model that aims to utilize periods of good weather to minimize the transportation costs and costs due to loss of production for the generated schedules. To solve real size problems, a heuristic for solving the mathematical model is proposed. The heuristic is compared with an exact solution method by evaluating the solution quality and the solution time. To capture the dynamic aspects of the problem, simulations using the heuristic iteratively over longer time periods have been performed. It is shown how these simulations can be used for analyzing more strategical issues, such as the vessel fleet mix and the effect of a joint vessel fleet for multiple wind farms compared to separate vessel fleets.

The thesis is organized as follows. In Chapter 2, relevant background information of O&M in offshore wind farms is presented. The problem studied in this thesis is described in Chapter 3, and relevant literature for the problem is presented in Chapter 4. The literature review includes literature on optimization of O&M in offshore wind farms and on vehicle routing problems. In Chapter 5, a mathematical model for the problem is presented, followed by an example to illustrate the model. The solution method used to solve the mathematical model are then described in Chapter 6. To test the model a simulator was developed. The simulator framework is described in Chapter 7, including an example to illustrate how the simulator works. Chapter 8 presents the computational study of the mathematical model. Concluding remarks and suggestions for further research are given in Chapter 9.

2 Background

In this chapter background information on O&M aspects necessary to understand the problem is outlined. In Section 2.1 an overview of the current status and future prospects of offshore wind farms and the offshore wind industry is presented. Helicopters and different types of vessels used for maintenance operations are then described in Section 2.2, followed by a description of different types of maintenance in Section 2.3 and a definition and description of downtime costs in Section 2.4.

2.1 Offshore Wind Farms - Current Status and Future Outlook

As Figure 2 and 3 showed, both the onshore and the offshore wind energy industry is growing rapidly. By 2014, 370 GW of wind energy was installed, with 8.8 GW coming from offshore wind turbines [37]. More than 90 % of the global offshore wind power is installed in northern Europe, with 63.3 % installed in the North Sea, 22.5 % in the Atlantic Ocean and 14.2 % in the Baltic Sea [36, 20].

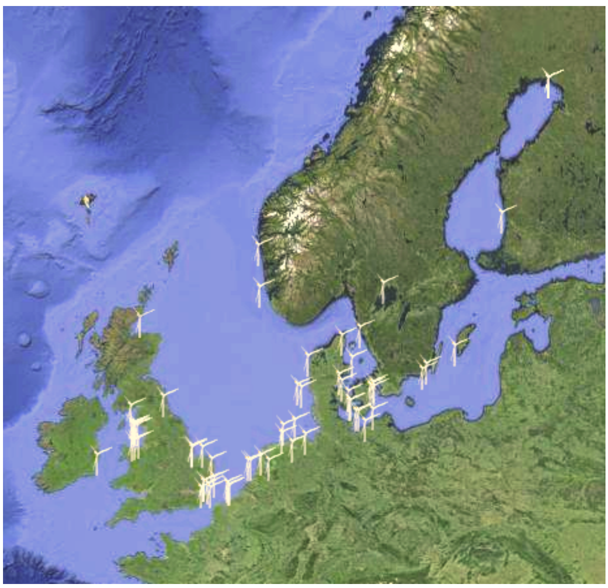


Figure 5: Offshore wind farms in northern Europe [18].

The average size of operating European offshore wind farms in 2014 was 368 MW, and the two largest offshore wind farms operating were London Array with 175 turbines and 630 MW and Greater Gabbard with 140 turbines and 504 MW, both located in the UK [20, 65]. The average wind turbine capacity installed in Europe in 2014 was 3.6 MW, but there also exists installed turbines with capacities as high as 7 to 8 MW [20, 37].

Wind farm locations are restricted by distance from shore due to accessibility of the sites. The turbines must be within a reasonable distance in order to perform operation and maintenance services. The average distance to shore for operating European offshore wind farms in 2014 was 32.9 km, however, several German wind farms are located more than 50 km from shore, with BARD Offshore 1 being located as far as 100 km from the coast [20, 75]. The location of offshore wind farms is also restricted by the depth of the location. Current commercial substructures are economically limited to maximum water depths of 40 to 50 m [4], and the average depth of operating European wind farms in 2014 was 22.4 m. The locations of wind farms are restricted to relatively shallow depths because the substructures of commercial turbines are attached to the seabed. Currently there are only two operating full scale wind turbines on floating substructures [20] that exist. One of these is the Hywind, a 2.3 MW turbine carried out by Statoil, which is based on a concept that is constructed for depths of 120 to 700 m [73].

As mentioned in Chapter 1, offshore wind farms are expected to increase in size, move further from shore and to locations with larger depths. This trend can be seen already when looking at projects being under construction, projects consented and projects in the planning phase, as illustrated in Figure 6 and 7. Examples of large planned wind farms are Blekinge Offshore, a 2.5 GW wind farm of up to 700 turbines planned 12 km outside the south east coast of Sweden [14], and Dogger Bank, a proposed offshore wind project consisting of six wind farms, each with a capacity of up to 1.2 GW and 200 turbines. Dogger Bank is located between 125 and 290 kilometres off the coast of Yorkshire, England, with water depths ranging from 18 to 63 metres [33]. Two of these wind farms have so far been given consent [80]. One way to reduce O&M costs for projects such as Dogger Bank, where several wind farms are located within a relatively small distance, can be through a joint vessel fleet concept. A joint vessel fleet may increase the efficiency of the utilization of the fleet and help achieve economies of scale [78].

To fully exploit the potential of offshore wind, one is dependent on being able to develop projects in locations with larger depths and further from shore than what is currently possible. With the technology from floating substructures, which Statoil aims to commercialize within 10-15 years [73], offshore wind farm developers

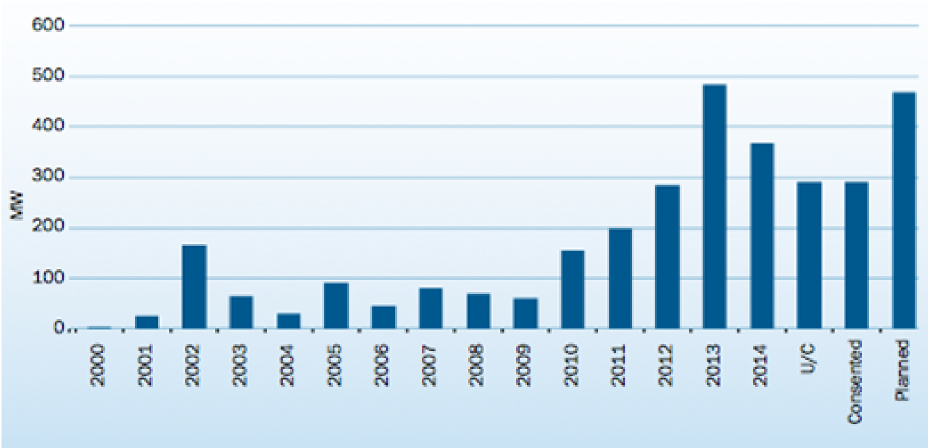


Figure 6: Average size of offshore wind farm projects from 2000. The figure is based on [20].

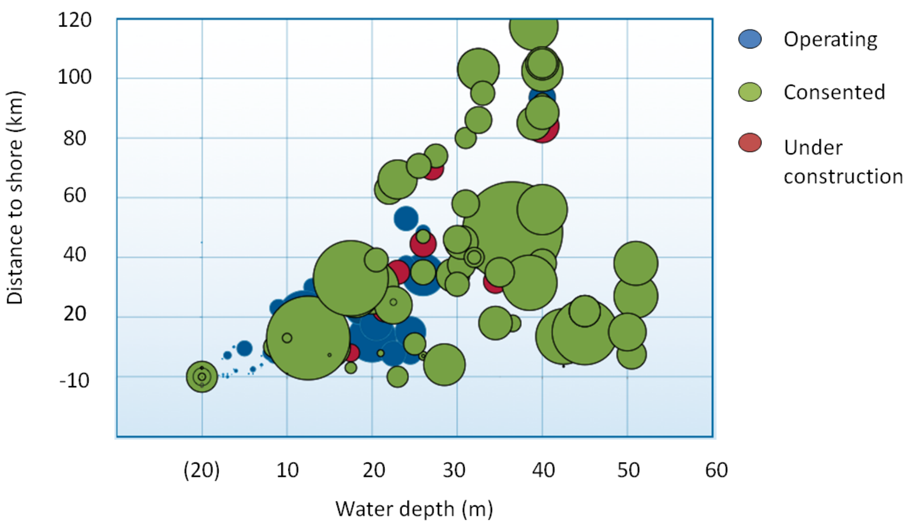


Figure 7: Average water depth and distance to shore of operating, under construction and consented wind farms. The figure is based on [20].

are less restricted by water depths when locating new projects. This opens up possibilities for new locations both close to shore and further away from shore. As a respond to the challenge of distance to shore, the concept of offshore stations has emerged. One type of offshore stations is a fixed offshore accommodation platform that can accommodate technicians and serve as a haven for smaller service vessels or helicopters. Another concept is the concept of motherships, which are larger supply ships that can stay offshore for up to a month, accommodating smaller service vessels and their technicians [5]. Motherships are described more in detail in Section 2.2.3.

2.2 Vessels and Helicopters

Different types of vessels can be used to transport technicians to turbines that require maintenance. These varies in properties such as speed, fuel consumption, equipment onboard and capacities of passengers, spare parts and equipment. Also daily cost rates and the sensitivity to rough weather and wave heights vary among different vessel types. Daily cost rates include capital expenditures and operational expenditures such as maintenance of the vessel and salary for the vessel crew, but not variable costs such as fuel. Offshore wind is a relatively new industry, and some of the vessels outlined in this section are still only concepts, not yet in use.

Most vessels can transport twelve passenger or more, which is more technicians than what is normally required for performing maintenance at one turbine [26]. It is therefore common that maintenance tasks that only require technicians and minor equipment are performed in parallel. Technicians are then left at the turbine and picked up after the task is performed. For tasks requiring subsea operations or more extensive equipment, such as lifting cranes, the vessels are required to stay by the turbine while the task is performed.

2.2.1 Crew Transfer Vessels

Crew transfer vessels (CTVs) can transfer personnel, minor equipment and spare parts to and from a turbine and can perform smaller maintenance tasks such as inspections, routine maintenance and replacements of smaller parts. The offshore time for a CTV is restricted by the length of one working shift; a CTV has to return to its depot within the shift. There are several different types of CTVs. Monohull vessels, catamarans and SWATH vessels, as illustrated in Figure 8, are among the most common ones [82]. Different CTVs varies greatly in capacities and equipment onboard. Typically a CTV can transport 10-15 passengers at the time, their cargo capacities can range from 1-50 tons and their speed from 15-30 knots. Also wave heights that restrict the vessels from transferring technicians to turbines and daily cost rates can vary for different types of CTVs. Daily cost rates for a CTV is approximately 1 700 £[74], and they can normally transfer technicians to turbines in wave heights up to 1.5 m [1].

Another concept of CTVs, a concept not yet in use at present time, is a design based on the principle of surface effect ships (SESes). A SES, shown in Figure 9, is a combination of a hovercraft and a catamaran [56]. They are capable of higher speeds and can transfer technicians to turbines in higher wave heights than regular CTVs. SESes will, however, be more expensive to operate, with daily rates estimated to approximately 5 000 £[74].

2.2.2 Helicopters

Helicopters are suitable for transferring technicians to turbines for inspections and minor maintenance tasks. Compared to CTVs and SESes helicopters can travel faster and respond more quickly and they can therefore reach the turbines faster. However, they are more expensive to use [46]. Helicopters have to return to a depot between delivering and picking up the technicians, they cannot stay in the wind farm while maintenance is performed. While helicopters are not restricted by wave heights when transferring technicians to turbines, they are restricted by weather in terms of both wind speeds and visibility.

2.2.3 Accommodation Vessels

Vessels that can accommodate their crew and therefore stay offshore longer than one shift are referred to as accommodation vessels (AVs), illustrated by Figure 11. As AVs can stay offshore between working shifts, they can stay close to the wind farms and minimize the travel time for the technicians. AVs are larger than CTVs. They often have large working decks and storage space and a crane for heavy lifting, hence, they are capable of performing heavy maintenance and major repairs. AVs are typically slower, can transport more passengers and can transfer technicians to turbines in higher wave heights than CTVs. They are also more expensive, with daily cost rates estimated to approximately 12 000 £[74]. AVs are still only a concept and not yet in use for O&M purposes in offshore wind farms.

A further development of the AV concept is motherships. Like an AV, a mothership can stay offshore for a longer time period, however, a mothership can normally accommodate more passengers. Motherships work as a haven for accompanying CTVs that transfer technicians from the mothership to the turbines, and they can therefore be seen as a short-term offshore station. Some motherships also include support facilities for helicopters. An example of a mothership concept is the Sea-Wind WMV which can accommodate up to 200 technicians and has facilities for both CTVs and helicopters [62].

2.2.4 Crane Ships and Jack-Up Barges

For heavy-lifting operations that cannot be performed by AVs, such as replacing a blade or the generator, a crane vessel or a jack-up barge is necessary. A jack-up barge, illustrated in Figure 13, is a self-elevating mobile platform or vessel. Crane vessels and jack-up barges are much more expensive to acquire and operate than AVs, and are therefore rarely used for maintenance tasks that can be performed by CTVs or AVs [16]. As maintenance tasks that require a crane vessel or a jack-up barge occur relatively rare, renting a crane vessel or jack-up barge when a certain number of these maintenance tasks have occurred can be a cheaper alternative than investing in one, or renting one as soon as one of these tasks occur.

(a) Odfjell Wind FOB Lady (Monohull) [58]

(b) Austal Wind Express 21 Catamaran [7]

(c) Austal Wind Express TRI SWATH 27 [6]

Figure 8: Examples of CTVs used for maintenance at offshore wind farms.

Figure 9: Example of a SES design: Umoe Mandal WaveCraft [83].

Figure 10: A helicopter transferring technicians to a turbine [47].

Figure 11: Example of an AV concept: Damen Walk-to-Work Vessel [22].

Figure 12: Example of a mothership concept: the Sea-Wind WMV [62].

Figure 13: Example of a jack-up barge: GeoSub Jack-Up Barge [48].

2.3 Maintenance Operations

Maintenance operations for a wind turbine are classified as either preventive or corrective maintenance. Corrective maintenance are maintenance tasks that are performed when a failure on a turbine has occurred, while preventive tasks are precautionary maintenance performed to prevent failures. For planning purposes, the distinction is usually made between scheduled preventive maintenance and unscheduled corrective maintenance. The classification of maintenance types is illustrated in Figure 14.

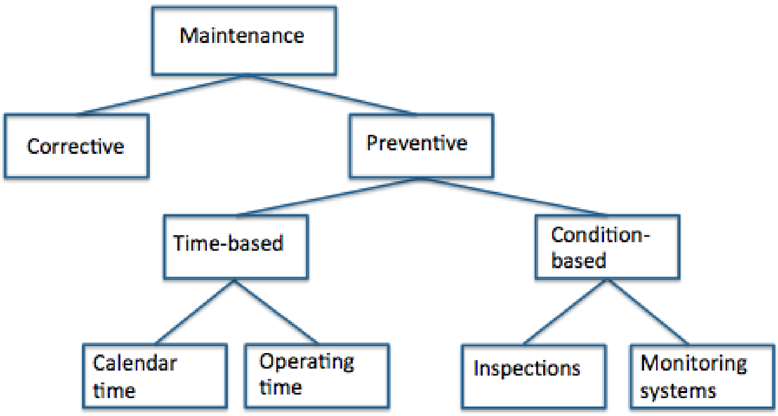


Figure 14: Classification of maintenance types.

2.3.1 Preventive Maintenance

Preventive maintenance is maintenance designed to prevent failures, reduced performance and breakdown of turbines [71]. Preventive maintenance include routine inspections, testings and maintenance such as calibrating the pitch mechanism, cleaning the blade and adjustment of oil levels in the gearbox and the hydraulic system [3, 55].

How often preventive maintenance is performed is dependent on the chosen maintenance strategy. For a corrective maintenance only strategy, maintenance is only performed when a failure occurs, i.e. no preventive maintenance is performed. In an opportunity maintenance strategy, corrective tasks are performed on demand and the opportunity of preventive maintenance being performed at the same time are exploited. The most common strategy is the periodic maintenance strategy, where preventive maintenance are performed periodically in addition to corrective maintenance tasks [3]. To minimize the O&M costs, a balance needs to be found between performing preventive maintenance too frequent and not frequent enough. Performing preventive maintenance too often increase maintenance costs and costs of spare parts and reduce incremental benefits. If maintenance is not performed often enough, the probability of failures and therefore the expected loss of revenue due to production stop increase.

There are two main approaches to decide how often preventive maintenance should be performed, a time-based approach and a condition-based approach. For the time-based approach, maintenance tasks are scheduled based on a pre-specified calendar time or on operational time for the turbine. The time of performance is often decided using statistical models based on recorded historical failure data [71]. For the condition-based approach, maintenance is scheduled based on monitoring the condition of different components of the turbine. There are two main approaches for condition monitoring: condition monitoring inspection and on-line condition monitoring/condition monitoring systems. Visual inspections, oil sample analyzes or vibration measurements are examples of condition monitoring inspections. Condition monitoring systems are systems that are installed for permanent monitoring. They perform specified measurements and report analysis results to the operators. Limits are defined for these measurements, and an alarm is triggered if a value is beyond its limit [71, 10].

Preventive maintenance is normally performed 1 to 2 times a year, with each turbine requiring 40 to 80 man-hours of service. Often a more major overhaul takes place every five years [84]. Maintenance operations can only be performed if there is an adequately long time period of good weather conditions where the wind speeds and wave heights are sufficiently low. Preventive maintenance is therefore usually planned and performed during summer.

2.3.2 Corrective Maintenance

Corrective maintenance is maintenance that is performed as a response of unplanned failures on or breakdowns of turbines. As with abnormal measurement values of condition monitoring systems, a failure at a turbine triggers an alarm that needs to be checked in order to know what maintenance is required at the turbine. The magnitude of the maintenance needed varies with different types of failures. Some failures can simply be abnormal measurements from condition monitoring systems with no need for maintenance beyond a visual inspection, while other failures can require replacement of damaged parts, possibly parts not in stock. When a failure occurs at a turbine, the turbine is shut down until the alarm is checked and the potential maintenance task is completed. The time the turbine is shut down is called downtime.

Estimates for the amount of corrective maintenance required in a wind farm are often based on historical data from other wind farms. As the offshore wind industry is relatively new, failure data is still limited. However, a number of studies have collected data on failures and downtime in onshore wind farms. Onshore failure statistics from two different German databases are given in Figure 15. WMEP, the Scientific Measurement and Evaluation Programme, is an incentive of the German Federal Government to fund electricity produced by wind turbines across Germany and contains failure statistics from 1,500 wind turbines from 1989 to 2006. LWK is failure statistics published by Landwirtschaftskammer Schleswig-Holstein (the Chamber of Agriculture) and contains failure data from more than 650 wind turbines from 1993 to 2006 [67]. These may not be entirely representative for offshore wind farms as offshore wind turbines are exposed to rougher conditions and maintenance operations are dependent on suitable weather for operating the vessels. However, they can be used as a guidance when estimating failure rates for offshore turbines.

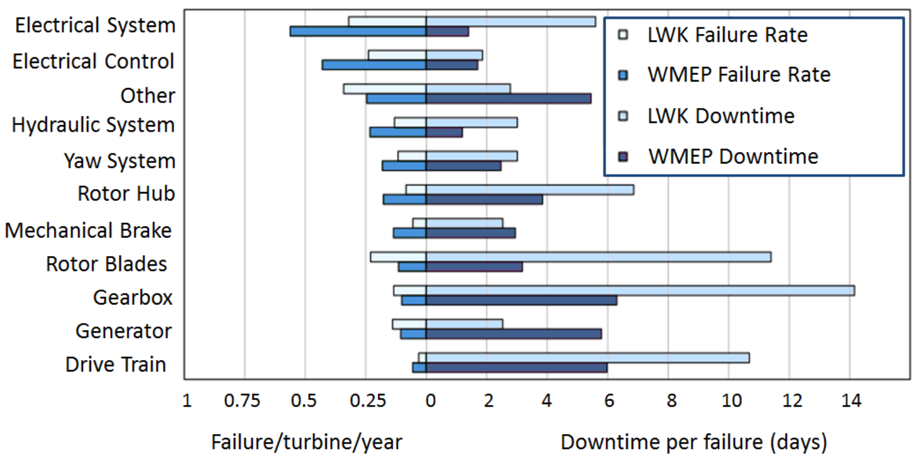


Figure 15: Failure rates and downtime per failure in days from the two German databases WMEP and LWK. WMEP contains failure statistics from 1500 onshore wind turbines from 1989 to 2006 and LWK from more than 650 onshore wind turbines from 1993 to 2006. The figure is based on [67].

Figure 16, which contains failure data from WMEP from 1997 to 2007, shows that the total yearly downtime caused by one type of failure is not only dependent on the failure rate, but also the time the turbine is shut down due to the failure.

The most common type of failures are failures in the electric systems. Failures in the gearbox are much less frequent, but due to its long downtime per failure, the total yearly downtime for the two types are almost the same. This illustrates that downtime can both be reduced by reducing failure frequency and the downtime of a failure.

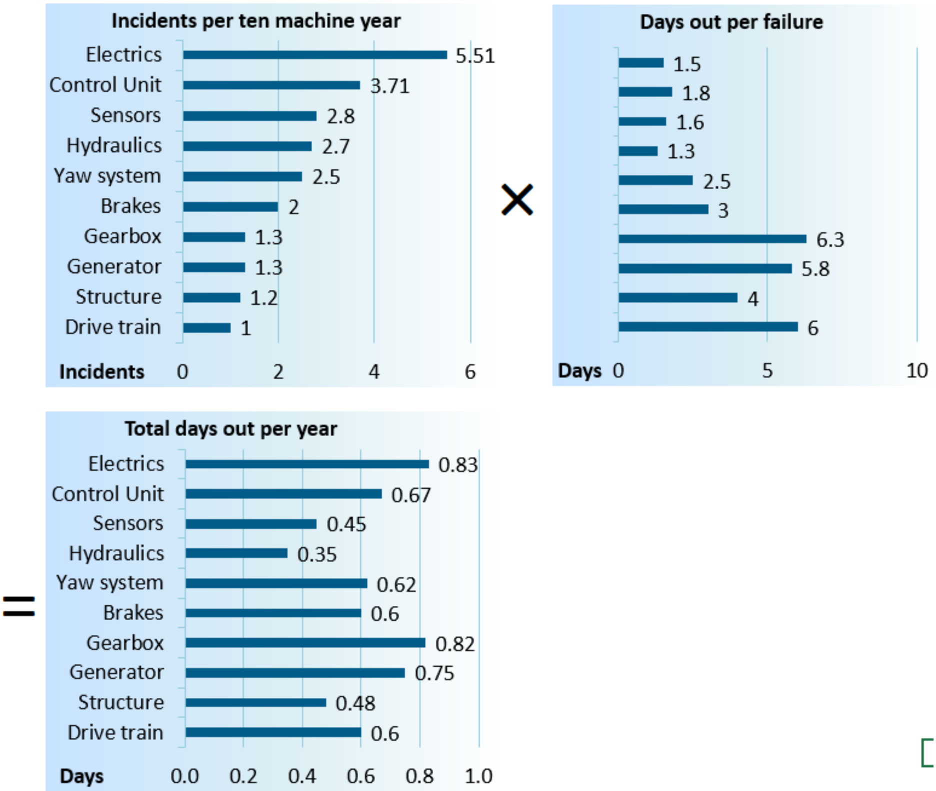


Figure 16: Failure rates per ten year, downtime per failure in days and total yearly downtime in days from WMEP; a database containing failure statistics from 1500 on-shore wind turbines from 1989 to 2006. The figure is based on numbers from [57].

2.4 Downtime Costs

To access a wind turbine for performing maintenance operations the turbine must be shut down and the lost revenues due to production stop when the turbine is shut down are called downtime costs. The downtime cost of a maintenance task is determined by how much power the turbine generates (the power output), the revenue obtained from the energy produced and how long the turbine is shut down (the downtime). Downtime costs can be calculated as

Downtime Costs [EUR] =

Turbine Efficiency given Wind Speed[-]

* Effect of Turbine [MW]

* (Electricity Price + Subsidies) [EUR/MWh]

* Time of shutdown [h]

The power output of the turbine is mainly determined by two factors; the capacity of the turbine and wind speeds. The larger the capacity, the greater loss of production and electricity sales are. How the wind speed affects the power output is illustrated by Figure 17. As the figure shows, a turbine does not generate any power until the wind speed is above a certain level, the cut-in speed. The power output will then increase with the wind speed until the wind reaches the rated speed, which is the minimum wind speed where the turbine generates its maximum output. When the wind speeds are too high, the turbine is shut down to prevent damages. This is called the cut-out speed [55]. As mentioned in Section 2.3.1 preventive maintenance is often planned and performed during summer. Another reason for this is that there are generally lower wind speeds during summer, and lower wind speeds cause lower downtime costs.

The revenue obtained from the energy produced is determined by electricity prices and subsidies from potential subsidy schemes. Whether a country has a subsidy scheme and how schemes for different countries are designed vary. The two most common types of schemes used in European countries are tradable green certificates, among others used in the UK and Belgium, and feed-in tariffs, used in countries such as Germany and Denmark [76, 41]. Both these types generates an extra income per MWh electricity produced. With feed-in tariffs, a fixed price is given to the energy producer for every MWh produced, while for a green certificate scheme, certificates are given for every MWh produced. These certificates can be sold in a certificate marked, and will therefore generate an extra income per produced MWh [41].

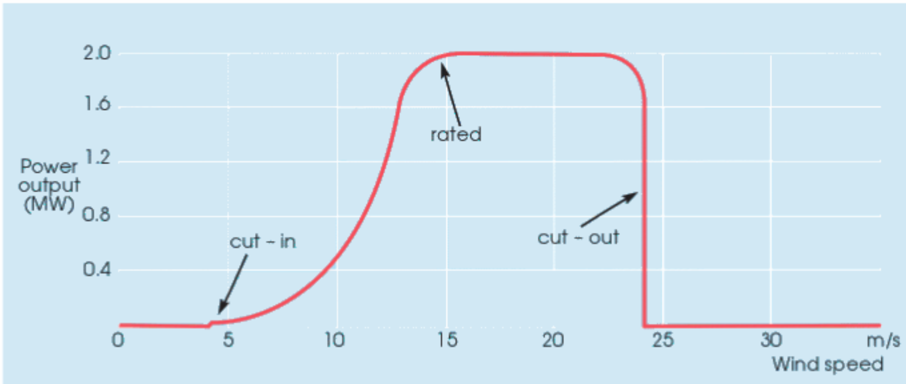


Figure 17: A typical power output for a 2 MW turbine for different wind speeds. The figure is taken from [55].

There are some differences in downtime for preventive and corrective maintenance tasks. When performing preventive maintenance tasks the turbines are only shut down when the task is performed and, hence, preventive tasks can be scheduled to favorable periods to minimize loss of revenue. For corrective maintenance tasks, the turbines are shut down from the time the failure occurs, and downtime costs start accumulate until the repair is done. Difficulties accessing the turbine and waiting periods for suitable weather conditions may lead to large downtime costs and can be very costly [82]. Downtime costs are therefore often a substantial part of the costs related to corrective maintenance [76], hence, it is important to reduce them in order to minimize costs of offshore wind. As was shown by Figure 16, the downtime can both be reduced by reducing failure frequency and the downtime of each failure. The probability of failures can be reduced by performing preventive maintenance. The downtime of a failure includes the time needed for identification of the failure, mobilisation of technicians, waiting for spare parts, vessels and access, transportation and the actual repair time. It can therefore be reduced by efficient planning and utilization of weather windows and maintenance resources.

3 Problem Description

This chapter describes the problem studied in this thesis and the assumptions related to the it. The problem is addressing the scheduling of maintenance tasks and routing of maintenance vessels for offshore wind farms. The problem is based on the situation where two or more wind farms have a joint vessel fleet with one onshore depot, but can also be used in the case of only one wind farm. All turbines within the same wind farm are assumed to be identical. It is a dynamic problem where corrective maintenance tasks are issued and long-term weather forecasts are updated dynamically. The problem is an operational, multi-periodic problem with a shorter planning period of a specified length, split into shorter time periods called shifts. The length of a shift is equal to the length of a technician's work day. It is assumed that there are enough time from one shift ends to the next shift starts so that AVs can travel between shifts.

Schedules for each shift of the planning period are generated based on minimizing the combined costs of transportation, downtime costs and penalty costs of tasks that are not performed. It is assumed that the costs of performing tasks are independent of when they are performed and therefore the costs regarding the actual execution of the tasks are not included. Due to a relatively short planning period, fluctuations in the energy and electricity certificate price for calculating downtime costs are assumed negligible.

3.1 Maintenance Tasks

The problem is based on a periodic maintenance strategy with a condition-monitoring system. Preventive maintenance tasks for the planning period are assumed known at the beginning of the planning period. When a failure occurs at a turbine, this triggers an alarm, and what type of corrective maintenance that is required is not known until the turbine is inspected by a technician crew. An alarm can result in a corrective task or it can be a false alarm which entails that no corrective maintenance task is required at the turbine. Corrective tasks due to alarms prior to the planning period and the alarms for the planning period is assumed known at the beginning of the planning period. To capture the correlation between an alarm and its potential corresponding corrective task, the corrective tasks are not known before the alarm is checked, and can hence not be performed before the corresponding alarm is checked. Some tasks cannot be performed until a specified shift in the planning period. This applies to tasks that require spare parts that are not in stock. For these tasks, the first possible shift they can be performed in is assumed known after the corresponding alarm is checked.

The downtime of turbines with corrective tasks starts running from the time the failures occurs and the alarms are triggered until the tasks are completed and the technicians are transferred from the turbine to the vessel. The time that is required to transfer technicians from a vessel to a turbine and conversely is referred to as transfer time. For preventive tasks the downtime starts running from the time during a shift a vessel starts transferring technicians to the turbine and until the technicians are done working on the task this shift and have returned to the vessel. The execution of a maintenance task is allowed to be paused before the task is completed. It is assumed that if a task is worked on during a shift, this must happen continuously, and if paused, performing the task cannot resume until the next shift. For corrective tasks the turbine cannot be started until the task is completed. For preventive tasks, however, the turbine is re-started between the shifts that the task is performed in. Only one vessel can perform a task during a shift, but if paused there are no restrictions on which vessels that continues performing the task during a later shift.

It is assumed that only one maintenance task can occur on each turbine each shift. If several failures occur they are grouped together as one maintenance task. All known corrective tasks are desired to be performed as soon as possible to minimize downtime costs. For preventive tasks, the number of desired tasks to be performed depends on the weather. To ensure that all yearly preventive tasks are performed, a desired number of preventive tasks are decided for the planning period. If the energy production during the planning period is low, it can be desirable to perform extra preventive tasks in addition to the original desired number of performed preventive tasks.

Maintenance tasks are allowed to be performed in parallel. This means that a vessel can leave technicians at turbines while delivering other technicians to different turbines. After working on the task for the scheduled amount of time, the technicians are picked up by the vessel, as illustrated in Figure 18. This allows for technician crews from the same vessel to perform maintenance at several turbines at the same time. This does not apply to tasks that require the vessel to stay at the turbine, such as tasks needing more extensive equipment or tasks involving sub-sea operations. When performing such tasks the vessel cannot leave the turbine to pick up technicians at other turbines if for instance an accident or a sudden change in weather occur. It is therefore restricted by HSE regulations to leave technicians at other turbines when performing a task requiring the vessel to stay at the turbine. The number of technicians required for different types of maintenance tasks is assumed fixed, i.e. the number of technicians to perform a task cannot be increased to reduce the completion time of the task. It is also assumed that a technician crew belongs to one vessel, the crew cannot be picked up by a different vessel during the shift.

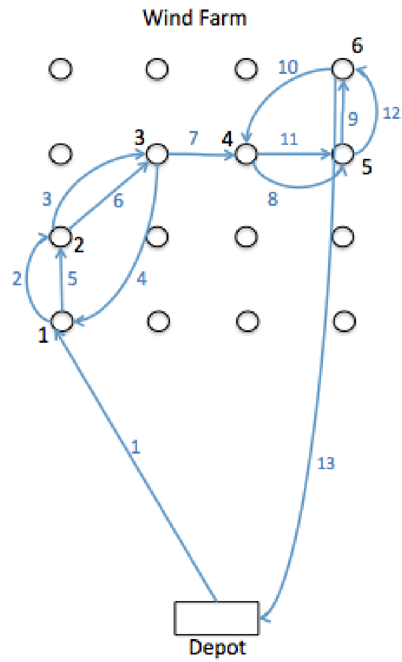
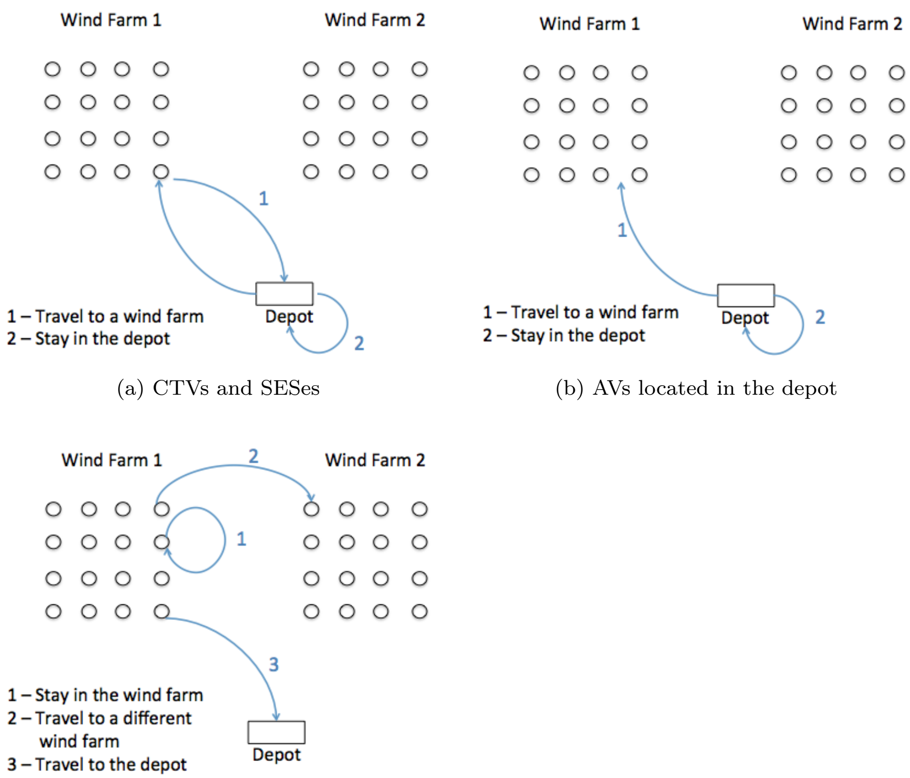


Figure 18: Example of a route for a vessel that performs tasks in parallel. The vessel delivers technicians to turbine 1, 2 and 3 and waits until the tasks are performed. The vessel then picks up the technicians and delivers them to turbine 4, 5 and 6. The arc numbers correspond to the order the distances are travelled.

3.2 Vessel Fleet

The vessel fleet is given and consists of three different categories of vessels. These are: AVs, and two types of CTVs: SESes and regular CTVs. Within all categories the vessels are assumed identical, but vessels of different categories vary in speed, fuel consumption, capacities, onboard equipment and how often they need to return to the depot. All vessel types may therefore not be compatible with all types of maintenance tasks. All types of vessels are also limited by weather conditions for when they can perform maintenance tasks, and these limits also varies for different vessel types.

Both AVs and CTVs can leave the depot at most one time during a shift. CTVs are required to return to the depot by the end of the shift, and they are not allowed to travel between wind farms. AVs are assumed to travel between shifts so that they do not loose valuable time where they can perform maintenance on travelling. However, when travelling from or to the depot this happens during shifts, as technicians can not leave the depot before thei first shift starts or return after their last shift ends. AVs can at most travel once between each shift, either from the depot to a wind farm, from a wind farm to the depot or between two wind farms. AVs are required to return to the depot within a given number of shifts. They cannot leave the depot the same shift they return to the depot due to the time needed for preparations and loading of equipment and spare parts.



(a) CTVs and SESes

(b) AVs located in the depot

(c) AVs located at a wind farm

Figure 19: Possible routes of AVs, SESes and CTVs for multiple wind farms.

Jack-up barges are not included in the problem because they are often routed separately. Tasks requiring jack-up barges do not occur often. As jack-up barges are expensive, these tasks are therefore often postponed and performed after several failures requiring jack-up barges have occurred.

3.3 Weather

The scheduling of maintenance is affected by the weather conditions during the planning period, both the wind speeds and the wave conditions. The energy production, and therefore also the downtime costs, varies with the wind speed. The wind speed is assumed constant within a shift, hence, also the unit downtime cost for a turbine is fixed within a shift.

Additionally, the vessels have limitations on wave conditions for when they can transfer technicians to and from turbines, making the availability of the wind turbines and which vessels to use dependent on the weather. The time slots within a shift when weather conditions are suitable for a vessel to transfer technicians to the turbine and perform maintenance are defined as weather windows. Factors that can influence these weather windows are wave heights, wave periods, wave directions, swell, currents and also wind speeds. A CTV can only leave the depot during a shift if its weather window during the shift is longer than a specified length. It is assumed that there are only one weather window each shift. If there are several weather windows only the longest one applies. This is because the weather conditions between the weather windows are assumed very unstable. The weather forecast for the current time period is known when planning the schedules. As wind forecasting has received great focus during the last years and reliable wind forecasting models have been developed to predict the wind speeds up till seven days ahead [35], it is assumed that the weather does not deviate from the forecast for shorter planning periods.

4 Literature Review

This chapter contains a review of relevant literature for the problem studied in this thesis. First an overview of existing literature on optimization of O&M in offshore wind farms is presented in Section 4.1. The problem is formulated based on routing the maintenance fleet between the depot and the wind farms and between the turbines where failures have occurred. Literature on O&M in offshore wind farms is therefore followed by a brief review of existing literature on the vehicle routing problem (VRP) in Section 4.2. Extensions of the VRP that involves similar characteristics as the problem studied in this thesis are outlined more in detail.

4.1 Optimization of O&M in Offshore Wind Farms

A review of the state-of-the-art of maintenance logistics in the offshore wind industry per 2014 is given by Shafiee in [66]. The article presents a classification framework where the reviewed literature is divided into strategic, tactical and operational issues. Literature on O&M in offshore wind farms is relatively limited, however, more than 140 journal papers, master and doctoral dissertations, text books, case study reports and conference proceedings are investigated in the article. This is a considerable amount of literature, and this review will therefore only outline a small part of papers investigating O&M issues. For a more thorough review and description of the mentioned papers in the following sections, the reader is referred to [66].

Strategic decision-making: The strategic branch of the classification framework consists of literature on long-term decision-making, generally with a life cycle perspective. It includes decisions regarding wind farm design for reliability, location and capacity of maintenance harbour and accommodations, selection of maintenance strategy and outsourcing the maintenance services [66].

A lot of research has been done regarding optimal offshore wind farm design. Several papers present optimization models where maintenance and repair costs are included, such as the models by Chen and MacDonald in [19] and Afanasyeva et al. in [2]. There is also a significant amount of literature on selection of maintenance strategies. Maintenance strategies are, in addition to in several papers, studied in different PhD dissertations the last years, such as in [52] by Karyotakis and [11] by Besnard. An example of a specific field of interest within maintenance strategies are opportunistic maintenance strategies, investigated by among others Ding and Tian in [24] and [25].

Location and capacity of maintenance accommodations and outsourcing the maintenance services are less investigated strategic issues. A model that determines the optimal location of maintenance accommodations in combination with other maintenance support organization aspects is presented by Besnard et al. in [12]. Literature on maintenance outsourcing is introduced and studied by Poore and Walford in [60].

Tactical decision-making: Tactical decision-making involves literature on decisions in a medium-term perspective, decisions that are updated between once a year and once every five years. Tactical issues typically include decisions regarding the maintenance support organization, such as the vessel and helicopter fleet and number of technicians, spare parts inventory management and decisions regarding purchase or lease of maintenance resources [66].

[43]: In this paper we study the vessel fleet size and mix problem that arises for the maintenance operations at offshore wind farms, and propose a stochastic three-stage programming model.

Several papers has been written on optimization of the maintenance support organization for offshore wind farms. Allocation of both technicians and CTVs and the use of helicopters and larger supply vessels have been investigated in the literature. Gundegjerde and Halvorsen [42], Gundegjerde et al. [43], Halvorsen-Weare et al. [44] and Vefsnmo [85] all use optimization models to investigate vessel fleets and determine the optimal fleet size and mix for an offshore wind farm. Their models determine the number of vessels of different types to acquire by scheduling different maintenance tasks to different types of vessels. In the models presented by Gundegjerde and Halvorsen [42], Gundegjerde et al. [43] and Halvorsen-Weare et al. [44] vessels are routed from different depots to different wind farms and maintenance tasks are assigned to the vessels. This is used to decide the number of vessels of each type to acquire within an investment budget. It is the accumulated number of vessels of each vessel type that are routed and assigned tasks, not each vessel individually. The models operate with total man-hours. They include multiple wind farms, but do not include delivering and pick-up of technicians. Halvorsen-Weare et al. [44] present a deterministic model and Gundegjerde et al. [43] present a stochastic three-stage model. Vefsmo [85] and Gundegjerde and Halvorsen [42] present both a deterministic and a stochastic model, Vefsmo presents a stochastic two-stage model and Gundegjerde and Halvorsen present a stochastic three-stage model.

The choice of vessels to use is also studied by Besnard et al. in [12]. This paper presents a model for optimizing the number of technicians and choice of transfer in addition to the strategic issue of maintenance accommodation location. The paper also investigates the use of a helicopter. Research on heavy lift vessels strategies are done by Dinwoodie and McMillan in [27], who have also investigated the cost-efficiency in purchasing versus leasing maintenance vessels in [28].

Operational decision-making: The problem studied in this thesis belongs to the class of operational problems. Operational decisions are day-to-day short-term decisions and includes scheduling of maintenance tasks, routing of maintenance vessels, and measuring the maintenance performance [66].

The amount of literature on optimization models on maintenance task scheduling is scarce. A method that uses genetic algorithms to schedule maintenance tasks for both onshore and offshore wind farms is presented and evaluated by Fonseca et al. in [32]. Besnard et al. propose in [12] a deterministic opportunistic optimization model for offshore wind farms for scheduling of corrective and preventive maintenance tasks. The model takes advantage of the possibility to perform preventive tasks when power production, hence downtime costs, are low, or when a turbine is shut down due to corrective maintenance. The objective of the model is an optimal planning of preventive and corrective maintenance tasks in regard to production forecasts and required corrective maintenance. The output of the model are daily schedules of corrective and preventive tasks for a short finite planning period.

A stochastic optimization model for opportunistic service maintenance of offshore wind farms is presented by Besnard et al. in [13]. Also this model generates schedules of which corrective and preventive tasks to perform which day in the planning period. The model is based on a rolling horizon and the optimization is performed on a daily basis to update the maintenance planning for updated production and weather forecasts.

Literature that combines routing of maintenance vessels with scheduling of maintenance tasks is also limited. As mentioned under tactical models, Halvorsen-Weare et al. [44] and Gundegjerde and Halvorsen [42] use routing and scheduling of vessels and tasks to determine the optimal vessel fleet. Dai et al. present an optimization model for the routing and scheduling problem of a given vessel fleet of CTVs for O&M in an offshore wind farm in [21]. The model minimizes costs related to travelling to the respective turbines and delaying tasks. The time aspect of the model is a finite, short planning horizon discretized in shorter time steps (days). It allows for different technician crews of the same vessel to perform tasks on different turbines at the same time and include pick-up and delivery of these technician crews. The routing and scheduling problem for a maintenance fleet of CTVs for an offshore wind farm is also addressed by Skaar in [68]. Skaar presents and compare an arc-flow formulation and a path-flow formulation of routing given a set of wind turbine maintenance tasks and a given vessel fleet. These models also allow for tasks being performed in parallel and include pick-up and delivery of personnel and models for CTVs, but as opposed to the model of Dai et al. [21], these models only model routing for one day. Common for these models is that they only apply to maintenance tasks with a duration shorter than a shift length.

4.2 Vehicle Routing Problems

The VRP can be defined as the problem to find the least-costs delivery routes from a depot to a set of customers given a set of constraints. The classical VRP is formally defined as follows: Let $G = (V, A)$ be a directed graph where $V = \{0, ..., n\}$ is the vertex set and $A = \{(i, j) : i, j \in V, i \neq j\}$ is the arc set. The depot is represented by vertex 0 and the customers by $v = \{1, ...n\}$. A fleet of m identical vehicles is located at the depot. The fleet size m is either given a priori or is a decision variable in the problem. Each customer i has a non-negative demand q_i. The VRP designs m least-costs routes such that all routes starts and ends in the depot and that each customer i is visited exactly once [54].

The VRP has been studied for more than 50 years and is considered to be one of the great successes of OR [45, 54]. The amount of literature on the VRP is enormous. The VRP is classified as an NP-hard problem, and exact methods are difficult to solve for more than 50-100 customers [45]. The VRP literature therefore includes extensive research on approximation methods, both heuristics and meta-heuristics, in addition to exacts methods. There exists several survey articles and books that give an overview of the literature such as Laporte [54], Kumar and Panneerselvam [53], Toth and Vigo [81] and Golden et al. [40]. These survey articles and books both describe the VRP and outline exact methods, heuristics and meta-heuristics used to solve the problem.

There exists a great variety in the characteristics and constraints of real-life VRPs and hence several variants including different extensions of the problem have emerged. These variants include the capacitated VRP (CVRP) and the VRP with time windows (VRPTW). In the CVRP the vehicles have a capacity limit, Q, of the goods they are delivering. In the VRPTW the customers can only be visited by a vehicle in certain time intervals (time windows) [53]. Both these extensions are relevant for the problem studied in this thesis, as this problem routes a capacitated vessel fleet and operates with time windows for when tasks can be performed. Extended VRPs are referred to as rich VRPs and the survey article of Caceres-Cruz et al. [17] summarizes problem combinations, contraints defined and approaches found. In addition, the books by Golden et al. [40] and by Toth and Vigo [81] and the survey article by Kumar and Panneerselvam [53] include some of the most common variants of the VRP.

The problem studied in this thesis has several similarities to a subclass of the VRP called the pick-up and delivery problem (PDP). PDPs differ from VRPs in that in PDPs the customers can both have a positive and a negative demand. As opposed to VRPs where the vehicles can only deliver goods to the customers, the vehicles can both deliver goods to and pick-up goods from the customers in PDPs. There are also various variants of the PDPs, such as wheter the flow of goods are between customers and the depot only or if there also exists a flow of goods between customers [17]. A survey on PDPs is given by Berbeglia et al. [8]. The problem studied in this thesis resembles PDPs as it includes delivery and pick-up of technicians on different turbines. However, as opposed to regular PDPs, in the problem studied in this thesis the delivery and pick-up locations are the same, the delivery and pick-up of the goods (technicians) are between the same customers (turbines).

The k-traveling repairman problem (kTRP) is an extension of the VRP where the waiting time for the customers are minimized in stead of the total route lengths of the k vehicles [31]. Part of the objective in the problem studied in this thesis is to minimize the downtime of the turbines. The downtime of a turbine with a corrective task is dependent on when the task is performed, and hence this is similar to minimizing waiting times. The kTRP is studied by among others Fakcharoenphol et al. in [31]. Jothi and Raghavachari [51] present an approximation algorithm for the kTRP with repairtimes larger than zero for the repairs required by the customers.

Another extension of the VRP is the dynamic aspect. In a dynamic VRP (DVRP) information is updated along the problem period. Some information is known in advance of the planning period, but as the planning period progresses, more information (for example new orders) is known, and this information is incorporated in the problem [53]. The dynamic aspect is also combined with pick-up and delivery in the literature and both Berbeglia et al. [9] and Pillac et al. [59] have contributed with survey articles on dynamic PDPs. This is relevant for the problem studied in this thesis as this problem is solved dynamically, the optimization is carried out before each shift starts with updated information on new tasks each shift.

The workover rig routing problem (WRRP) is another extension of the VRP with several similarities to the problem studied in this thesis. The WRRP originates from O&M in onshore oil fields, where a set of workover rigs located at different positions service oil wells that require maintenance. For safety reasons, the production of a well that requires maintenance is either reduced or stopped. In order to minimize the lost production a workover rig must service the oil well as soon as possible. The objective of the WRRP is hence to minimize the total lost production, as opposed to classical VRPs that minimize the route length. This is similar to the problem studied in this thesis, where parts of the objective is to minimize the downtime costs. The routing of the AVs in the problem studied in this thesis is similar to the routing of the workover rigs. Like the workover rigs, the AVs can be located at different positions when the optimization starts, and unless an AV has reached its limit of shifts allowed offshore it does not have to return to the depot each shift. The WRRP are studied by Ribeiro et al. [64, 63] and Duhamel et al. [29]. Duhamel et al. [29] propose and compare three mixed integer models for solving the problem. Ribeiro et al. compare three different meta-heuristics in [64] and present an exact branch-price-and-cut algorithm for solving the problem in [63].

5 Mathematical Model

In this chapter the mathematical formulation of the problem studied in this thesis is presented. In Section 5.1 the sets, indices, constants and variables used to formulate the problem are defined. The objective function and the constraints are presented in Section 5.2. The presentation of the mathematical formulation is followed by a simple numerical example to illustrate the model in Section 5.3.

The problem is formulated as a static, deterministic, mixed-integer, routing problem. The time aspect of the model is a finite, short planning period discretized in shorter time steps (shifts). The output of the model are maintenance schedules for the planning period, where the solutions of each shift represent maintenance schedules for the respective shifts. There are two levels of routing in the model, where the first level is routing of maintenance vessels between the depot and the wind farms. The problem is considered as a graph, where the depot and the wind farms are called nodes. The depot is represented by two nodes, a start depot node where each vessel starts a route, and a end depot node where the routes end. If a CTV or a SES stay in the depot during a shift, it is routed directly from the start depot node to the end depot node. The arcs between the nodes are represented by both travelling times and travelling costs.

The second level of routing consists of routing vessels between turbines that requires maintenance in the wind farm the vessels have travelled to. The turbines requiring maintenance are represented by maintenance tasks. To simplify the model, the location of the turbines within a wind farm is ignored, and the travel times between turbines are not differentiated. This is because the distance between the turbines are considered negligible compared to the distance between nodes. To capture the time needed to travel between tasks and the related costs, an average internal transport time and transport cost are used in stead. For these reasons, the routing between turbines is equivalent to, and hereby referred to as, scheduling of maintenance tasks within a wind farm.

The scheduling of maintenance tasks is similar to the PDP, each turbine requiring maintenance is represented by two tasks, one delivery task and one pick-up task. As vessels can perform maintenance in parallel, technicians needs to be both dropped of at the turbine and then later picked up. The delivery task represents the actual task, i.e. the delivery task has the duration time of the maintenance required and the pick-up task has a duration of zero time units. The depot is also included in the second level of routing, and represented by tasks in addition to being represented by nodes. As for the other tasks, the depot is split into two tasks, the start depot task and the end depot task. All vessels that start in the depot in one shift perform the start depot task this shift and all vessels that end the shift in the depot perform the end depot task. If a vessel stays in the depot during a shift, then the end depot task is performed directly after the start depot task.

The number of preventive tasks to be completed during the planning period is mainly determined by the maintenance strategy of the wind farms. The model is, however, designed to allow for some flexibility in the number of preventive tasks to be performed. There are more preventive tasks available than the amount of preventive tasks desired to be completed. This is to allow for performing more preventive maintenance when the energy production is low. The number of preventive tasks that are desired to be completed during the planning period, independent of the energy production, are referred to as desired preventive tasks.

The following notation are used throughout the rest of the report: *CTVs* is defined as all CTVs, including both regular CTVs and SESes. *Regular CTVs* is used for CTVs not including SESes, and *SESes* is used for only SESes. There is also a distinction between *performing* a task and *completing* a task. Performing a task during a shift means working on the task during this shift, independent of wheter the task is finished or not this shift. Completing a task during a shift means finishing the task during this shift.

5.1 Definitions

Lower-case letters are used to represent variables and indices, and capital letters are used to represent sets, constants and to differentiate between sets and constants with equal names.

Indices

i,j	Nodes
m,n, l	Maintenance tasks
k	Type of maintenance tasks
v	Vessels
s	Shifts

Sets

N^W	All wind farm nodes, $N^W = \{1, 2, \ldots, \lvert N^W\rvert\}$, $N^W \subset N$
N	All nodes, $N = \{0, 1, 2, \ldots, (\lvert N^W\rvert + 1)\}$. Nodes $i \in \{1, 2, \ldots, \lvert N^W\rvert\}$ are wind farms and nodes $i \in \{0, (\lvert N^W\rvert + 1)\}$ are the depot
K	All maintenance task types
M	All maintenance tasks including both delivery tasks, pick-up tasks and the depot tasks, $M = \{0, 1, 2, \ldots, \lvert M\rvert\}$
M^-	All delivery tasks (representing the actual maintenance tasks), $M^- = \{1, 2, \ldots, \lvert M^-\rvert\}$, $M^- \subset M$
M_i^-	All delivery tasks at wind farm i, $i \in N^W$, $M_i^- \subseteq M^-$
M_{ik}^-	All delivery tasks of type k at wind farm i, $i \in N^W$, $k \in K$, $M_{ik}^- \subseteq M_i^-$
M^+	All pick-up tasks $M^+ = \{(\lvert M^-\rvert + 1), (\lvert M^-\rvert + 2), \ldots, (2\lvert M^-\rvert)\}$, $M^+ \subset M$
M_i^+	All pick-up tasks at wind farm i, $i \in N^W$, $M_i^+ \subseteq M^+$
M^C	All corrective maintenance tasks, $M^C \subseteq M^-$
M^P	All preventive maintenance tasks, $M^P \subseteq M^-$
V	All vessels
V^A	All AVs, $V^A \subseteq V$
V^C	All CTVs, $V^C \subseteq V$
V_m	All vessels that can perform maintenance task m, $V_m \subseteq V$
V_m^A	All AVs that can perform maintenance task m, $V_m^A = V_m \cap V^A$
V_m^C	All CTVs that can perform maintenance task m, $V_m^C = V_m \cap V^C$
S	All shifts of the planning period
S^0	All shifts of the planning period, including the last shift of the previous planning period, shift 0

Constants

T^T_{ijv}	Transportation time between node $i \in N$ and node $j \in N$ for vessel $v \in V$
T^{MT}_m	Duration of task $m \in M^-$
T^{PD}	Time to transfer technicians from vessel to turbine and from turbine to vessel (transfer time)
T^{IT}_{iv}	Average time to travel between turbines in wind farm $i \in N^W$ for vessel $v \in V$
D^{START}_v	Number of shifts a vessel $v \in V^A$ has been offshore when the planning period starts
D^{LIMIT}_v	Number of shifts a vessel $v \in V^A$ can stay offshore without returning to the depot
P^{START}_{iv}	1 if vessel $v \in V^A$ is located at node $i \in N$ at the start of the planning period, 0 otherwise
T^{DAY}	Number of time units in a day
T^{SHIFT}_s	Length of shift $s \in S$
T^{MIN}	Minimum length of weather window in a shift for a CTV to leave the depot during the shift
L^W_{vs}	Lower bound for the weather window of vessel $v \in V$ in shift $s \in S$
U^W_{vs}	Upper bound for the weather window of vessel $v \in V$ in shift $s \in S$
B	The desired number of preventive maintenance tasks to be completed during the planning period
R_{ms}	1 if all necessary spare parts and equipment for performing task $m \in M^-$ are available in shift $s \in S$, 0 otherwise
E_m	1 if task m requires that the vessel performing the task is located at the turbine while the task is being performed, 0 otherwise
Q_v	Technician capacity of vessel $v \in V$
P_m	Number of technicians needed to perform task $m \in M$, positive for delivery tasks and negative for pick-up tasks
C^T_{ijv}	Transportation costs between node $i \in N$ and node $j \in N$ for vessel $v \in V$
C^{LP}_{ms}	Downtime costs per time unit during shift $s \in S$ due to loss of production when shutting down the turbine where maintenance task $m \in M^-$ is located
C^{OUT}_v	The cost for vessel $v \in V^A$ to stay offshore between two shifts
C^{IT}_v	The average internal transportation cost for vessel $v \in V$ to travel to a maintenance task $m \in M^-$ inside a wind farm
C^{NP}_m	The penalty cost per shift of not completing a preventive maintenance task during the planning period
C^{NC}_m	The penalty cost per shift of not completing a corrective maintenance task $m \in M^C$ during the planning period
C^{NP*}_m	The penalty cost per time unit of not working on task $m \in M^P$ that is not completed within the planning period
C^{NC*}_m	The penalty cost per time unit of not working on task $m \in M^C$ that is not completed within the planning period
K_{ms}	1 if the energy production during shift $s \in S$ is below a specified limit for when to perform $m \in M^- \cap M^P$ as extra preventive maintenance, 0 otherwise
δ	Small value greater than zero

Decision Variables

x_{mvs}	1 if vessel $v \in V_m$ is used to perform maintenance task $m \in M$ during shift $s \in S$, 0 otherwise
y_{ijvs}	1 if vessel $v \in V$ travels directly between node $i \in N$ and $j \in N$, $i \neq j$, during shift $s \in S$, 0 otherwise
z_{mnvs}	1 if vessel $v \in V_m \cap V_n$ performs maintenance task $n \in M$ directly after maintenance task $m \in M$ during shift $s \in S$, 0 otherwise
w_{ivs}	1 if vessel $v \in V^A$ stays at node $i \in N$ between shift $s \in S$ and $(s+1) \in S$, 0 otherwise
t_{mvs}	The time vessel $v \in V_m$ starts maintenance task $m \in M$ during shift $s \in S$
l_{ms}	Time counter for how long the turbine where maintenance task $m \in M^-$ is located is shut down during shift $s \in S$. The time counter for shift s starts at 0 when the shift starts and reaches its maximum at the beginning of the next shift, $s+1$
c_m	The penalty cost of not working on a task $m \in M^-$ that is not completed during the planning period
p_{mvs}	The number of technicians at vessel $v \in V_m$ immediately after visiting the turbine of task $m \in M$ during shift $s \in S$
f_{ms}	1 if task $m \in M^-$ is completed before the end of shift $s \in S$ (during shift s or during earlier shifts than s), 0 otherwise

5.2 Mathematical Formulation

In this section the deterministic model is explained in detail, starting with the objective function and continuing with the constraints.

5.2.1 Objective Function

$$\text{Min Z} = \sum_{i \in N} \sum_{j \in N} \sum_{v \in V} \sum_{s \in S} C^{T}_{ijv} y_{ijvs}, \tag{1a}$$

$$+ \sum_{m \in M^{-}} \sum_{v \in V_m} \sum_{s \in S} C^{IT}_{v} x_{mvs}, \tag{1b}$$

$$+ \sum_{i \in N^{W}} \sum_{v \in V^{A}} \sum_{s \in S} C^{OUT}_{v} w_{ivs}, \tag{1c}$$

$$+ \sum_{m \in M^{-}} \sum_{s \in S} C^{LP}_{ms} l_{ms}, \tag{1d}$$

$$+ \sum_{m \in M^{C}} \sum_{s \in S} C^{NC}_{m} (1 - f_{ms}), \tag{1e}$$

$$+ \sum_{m \in M^{P}} \sum_{s \in S} C^{NP}_{m} (1 - f_{ms}), \tag{1f}$$

$$+ \sum_{m \in M^{-}} c_m \tag{1g}$$

The objective function aims to minimize the total costs of the problem. This includes both real costs and penalty costs. The real costs of the problem are represented by part (1a) – (1d). Part (1a) represents the transportation costs for the vessels between the depot and the wind farms, while part (1b) represents the internal transportation costs within a wind farm. Part (1c) represents the costs for AVs to stay offshore between shifts, i.e. night costs, and part (1d) represents the downtime costs.

Penalty costs are introduced to give incentive to perform tasks, and are represented by part (1e) – (1g). Part (1e) and part (1f) are penalty costs for not completing a task during a shift, where (1e) applies for corrective tasks and (1f) for preventive tasks. These parts force the respective tasks to be performed and completed within a shift if there is free vessel capacity. There is also given incentive to work on tasks that there are not enough time to complete during the planning period is if there is free vessel capacity. Part (1g) gives a penalty cost for each task that is not completed based on how much time there is left of the task at the end of the planning period.

5.2.2 Constraints

The constraints are grouped in constraints concerning flow of CTVs, flow of AVs, execution of tasks, time management, precedence of tasks, downtime, technicians balances and the domain of the decision variables.

Flow of CTVs:

$$\sum_{j \in N} y_{0jvs} = 1, \qquad v \in V^C,\ s \in S, \tag{2}$$

$$\sum_{i \in N} y_{i|N|vs} = 1, \qquad v \in V^C,\ s \in S, \tag{3}$$

$$y_{0|N|vs} = 1, \qquad v \in V^C,\ s \in S \mid (U^W_{vs} - L^W_{vs}) < T^{MIN}, \tag{4}$$

$$\sum_{i \in N} y_{ijvs} = \sum_{i \in N} y_{jivs}, \qquad j \in N^W,\ v \in V^C,\ s \in S, \tag{5}$$

$$\sum_{i \in N} \sum_{j \in N} y_{ijvs} \leq 2, \qquad v \in V^C,\ s \in S. \tag{6}$$

All CTVs must during each shift leave the start depot node, $i = 0$, and arrive at the end depot node, $i = |N|$. This is ensured by constraints (2) and (3). Constraints (4) prevent that a CTV leaves the depot during a shift where the weather window for this vessel is shorter than a specified minimum requirement. Constraints (5) conserve node flow for CTVs by ensuring that when a CTV visits a wind farm node during a shift, it also leaves the node during the same shift. As CTVs cannot travel between wind farms during shifts, they can travel at maximum twice during each shift. This is restricted by constraints (6).

Flow of AVs:

$$w_{iv(s-1)} + \sum_{j \in N} y_{jivs} = \sum_{j \in N} y_{ijvs} + w_{ivs}, \qquad i \in N^W,\ v \in V^A,\ s \in S^0 \setminus \{0\}, \tag{7}$$

$$\sum_{j \in N} y_{0jvs} = w_{|N|v(s-1)}, \qquad v \in V^A,\ s \in S^0 \setminus \{0\}, \tag{8}$$

$$w_{|N|vs} = \sum_{j \in N} y_{j|N|vs}, \qquad v \in V^A,\ s \in S. \tag{9}$$

Constraints (7) conserve node flow for AVs. If an AV is located at a wind farm at the beginning of a shift, it either has to depart from this wind farm at the end of this shift or stay at this wind farm until the next shift. Constraints (8) and (9) conserve node flow for AVs to and from the depot node. An AV can only leave the depot during a shift if it was located at the depot at the end of the previous shift, which is ensured by constraints (8). Constraints (9) ensures that $w_{|N|vs}$ shows that vessel v is situated in the depot at the end of the shift if v travels to the depot during shift s.

$$\sum_{i \in N} \sum_{j \in N} y_{ijvs} \leq 1, \qquad v \in V^A,\ s \in S, \tag{10}$$

$$w_{iv0} = P_{iv}^{START}, \qquad i \in N,\ v \in V^A, \tag{11}$$

$$\sum_{i \in N^W} \sum_{s=1}^{D_v^{LIMIT} - D_v^{START}} y_{i|N|vs} \geq 1, \qquad v \in V^A \ \mid\ D_v^{LIMIT} - D_v^{START} \leq |S|. \tag{12}$$

Constraints (10) prevent an AV from doing more than one trip during or prior to each shift. Where the AVs are located when the planning period starts are given by constraints (11). While constraints (12) ensure that the AVs do not stay offshore for longer than a specified allowed limit.

Execution of Tasks:

$$\sum_{v \in V_m} x_{mvs} \leq 1, \qquad m \in M^-,\ s \in S, \tag{13}$$

$$x_{mvs} = 1, \qquad v \in V^C, m = 0 \cup |M|, \; s \in S, \tag{14}$$

$$x_{0vs} = w_{|N|v(s-1)}, \qquad v \in V^A,\ s \in S^0 \mid s > 0, \tag{15}$$

$$x_{|M|vs} = w_{|N|vs}, \qquad v \in V^A,\ s \in S, \tag{16}$$

$$x_{mvs} \leq \sum_{j \in N} y_{jivs}, \qquad i \in N^W,\ m \in M_i^- \cup M_i^+, \; v \in V_m^C,\ s \in S, \tag{17}$$

$$x_{mvs} \leq \sum_{j \in N} y_{jivs} + w_{iv(s-1)} - \sum_{j \in N} y_{ijvs}, \qquad i \in N^W,\ m \in M_i^- \cup M_i^+, \; v \in V_m^C,\ s \in S. \tag{18}$$

Tasks can be performed by maximum one vessel each shift and this is ensured by constraints (13). As CTVs start each shift in the depot, constraints (14) force the CTVs to perform the depot task in each shift. For AVs, the depot task should only be performed if the AVs are located at the depot during the shift. This is handled by constraints (15) for the start depot task and (16) for the end depot task. A maintenance task at wind farm i can only be performed by a vessel that is located at this wind farm for the specified shift. This is restricted by constraints (17) and (18) for CTVs and AVs, respectively.

$$x_{mvs} = x_{(m+|M^-|)vs}, \qquad m \in M^-, v \in V_m, s \in S, \tag{19}$$

$$\sum_{v \in V_m} x_{mvs} = 0, \qquad m \in M^-,\ s \in S \mid R_{ms} = 0, \tag{20}$$

$$\sum_{m \in M^P} \sum_{v \in V_m} x_{mvs} \leq B, \qquad s \in S\ |K_{ms} = 0. \tag{21}$$

Constraints (19) make sure that the delivery task and pick-up task at the same turbine are performed by the same vessel. Performing tasks that cannot be performed until a specified shift during the planning period are restricted by constraints (20). They ensure that a task is not performed during a shift if the task is not ready to be performed this shift. For shifts where the energy production is higher than a specified limit, constraints (21) ensure that the number of preventive tasks performed this shift does not exceed the desired number of preventive tasks to be performed during a shift.

$$\begin{aligned} T_m^{MT} - \sum_{v \in V_m} \sum_{h=1}^{s} (t_{(m+|M^-|)vh} - t_{mvh} - T^{PD} x_{mvh}) \qquad & m \in M^-, \\ + (T_s^{SHIFT} - T^{PD}) f_{ms} \geq \delta, \qquad & s \in S, \end{aligned} \tag{22}$$

$$\begin{aligned} \sum_{v \in V_m} \sum_{h=1}^{s} (t_{(m+|M^-|)vh} - t_{mvh} - T^{PD} x_{mvh}) \qquad & m \in M^-, \\ \geq T_m^{MT} f_{ms}, \qquad & s \in S, \end{aligned} \tag{23}$$

$$\begin{aligned} \sum_{v \in V_m} x_{mvs} \leq 1 - f_{m(s-1)}, \qquad & m \in M^-, \\ & s \in S \backslash \{1\}. \end{aligned} \tag{24}$$

Constraints (22) – (24) concern the variables that indicate in which shifts each task is completed. Constraints (22) force f_{ms} to one if task m is completed within shift s and constraints (23) force f_{ms} to zero if task m is not completed within shift s. Constraints (24) prohibits that a task m is performed during shifts after the task is completed.

$$c_m \geq C_m^{NC*}(T_m^{MT} - \sum_{v \in V_m} \sum_{s \in S} (t_{(m+|M^-|)vs} - t_{mvs} - T_m^{PD} x_{mvs})), \quad m \in M^C \cap M^-, \tag{25}$$

$$c_m \geq C_m^{NP*}(T_m^{MT} - \sum_{v \in V_m} \sum_{s \in S} (t_{(m+|M^-|)vs} - t_{mvs} - T_m^{PD} x_{mvs}), \quad m \in M^P \cap M^-. \tag{26}$$

Constraints (25) and (26) give incentive to work on tasks that are not completed during the planning period. If task m is completed, then c_m is given the value of zero. If it is not completed, c_m is equal to a penalty cost parameter multiplied with how much time is left of the task. Corrective tasks are given incentive by constraints (25) and preventive tasks are given incentive by constraints (26).

Time Management:

$$t_{mvs} \leq T^{SHIFT} x_{mvs}, \qquad m \in M,\ v \in V_m,\ s \in S, \tag{27}$$

$$t_{mvs} \geq L^W_{vs} \sum_{j \in N} y_{jivs} - T^{SHIFT}_s (1 - x_{mvs}), \qquad i \in N^W,\ m \in M^-_i,\ v \in V^C_m,\ s \in S, \tag{28}$$

$$t_{mvs} \geq \sum_{j \in N} T^T_{jiv} y_{jivs} - T^{SHIFT}_s (1 - x_{mvs}), \qquad i \in N^W,\ m \in M^-_i,\ v \in V^C_m,\ s \in S, \tag{29}$$

$$t_{mvs} \geq L^W_{vs} (\sum_{j \in N} y_{jivs} + w_{iv(s-1)}) - T^{SHIFT}_s (1 - x_{mvs}), \qquad i \in N^W,\ m \in M^-_i,\ v \in V^A_m,\ s \in S, \tag{30}$$

$$t_{mvs} \geq \sum_{j \in N^W} T^T_{0iv} y_{0ivs} - T^{SHIFT}_s (1 - x_{mvs}), \qquad i \in N^W,\ m \in M^-_i,\ v \in V^A_m,\ s \in S, \tag{31}$$

$$t_{mvs} + T^{PD} x_{mvs} \leq U^W_{vs}, \qquad m \in M^+,\ v \in V_m,\ s \in S. \tag{32}$$

Constraints (27) force the delivery and pick-up start times of tasks that are not performed to zero. For tasks that are performed, the start times of the delivery tasks are handled by constraints (28) – (31). For tasks performed by CTVs, start times of the delivery tasks must both be higher than the lower bound of the weather windows and the transportation time from the depot to the wind farms. This is ensured by constraints (28) and constraints (29). The start time of delivery tasks performed by AVs must also be higher than the lower bound of the weather windows, which is ensured by constraints (30). The start time of delivery tasks performed by AVs are only restricted by transportation time during shifts where the AVs leave the depot. This is because AVs travel between shifts when they travel between wind farms. This is not the case when AVs travels from or to the depot as this has to happen within the start and end shift of the technicians, respectively. Constraints (31) ensures that if an AV leaves the depot during a shift, it cannot start performing tasks before it has arrived at a wind farm. Constraints (32) make sure that all pick-up tasks are started so that there is time to transfer the technicians from the turbine to the vessel within the weather window.

$$t_{(m+|M^-|)vs} \geq t_{mvs} + T^{PD} x_{mvs}, \qquad m \in M^-, v \in V_m, s \in S, \tag{33}$$

$$\begin{aligned} t_{mvs} - t_{nvs} + T^{IT}_{iv} + T^{PD} & \qquad i \in N^W,\ m \in M \backslash \{|M|\}, \\ \leq T^{SHIFT}_s (1 - z_{mnvs}), & \qquad n \in M^-_i \cup M^+_i, v \in V_m \cap\ V_n, \\ & \qquad s \in S \mid m \neq n, \end{aligned} \tag{34}$$

$$\begin{aligned} t_{mvs} - t_{|M|vs} + T^{PD} x_{mvs} + T^{T}_{i|N|v} y_{i|N|vs} & \qquad i \in N^W,\ m \in M^-_i \cup M^+_i, \\ \leq T^{SHIFT}_s (1 - z_{m|M|vs}), & \qquad v \in V_m \cap\ V_n, s \in S. \end{aligned} \tag{35}$$

A delivery task must be performed before the corresponding pick-up task, and the pick-up task cannot start before the technicians are transferred from the vessel to the turbine. This is ensured by constraints (33). The start times of tasks are also restricted by the order in which the tasks are performed. Constraints (34) force the start time of task n to be greater than the start time of task m plus the time for pick up and delivery and internal travel, if task m is performed directly before task n.

Constraints (34) also ensure that if an AV does not travel back to the depot during a shift, then the AV will have time to transfer the technicians from the last pick-up task it performs during the shift and travel out of the wind farm within the shift. The travel time of leaving a wind farm is set equal to the average internal travel time of the wind farm. Constraints (35) are special cases of constraints (34) for tasks being performed directly before the end depot task. They always apply for CTVs, but for AVs they only apply in shifts where they return to the depot. Constraints (35) make sure that all pick-up tasks are started in time for the technicians to be transferred from the turbine to the vessel and for the vessel to return to the depot within the shift.

Precedence of Tasks:

$$x_{mvs} = \sum_{n \in M \setminus \{0\}} z_{mnvs}, \qquad m \in M \setminus \{|M|\}, \quad v \in V_m^C \cap V_n^C, \; s \in S, \tag{36}$$

$$x_{mvs} = \sum_{n \in M \setminus \{|M|\}} z_{nmvs}, \qquad m \in M \setminus \{0\}, \quad v \in V_m^C \cap V_n^C, \; s \in S, \tag{37}$$

$$x_{mvs} \geq \sum_{n \in M \setminus \{0\}} z_{mnvs}, \qquad m \in M \setminus \{|M|\}, \quad v \in V_m^A \cap V_n^A, \; s \in S, \tag{38}$$

$$x_{mvs} \geq \sum_{n \in M \setminus \{|M|\}} z_{nmvs}, \qquad m \in M \setminus \{0\}, \quad v \in V_m^A \cap V_n^A, \; s \in S, \tag{39}$$

$$\sum_{m \in M \setminus \{|M|\}} \sum_{n \in M \setminus \{0\}} z_{mnvs} \geq \sum_{m \in M} x_{mvs} - 1, \qquad v \in V_m^A \cap V_n^A, \; s \in S, \tag{40}$$

$$z_{mnvs} = x_{mvs}, \qquad m \in M^-, \; n = m + |M^-|, \quad v \in V_m, \; s \in S \quad | \; E_m = 1. \tag{41}$$

Constraints (36) – (40) concern the precedence of tasks. Precedence of tasks is also handled by constraints (33) – (35) as these constraints ensure that the start time of a task, m, that is performed immediately before another task, n, is lower than the start time of task n. For all tasks performed by a CTV, excluding the depot tasks, exactly one task must be performed directly before and directly after every task. Constraints (36) ensure that if task m is performed, exactly one task is performed directly after task m, and if task m is not performed zero tasks are performed directly after task m. Constraints (37) are equivalent for tasks performed directly before task m.

As AVs do not have to start and end at the depot each shift, tasks performed by AVs must be handled somewhat differently, and this is done by constraints (38) – (40). If an AV does not start a shift in the depot, there will not be a task performed directly before the first task it performs during this shift. The same applies for the last task it performs during a shift if it does not end this shift in the depot. As it is not known in advance when solving the model which tasks that are performed first and last, constraints (36) and (37) do not apply for AVs. It is, however, known that for each task maximum one task can be performed directly after and directly before this task. It is also known that for tasks not performed, zero tasks can be performed directly before or after these tasks. This is restricted by constraints (38) and (39). Constraints (40) give a lower limit on the number of z_{mnvs} that get the value one for for $v \in V^A$. This number equals the number of tasks performed minus one.

Constraints (41) apply for tasks that require the vessel performing the task to stay by the turbine when the task is being performed. For these tasks, the pick-up task is forced to be performed directly after the delivery task if the delivery task is performed.

Downtime:

$$l_{ms} \geq T^{DAY}(1 - f_{ms}), \qquad m \in M^C,\ s \in S, \tag{42}$$

$$\begin{aligned} l_{ms} \geq \sum_{v \in V_m} &(t_{(m+|M^-|)vs} + T^{PD} x_{mvs}) \\ &- T_s^{SHIFT}(1 - (f_{ms} - f_{m(s-1)})), \qquad m \in M^C,\ s \in S \backslash \{1\}, \end{aligned} \tag{43}$$

$$\begin{aligned} l_{ms} \geq \sum_{v \in V_m} &(t_{(m+|M^-|)vs} + T^{PD} x_{mvs}) \\ &- T_s^{SHIFT}(1 - f_{ms}), \qquad m \in M^C,\ s = 1. \end{aligned} \tag{44}$$

For corrective tasks the turbines are shut down from the failure occurs to the task is completed. The time counter, l_{ms}, of corrective tasks therefore include the total hours from the planning period starts to the tasks are completed. Constraints (42) – (44) concern this time counter. If a task m is not completed within the end of shift s, then the time counter of shift s is given the value of the time from the start of shift s to the start of the next shift, shift $s + 1$. This is ensured by constraints (42). Constraints (43) apply to the shifts where the tasks are completed. The time counter is then given the value of the time the turbine can be turned on, which is when the technicians are transferred from the turbine to the vessel after the task is completed. Constraints (44) are special cases of constraints (43) for tasks that are completed during the first shift.

$$l_{ms} \geq \sum_{v \in V_m} (t_{(m+|M^-|)vs} + T^{PD} x_{mvs} - t_{mvs}), \qquad m \in M^P,\ s \in S, \tag{45}$$

$$\begin{aligned} &\sum_{v \in V_m} (t_{(m+|M^-|)vs} + T^{PD} x_{mvs} - t_{mvs}) \\ &\quad \geq T^{MIN} x_{mvs}, \qquad m \in M^P,\ s \in S. \end{aligned} \tag{46}$$

For preventive tasks, the turbines are shut down only during the performance of the tasks. It starts when a vessel arrives at the turbine and transfers technicians to the turbine, and ends when the technicians have returned to the vessel after performing the task. Constraints (45) gives value to the time counter for shifts that preventive tasks are performed. To avoid that technicians are left at a turbine for a time period that is so short that they in reality do not have time to perform any maintenance, constraints (46) ensure that preventive maintenance must be performed continuous for a minimum amount of time.

Technicians Balances:

$$z_{mnvs}(p_{mvs} - P_n - p_{nvs}) = 0, \qquad m \in M \backslash \{|M|\},\ n \in M \backslash \{0\},\ v \in V_m \cap V_n,\ s \in S, \tag{47}$$

$$p_{mvs} - P_n - p_{nvs} \leq (Q_v - P_n)(1 - z_{mnvs}), \qquad m \in M \backslash \{|M|\},\ n \in M \backslash \{0\},\ v \in V_m \cap V_n,\ s \in S, \tag{48}$$

$$p_{mvs} - P_n - p_{nvs} \geq (-P_n - Q_v)(1 - z_{mnvs}), \qquad m \in M \backslash \{|M|\},\ n \in M \backslash \{0\},\ v \in V_m \cap V_n,\ s \in S. \tag{49}$$

The technician flow for each task is handled by constraints (47). These constraints ensure that if task n is performed directly after task m by vessel v, then the number of technicians onboard vessel v after visiting task n must be equal to the number of technicians onboard vessel v after visiting task m and the technicians leaving or entering the turbine of task n. The demand for delivery tasks is positive and the demand for pick-up tasks is negative. Constraints (47) are non-linear and are linearized by replacing them with constraints (48) and (49).

$$p_{mvs} \leq (Q_v - P_m)x_{mvs}, \qquad m \in M^-,\ v \in V_m,\ s \in S, \tag{50}$$

$$p_{mvs} \leq Q_v x_{mvs}, \qquad m \in M^+,\ v \in V_m,\ s \in S, \tag{51}$$

$$p_{mvs} \geq -P_m x_{mvs}, \qquad m \in M^+,\ v \in V_m,\ s \in S, \tag{52}$$

$$p_{mvs} \leq Q_v x_{mvs}, \qquad m = \{0\} \cup m = \{|M|\}, \quad v \in V_m,\ s \in S. \tag{53}$$

$$p_{mvs} \geq (Q_v - P_m)x_{mvs}, \qquad m \in M^-,\ v \in V_m, \quad s \in S \mid E_m = 1, \tag{54}$$

Constraints (50) – (53) handle the technician capacity of the vessels for delivery, pick-up and depot tasks. When a vessel is performing a task m that requires the vessel to stay by the turbine, the vessel are not allowed to have other technicians performing tasks in parallel at other turbines. This is prevented by constraints (54), together with constraints (50). These constraints force the number of technicians onboard the vessel after performing task m to be equal to the capacity of the vessel minus the technician demand at task m. For these types of tasks, the pick-up task must be performed directly after the delivery task. This means that except for the technicians performing task m, all other technicians have to be onboard the vessel for the entire time task m is being performed.

Domain of Decision Variables:

$$x_{mvs} \in [0,1], \qquad m \in M,\ v \in V_m,\ s \in S, \tag{55}$$
$$y_{ijvs} \in [0,1], \qquad i,j \in N,\ v \in V,\ s \in S,\ i \neq j, \tag{56}$$
$$z_{mnvs} \in [0,1], \qquad i \in N^W,\ m,n \in M_i,\ v \in V_m \cap V_n,\ s \in S, \tag{57}$$
$$w_{ivs} \in [0,1], \qquad i \in N,\ v \in V^A,\ s \in S, \tag{58}$$
$$f_{mvs} \in [0,1] \qquad m \in M,\ v \in V_m,\ s \in S, \tag{59}$$
$$t_{mvs} \geq 0, \qquad m \in M,\ v \in V,\ s \in S, \tag{60}$$
$$l_{ms} \geq 0, \qquad m \in M,\ s \in S, \tag{61}$$
$$p_{mvs} \geq 0,\ integer \qquad m \in M,\ v \in V_m,\ s \in S, \tag{62}$$
$$c_m \geq 0,\ integer \qquad m \in M. \tag{63}$$

The domain of the decision variables are defined by constraints (55)-(63).

5.3 Numerical Example of the Mathematical Model

To illustrate the mathematical model, a simple numerical example with two wind farms and a planning period of two shifts is presented. There are 30 turbines in each wind farm and a total of seven maintenance tasks generated for the planning period. The vessel fleet consists of two vessels, one AV and one SES. The AV is located at the depot at the beginning of the planning period, hence, it can stay offshore for the entire planning period if it departs from the depot. The weather windows for both the AV and the SES are entirely open during both shifts, and for both shifts it is desirable to perform extra preventive maintenance due to low energy production. The input data of the example are summarized in Table 1, 2 and 3.

An illustration of the routing and the tasks performed during the two shifts are given in Figure 21 and 22. The turbines of the two wind farms are illustrated by circles and the turbines that require maintenance are numbered with maintenance task numbers. The routes of the vessels are represented by arcs. How Figure 21 and 22 show the order that the turbines are visited in, the number of technicians onboard the vessels after each turbine visit, and the time period of the shift when the turbines are shut down, are explained by Figure 20. The turbines are shut down from the moment a vessel arrives at the turbine until the vessel has departed the turbine after picking up the technicians. This includes the time

Table 1: Input data of the numerical example of the mathematical model.

	Number
Wind farms	2
Corrective tasks	5
Desired preventive tasks	1
Generated preventive tasks	2
AVs	1
SESes	1
Regular CTVs	0
Shifts	2
Hours in a shift	12

Table 2: Generated tasks and corresponding task input data of the numerical example of the mathematical model.

Wind farm	Task	Task type	Duration of task [h]	Required technicians	Vessel type compliance
1	1	Manual Reset	3	2	All
1	2	Manual Reset	3	2	All
1	3	Alarm	0.5	2	All
1	4	Alarm	0.5	2	All
1	5	Alarm	0.5	2	All
1	6	Preventive	60	3	All
2	7	Preventive	60	3	All

Table 3: Input data on vessels of the numerical example of the mathematical model.

	Number of vessels	Travel time to wind farm 1 [h]	Travel time to wind farm 2 [h]	Travel time between farms [h]	Internal wind farm transportation time [h]	Transfer time [h]
AV	1	3.60	3.15	2.25	0.19	0.5
SES	1	0.93	0.81	-	0.05	0.5

of transferring technicians to the turbine, performing the task, potential waiting time for the vessel, and transferring technicians from the turbine.

During the first shift, illustrated by Figure 21, the AV travels to wind farm 1 and the SES travels to wind farm 2. Tasks are performed in parallel by both vessels, and during the first shift, all corrective tasks are completed and both preventive tasks are started. For the second shift, illustrated by Figure 22, only the two preventive tasks are performed as these tasks are the only tasks that were not

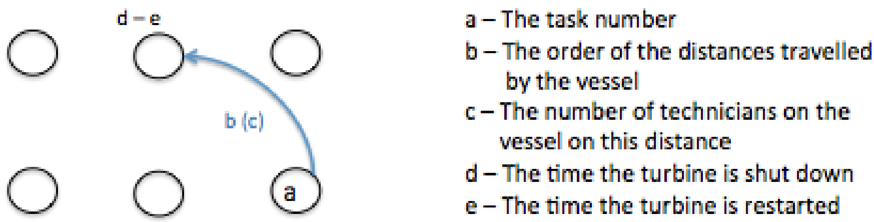


Figure 20: Explanation of the illustration figures of the numerical example of the mathematical model.

completed during the first shift. For both shifts, the entire shifts are utilized by both vessels. This complies with the weather windows being entirely open.

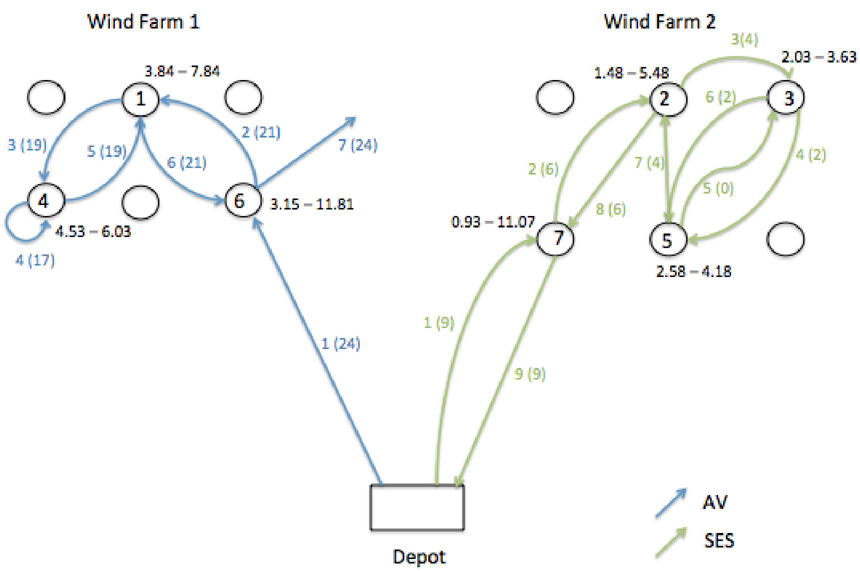


Figure 21: Illustration of shift 1 of the numerical example of the mathematical model.

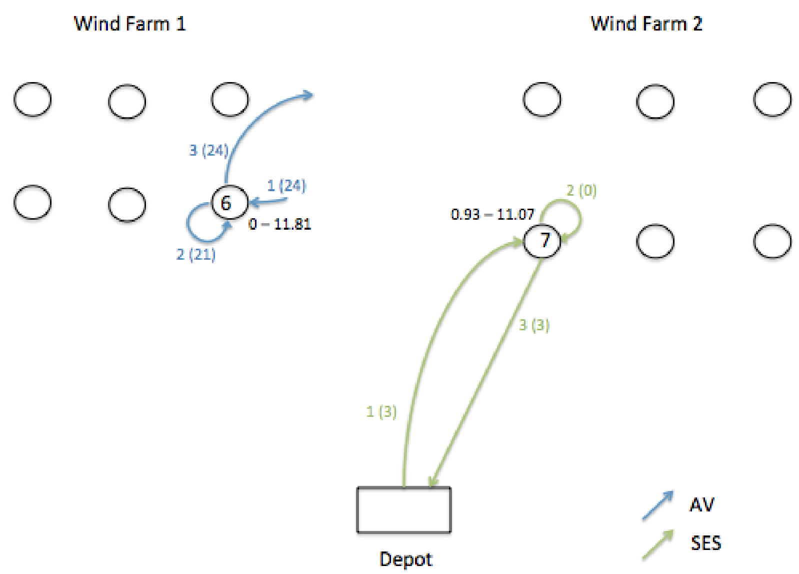


Figure 22: Illustration of shift 2 of the numerical example of the mathematical model.

When looking closely at the arrival times of the figures, it can be seen that the transportation time constraints for both internal transportation and transportation between the depot and the wind farms are complied. For example, the first task performed by the AV, task 6, is not started until the AV has arrived at the wind farm (0 h + 3.15 h = 3.15 h). The next task, task 1, is not started until the AV has transferred technicians to the turbine of task 6 and travelled from this turbine to the turbine of task 1 (3.15 h + 0.5 h + 0.19 h = 3.84 h). It can also be seen from task 6 and task 7 that the vessels finish performing tasks in time to travel to the depot or out of the wind farm within the shift (SES: 12 h - 0.93 h = 11.07 h and AV: 12 h - 0.19 h = 11.81 h).

When studying the time periods the turbines are shut down, it can be seen that the tasks that are completed are shut down for the task duration plus the transfer time of the technicians. For example for task 2, the SES arrives at the turbine at 1.48 h. The technicians are then transferred to the turbine, the task is completed and the technicians transferred from the turbine (1.48 h + 0.5 h + 3 h + 0.5 h = 5.48 h). The figures also show that the number of technicians onboard the vessels after a turbine is visited corresponds to the technician demand of the task for both delivery and pick-up tasks. For task 3, the demand is two technicians.

When task 3 is visited for delivery, the technicians at the SES decreases by two, while when task 3 is visited for pick-up, the technicians at the SES increases by two.

6 Solution Method

Due to the complexity of the problem studied in this thesis, exact solution methods are struggling to solve problems of a certain size within a reasonable time. This motivates for the use of an alternative solution method that reduces the solution time while still producing solutions of acceptable quality. Two different rolling horizon heuristics were proposed for the problem, described in Section 6.1. The solution space includes solutions that are mathematical different, however, in practice identical. Symmetry breaking constraints were therefore included in the model formulation to eliminate some of these identical solutions and by that reduce the solution space and probably the computational time. The symmetry breaking constraints included are described in Section 6.2.

6.1 Rolling Horizon Heuristics

Rolling horizon methods are heuristic methods that solve mixed integer problems (MIP) by iteratively solving shorter sub-horizons of the planning period (planning horizon). Each sub-horizon are split into two time blocks, one detailed time block (DTB) and one aggregate time block (ATB). For each iteration k, the DTB is modelled in detail, while the ATB is simplified according to a simplification strategy and represented in an aggregate manner to evaluate the impact of future available capacity when solving for the DTB [23]. Before solving for the next iteration, $k+1$, some or all of the decisions made for the DTB are fixed according to a specified fixing strategy. These variables remain fixed for all subsequent iterations [23]. The fixed part of the DTB are referred to as the fixed DTB, while the free variables of the DTB are referred to as the free DTB. For the next iteration, $k + 1$, the DTB is expanded with a specified number of time periods so that the first part of ATB_k becomes a part of DTB_{k+1}, and the ATB_{k+1} is shifted towards the end of the planning period with an equal number of time periods. If the length of the planning period is equal to the combined length of the DTB and the ATB, then the length of the ATB decreases in each iteration [23]. The problem is solved when the entire planning period is included in, and solved for, the DTB. The fixed DTB, the free DTB and the ATB of a general rolling horizon heuristic are illustrated graphically by Figure 23. How they are shifted for each iteration are illustrated by Figure 24.

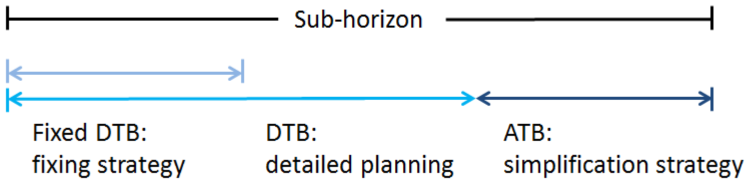


Figure 23: Illustration of the fixed DTB, the free DTB and the ATB of a general rolling horizon heuristic.

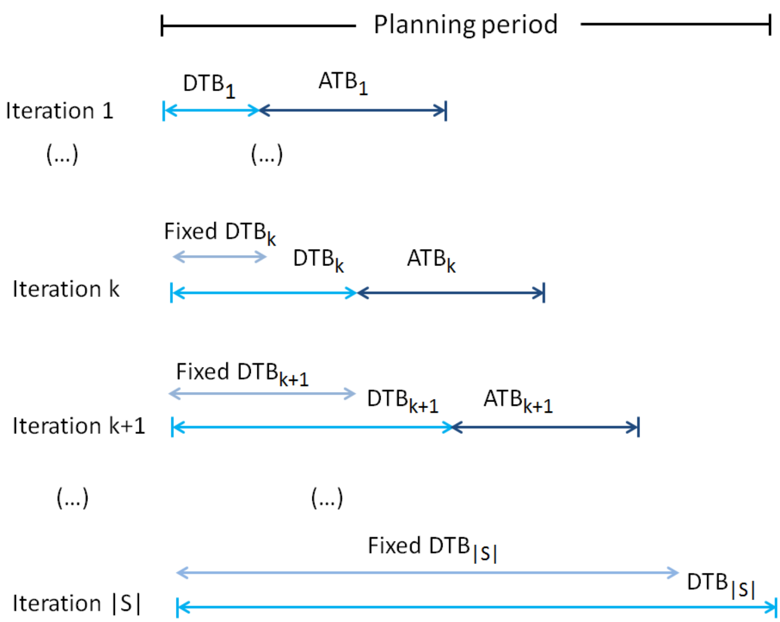


Figure 24: Illustration of how the fixed DTB, the free DTB and the ATB of a general rolling horizon heuristic are iteratively shifted through the entire planning period, from shift 1 until shift $|S|$.

Rolling horizon heuristics can reduce the computational requirements significantly, while still producing close to optimal solutions. The heuristics' effectiveness are, however, highly dependent on the simplification strategy used for the ATB and fixing strategy used for the fixed DTB [23]. There exist several varieties of the simplification strategy. When deciding on a simplification strategy, two issues that need to be considered are the length of the ATB and the restrictions on the variables in the ATB. By adding an ATB in stead of just solving for the DTB, information about a larger part of the planning period is utilized. This can enhance the chance of avoiding sub-optimal solutions of the DTB. The longer the ATB is, the more relevant information of the problem is known, hence, a better performance of the rolling horizon heuristic can be expected. However, there exists a trade-off between the quality of the solution and the solution time, and in order for the ATB to be effective, the length of the ATB cannot be too long [61].

Variables that are binary and integer can either be kept binary and integer in the ATB, or represented by continuous variables in the ATB. Using continuous variables, the computational effort required to solve the problem for the ATB is reduced. However, if the variables take fractional values, this give less accurate forecasting information than binary and integer variables. When continuous variables are used, binary and integer restrictions are imposed to the variables that enters the DTB in each iteration [61]. As for the simplification strategy for the ATB, there exist several different fixing strategies for fixing variables of the DTB. Fixing strategies can involve either fixing all variables of the solved free DTB, or only some of the variables. The aim is to reduce the computational complexity when solving subsequent iterations. The more variables that are fixed, the greater is the reduction in complexity. A disadvantage of fixing all variables is that no decisions can be changed in later iterations. Keeping some variables free has the advantage of allowing each iteration to re-assess decisions made in earlier iterations and potentially compensate for any inaccuracies caused by the use of the aggregate formulation [23].

Two different rolling horizon heuristics, RHH-1 and RHH-2, are proposed for the problem studied in this thesis, both illustrated by Figure 25. The length of the free DTB is set to one shift and identical simplification strategies are implemented for both RHH-1 and RHH-2. As the planning period of the problem is relatively short, the length of the ATB is set equal to the remaining part of the planning period, as illustrated by Figure 26. All variables with binary or integer restrictions are LP-relaxed in the ATB.

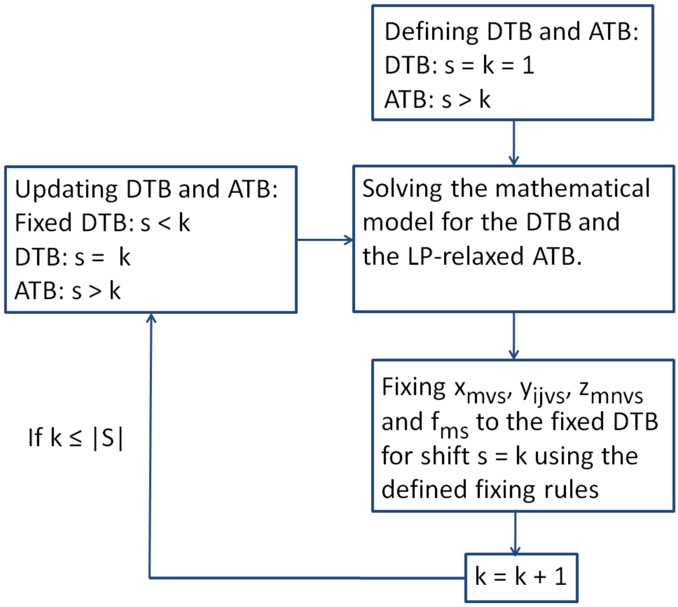


Figure 25: Illustration of the steps of the proposed rolling horizon heuristics. The two different heuristics are differentiated by the fixing rules applied for the DTB. The length of the planning period is represented by $|S|$, shifts by s and the iteration number by k.

To account for the inaccuracies caused by variables that take fractional values, and to tighten the model formulation for the ATB, an additional set of constraints, constraints (64), is introduced. These constraints ensure that the total number of man-hours that maintenance are performed in the planning period does not exceed the man-hour capacity of the vessel fleet for the planning period. To represent the total capacity of the vessel fleet, the parameter W_{ivs} is introduced. This parameter contain the available number of hours in shift s that vessel v can perform maintenance in wind farm i. The number of available hours for the vessel fleet is then multiplied by the technician capacity of the vessel fleet to represent the total number of available man-hours. The W_{ivs} parameter is adjusted for weather windows during shift s and transportation times to node i for vessel v. As transportation times for AVs are dependent on where the AVs are located during the respective shifts, the transportation times for AVs are not known when W_{ivs} is calculated. The W_{ivs} therefore only gives an estimate of the total available hours for the vessel fleet to perform maintenance. This means that the man-hour capacity of the vessel fleet in constraints (64) is an estimate of the actual man-hour capacity of the vessel fleet. However, including the constraints

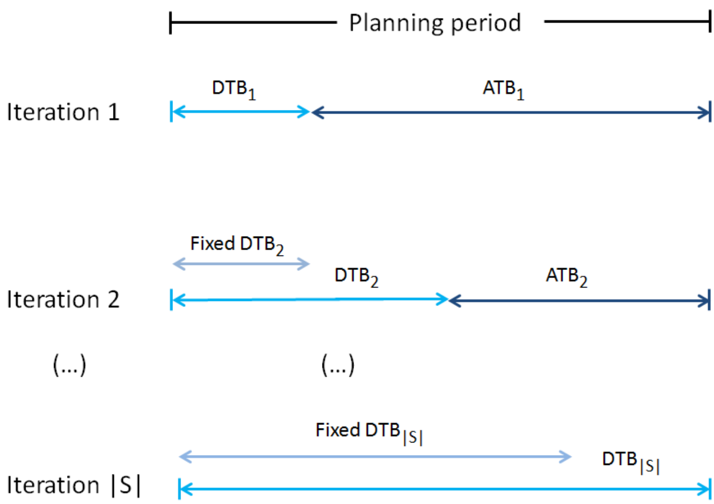


Figure 26: Illustration of how the fixed DTB, the free DTB and the ATB of RRH-1 and RRH-2 are iteratively shifted through the entire planning period, from shift 1 until shift $|S|$.

will still provide a tighter formulation than not including them.

$$\sum_{m \in M_i^-} P_m (t_{(m+|M^-|)vs} - t_{mvs} + T^{PD} x_{mvs}) \leq Q_v W_{ivs}, \qquad i \in N^W,\ v \in V,\ s \in S. \quad (64)$$

As the length of the DTB and the simplification strategy of the ATB for RHH-1 and RHH-2 are identical, the fixing strategy of the DTB is what separates the two heuristics. Firstly, it is chosen wheter to fix all the variables or just some of them. For both the heuristics it is chosen to only fix the decisions which involve performing tasks or travelling between nodes, and not fix decision regarding tasks that are not performed or distances that are not travelled. This is to prevent that good solutions in subsequent iterations which involves doing more than originally planned are infeasible (prohibited). Secondly, it is chosen which decisions regarding the distances scheduled to be travelled and the maintenance tasks scheduled to be performed, to fix. For the decisions regarding the distances scheduled to be travelled, the choices of fixing strategies include to fix what specific vessels that travel the specific distances, or to fix how many vessels that travel each distance, however, not which specific vessels that travel the distances. For the maintenance tasks scheduled, different fixing strategies include wheter or not the order of the tasks performed should be fixed, wheter or not it is allowed to remove or add extra maintenance tasks to the schedules and wheter or not the tasks must be performed by the specific vessels that are scheduled to perform them. The amount of decisions that are fixed are considerably less for RHH-1 than for RHH-2, hence, RHH-1 allows, to a greater extent, for re-assessing sub-optimal solutions due to inaccuracies caused by the use of the aggregate formulation, when more accurate information is obtained in later iterations.

For RHH-1, it is chosen to allow for adding new tasks to the schedules at later iterations, but not removing any tasks from the schedules or change the order of existing tasks. Which vessels that are scheduled to perform the tasks are not fixed, but if a task is scheduled to be performed in shift s a vessel $u \in V_m$ has to perform it. Similar, if vessel v travels between two nodes i and j during shift s, then it is fixed that a vessel $u \in V_m$ must travel between node i and node j during shift s. If a task is scheduled to be completed during shift s, the decision can not be altered. To allow for adding new tasks, but not to change the order of existing tasks, the z_{mnvs}-variables are fixed for tasks that are performed, but not performed in sequence. By keeping the z_{mnvs}-variables of tasks performed in sequence free, new tasks can be scheduled in between these tasks. As for the x_{mvs}-variables, the z_{mnvs}-variables are not fixed with respect to what specific vessel that performs the different sequences of tasks. In order to allow for additional tasks to be included for earlier shifts in later iterations, the variables l_{ms}, t_{mvs} and p_{mvs} are not fixed. As l_{ms} and t_{mvs} are not fixed, this opens up for the possibility to change the amount of time that maintenance tasks are scheduled for in earlier shifts when solving for later iterations. This does not increase the complexity of the heuristic significantly, as these variables are continuous in the DTB. The combination of the rules presented for RHH-1 also allows for AVs to be relocated during later iterations. As an AV constitutes a significant amount of the capacity of a vessel fleet, it could be unfortunate for the solution quality to for example fix an AV to the depot during a shift.

The mathematical formulations of the fixing strategy for RHH-1 are given by the following equations. The notation with *, e.g. x^*_{mvs} is used for the solutions of the mathematical model solved in the iteration, and without the *, e.g. x_{mvs} for the variables that are fixed to the solutions of the iteration.

$$x^*_{mvs} = 1 \quad \Rightarrow \quad \sum_{u \in V_m} x_{mus} \geq x^*_{mvs}$$

$$y^*_{ijvs} = 1 \quad \Rightarrow \quad \sum_{u \in V_m} y_{ijus} \geq y^*_{ijvs}$$

$$x^*_{mvs} \text{ and } x^*_{nvs} = 1 \quad \Rightarrow \quad \sum_{u \in V_m \cap V_n} z_{mnus} \leq z^*_{mnvs}$$

$$f^*_{ms} = 1 \quad \Rightarrow \quad f_{ms} = f^*_{ms}$$

In RHH-2 most of the decisions regarding how the vessels move and which tasks they perform are fixed. The only decisions regarding vessels that are not fixed, are for vessels that are not scheduled to perform maintenance. This means that vessels that originally were scheduled not to perform maintenance can be rescheduled in later iterations. For decisions regarding scheduled tasks, also most of these are fixed for RHH-2. Scheduled tasks cannot be removed from the schedules in later iterations, additional tasks cannot be scheduled in between scheduled tasks and the order of the tasks cannot be changed. However, tasks can be added at the beginning and/or the end of the scheduled tasks. The l_{ms}- and t_{mvs}-variables are not fixed, which allows for the scheduled amount of time to perform each task to be changed in later iterations. As mentioned above in the explanation of RHH-1, this will not increase the complexity of the heuristic significantly. Decisions regarding tasks that are not scheduled to be performed are not fixed, and these tasks are therefore in later iterations allowed to be scheduled to vessels that originally were scheduled not to perform maintenance, or at the beginning and/or end of a schedule for a vessel already in the schedule. The mathematical formulations of the fixing strategy for RHH-2 are given by the following equations.

$$x^*_{mvs} = 1 \quad \Rightarrow \quad x_{mvs} = x^*_{mvs}$$

$$y^*_{ijvs} = 1 \quad \Rightarrow \quad y_{ijvs} = y^*_{ijvs}$$

$$x^*_{mvs} \text{ and } x^*_{nvs} = 1 \quad \Rightarrow \quad z_{mnvs} = z^*_{mnvs}$$

$$f^*_{ms} = 1 \quad \Rightarrow \quad f_{ms} = f^*_{ms}$$

6.2 Symmetry Breaking Constraints

Symmetry in a problem is problematic as it increases the size of the search space. This can make it harder to prove optimality of the solutions of the problem and therefore increase the computational time. One way to reduce symmetry in a problem is to add symmetry breaking constraints in the model formulation. Symmetry breaking constraints eliminate some of the symmetric solutions from the solution space, and by that, also the amount of searches needed to solve the problem are reduced. There can, however, be some problems associated with adding symmetry breaking constraints to heuristic methods. When adding these constraints, particular solutions are eliminated, and this may conflict with the direction of the branching heuristic [86]. Which symmetry breaking constraints that should be added to the model formulation is therefore problem specific.

For the problem described in this thesis, symmetries are caused by tasks of the same type within the same wind farm and vessels of the same type. Tasks of the same type within a wind farm are assumed identical, and the same applies for vessels of the same type. This causes mathematical different solutions which in practice are identical. For example, if vessel 1 and vessel 2 of a vessel fleet are of the same type, and both are scheduled to perform tasks in the same wind farm, it is in practice indifferent which of these vessels that perform which of these schedules. Likewise, if a schedule for a vessel consists of performing a task of type 1 and a task of type 2, then, as long as turbine locations are neglected, it is in practice indifferent which task of type 1 and which task of type 2 in the wind farm that are performed by the vessel.

The symmetry breaking constraints added to the model formulation dictate that during each shift, tasks of lower task numbers must be performed before tasks of higher task numbers for tasks of the same type within the same wind farm. If multiple vessels are located in the same wind farm, the vessels of lower indices must perform the tasks of lower indices as long as the tasks are of the same type. The mathematical formulation of the symmetry breaking constraints implemented in the mathematical model presented in Chapter 5 are given by the following equations.

$$\sum_{v \in V_m} \sum_{h=1}^{s} x_{mvh} \geq \sum_{v \in V_n} x_{nvs}, \qquad i \in N^W,\ k \in K,\ m, n \in M_{ik}^{-},\ s \in S \mid m < n,\ R_{ms} = 1,\ R_{ns} = 1, \tag{65}$$

$$\sum_{h=1}^{s} f_{mh} \geq f_{ns}, \qquad i \in N^W,\ k \in K,\ m, n \in M_{ik}^{-},\ s \in S \mid m < n,\ R_{ms} = 1,\ R_{ns} = 1, \tag{66}$$

$$x_{nvs} \leq \sum_{u=1}^{v} x_{mus} + f_{ms}, \qquad i \in N^W,\ k \in K,\ m, n \in M_{ik}^{-},\ v \in V_m,\ s \in S \mid m < n,\ R_{ms} = 1,\ R_{ns} = 1, \tag{67}$$

$$x_{nvs} \leq \sum_{u=1}^{v} x_{mus} + f_{(m-|M^-|)s}, \qquad i \in N^W,\ k \in K,\ m, n \in M_{ik}^{+},\ v \in V_m,\ s \in S \mid m < n,\ R_{ms} = 1,\ R_{ns} = 1. \tag{68}$$

Constraints (65) – (68) concern the order of the tasks performed across shifts. Tasks cannot be performed during a shift unless all tasks of the same task type within the same wind farm of lower indices are performed during the same or earlier shifts. This is ensured by constraints (65). The same applies for completing tasks which is ensured by constraints (66). Constraints (67) and (68) handle the chosen symmetry restrictions of vessels. If multiple vessels are located within the same wind farm, then the vessels of lower indices must perform the tasks of lower indices for tasks of the same type. Constraints (65) – (68) only apply for tasks were all necessary spare parts and equipment are available from shift $s = 1$. This is to avoid that tasks of lower indices that cannot be performed until later shifts restrict tasks of higher indices to be performed in earlier shifts.

$$t_{mvs} \leq t_{nvs} + (1 - x_{nvs})T_s^{SHIFT}, \qquad i \in N^W,\ k \in K,\ m, n \in M_{ik}^-,\ v \in V_m,\ s \in S \mid m < n,\ R_{ms} = 1,\ R_{ns} = 1, \tag{69}$$

$$t_{mvs} \leq t_{nvs} + (1 - x_{nvs})T_s^{SHIFT}, \qquad i \in N^W,\ k \in K,\ m, n \in M_{ik}^+,\ v \in V_m,\ s \in S \mid m < n,\ R_{ms} = 1,\ R_{ns} = 1. \tag{70}$$

Constraints (69) and (70) concern the order of the tasks performed within a shift. If task m and task n are performed during shift s, are of the same task type, are located in the same wind farm, and if task m is of lower index than task n, then the constraints ensure that task m has a lower start time than task n. Constraints (69) apply for delivery tasks, and constraints (70) for pick-up tasks. As for constraints (65) – (68), constraints (69) and (70) only apply for tasks were all necessary spare parts and equipment are available from shift $s = 1$.

$$z_{mnvs} = 0, \qquad i \in N^W,\ k \in K,\ m,n \in M^-_{ik}, \\ v \in V_m,\ s \in S \mid m > n, \\ R_{ms} = 1,\ R_{ns} = 1, \tag{71}$$

$$z_{mnvs} = 0, \qquad i \in N^W,\ k \in K,\ m,n \in M^+_{ik}, \\ v \in V_m,\ s \in S \mid m > n, \\ R_{ms} = 1,\ R_{ns} = 1, \tag{72}$$

$$z_{nmvs} = 0, \qquad i \in N^W,\ k \in K,\ m \in M^-_{ik},\ n \in M^+_{ik}, \\ v \in V_m,\ s \in S \ \mid\ m < n - |M^-|, \\ R_{ms} = 1,\ R_{ns} = 1, \tag{73}$$

$$z_{mnvs} = 0, \qquad i \in N^W,\ k \in K,\ m,n,l \in M^-_{ik}, \\ v \in V_m,\ s \in S \ \mid\ m < l < n, \\ R_{ms} = 1,\ R_{ns} = 1, \tag{74}$$

$$z_{mnvs} = 0, \qquad i \in N^W,\ k \in K,\ m,n,l \in M^+_{ik}, \\ v \in V_m,\ s \in S \ \mid\ m < l < n, \\ R_{ms} = 1,\ R_{ns} = 1. \tag{75}$$

The z_{mnvs}variables of tasks of the same type within the same wind farm are handled by constraints (71) – (75). Constraints (71) and (72) restrict that a task m of a higher index than task n are performed directly before task m for delivery and pick-up tasks, respectively. Constraints (73) ensure that a pick-up task n cannot be performed directly before a delivery task m if the delivery task corresponding to task n is of a higher index than task m. If there exists a task l that is of higher index than task m and of lower index than task n, and if task m, l and n are of the same task types and located in the same wind farm, then task m cannot be performed directly before task n. This is restricted by constraints (74) and (75) for delivery tasks and pick-up tasks, respectively. Constraints (71) – (75) only apply for tasks were all necessary spare parts and equipment are available from shift $s = 1$.

7 Simulation Framework

A simulator is implemented in MATLAB to solve the problem for several consecutive planning periods. It is developed to test the static mathematical model in a dynamic setting, and to test the applicability of the mathematical model for real offshore wind farms. How the simulator works is explained in detail in Section 7.1, followed by a numerical example to illustrate this in Section 7.2. The input data used for simulations is then described in Section 7.3.

For real offshore wind farms, the mathematical model is intended to be solved for a specified planning period prior to each shift. The user of the model then implements the solutions of the first shift of this planning period in the shift that the model is solved prior to. When re-solving the model for the next shift, the user has obtained new information about the input data of the problem. This includes information about what happened during the previous shift, such as which tasks are completed or performed, which new tasks occur and updated weather forecasts for the following shifts.

The mathematical model presented in Chapter 5 is a static model that solves the scheduling problem for one planning period. The problem of scheduling maintenance in real offshore wind farms is, however, a dynamic problem where the model is solved for several consecutive planning periods, where each new planning period is shifted by one shift. In the simulations the static mathematical model is solved in a dynamic setting to capture the dynamic aspect of the problem. For dynamic problems the decisions that are made in one time period, affect the solutions of following time periods. The simulator captures how the schedules implemented during one shift affect the schedules generated for the following shifts in terms of which tasks are performed and completed during each shift.

7.1 The Simulator

The simulator recreates the context in which the model is intended to be used when solving real problems. It solves a problem iteratively for each shift, s, in a specified simulation period of length n. In each iteration a planning period of a specified length, $|S| \leq n$, is solved. The simulation period and how the planning periods are shifted for each iteration are illustrated graphically by Figure 27. How the simulator works is illustrated by Figure 28.

When performing simulations, a scenario is, together with the length of the planning periods, taken as input in the simulator. A scenario is a data file that contains information about tasks and weather forecasts for a specified set of wind

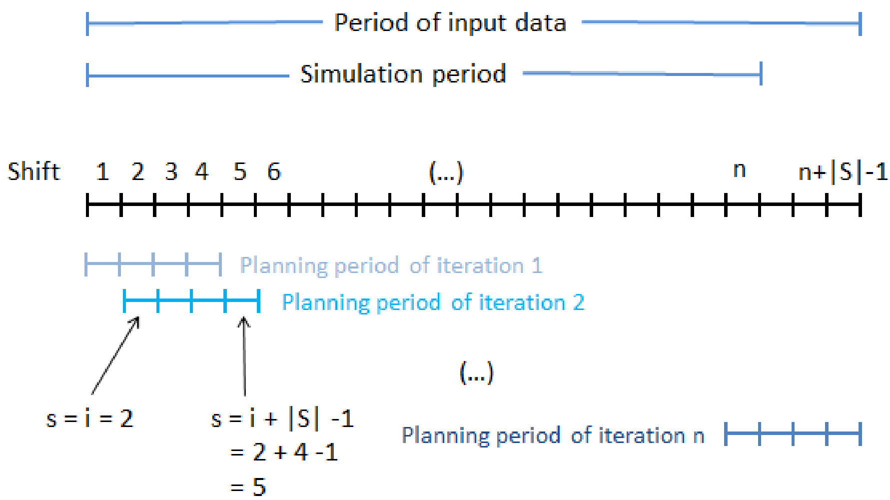


Figure 27: Simulation and planning periods of the simulations.

farms and the appurtenant vessel fleet for the entire simulation period. This includes input data of the planning period of iteration n, i.e. input data for shift 1 to shift $n + |S| - 1$, as shown in Figure 27. For each iteration i of the simulation period an instance i is created. An instance is an input data file that contains tasks and weather forecasts only for the shifts of the planning period corresponding to the iteration, from shift $s = i$ to shift $s = i + |S| - 1$, illustrated for $i = 2$ in Figure 27.

In the first iteration of a simulation the input data of instance $i = 1$ is taken solely from the scenario file. Instance $i = 1$ contains weather forecasts for shift $s = 1$ to shift $s = |S|$ of the scenario, triggered alarms that occur in shift $s = 1$, corrective tasks due to checked alarms during shifts prior to the simulation period and the sets and parameters that are not shift or task dependent. Preventive tasks for the planning period are generated by the simulator based on the number of turbines in the wind farms. Sets and parameters that are shift and task dependent are also generated by the simulator, which is described more in detail in Section 7.3. After processing the input data, the instance is solved by the mathematical model. The schedules generated for the first shift of the planning period is then performed during shift $s = 1$ of the simulations.

For each iteration subsequent to the first, instance $i > 1$ is updated based on the

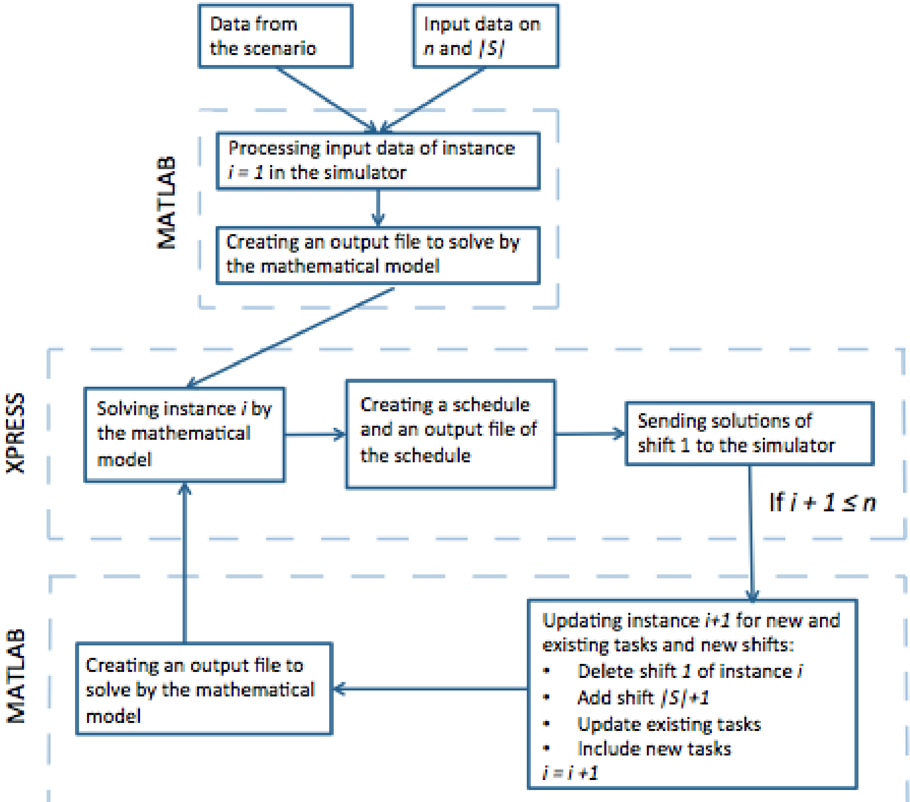


Figure 28: Illustration of how the simulator works. The length of the simulation period is represented by n, the length of the planning period by $|S|$ and the iteration number by i.

schedules implemented in iteration $i-1$ and on new information given from the scenario file. The planning period of instance i is updated by deleting the first shift of the planning period of instance $i-1$ and by adding shift $i+|S|-1$. This is illustrated graphically by Figure 29. Weather forecast and weather windows of the added shift is included from the scenario file. In addition to the planning period, the locations of AVs must be updated for each instance, as the AVs can change position during shifts. If any AV has moved between nodes during shift $s = i-1$, then the location parameter of the AV is updated. Also the parameter of how long the AV has stayed offshore is updated based on whether the AVs are located offshore or in the depot at the end of shift $s = i-1$ of the simulations.

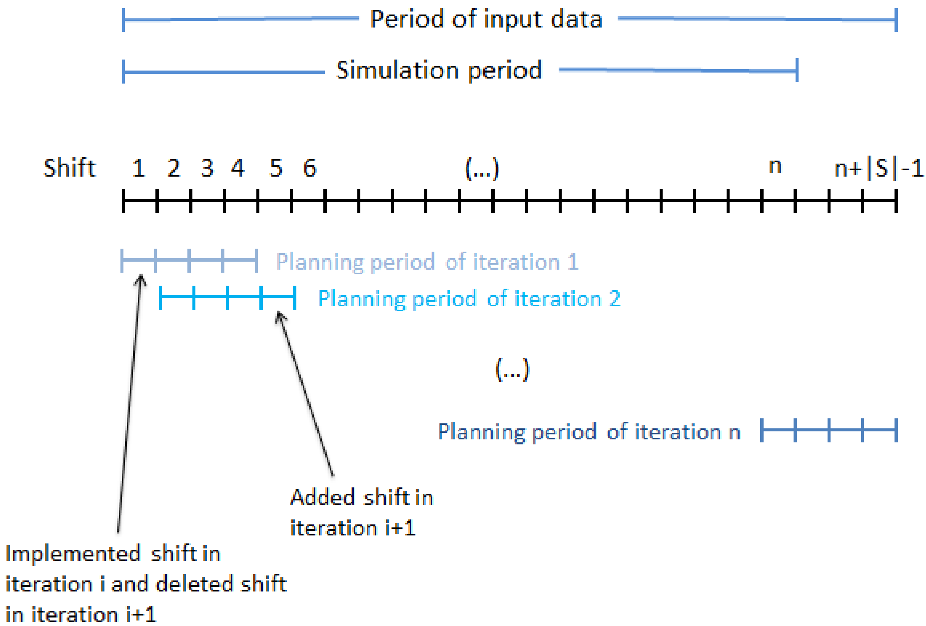


Figure 29: Illustration of how shifts are updated in each iteration of the simulations.

Maintenance tasks for instance $i > 1$ are updated based on both data from the scenario file and on the schedules performed during shift $s = i - 1$ of the simulations. New triggered alarms of shift $s = i$ are included in instance i from the scenario data. For triggered alarms that are checked during shift $s = i - 1$, the corresponding corrective tasks are added from the scenario file to instance i. Existing tasks from iteration $i - 1$ are updated for instance i based on the schedules performed during shift $s = i - 1$. Tasks that are completed during shift $s = i - 1$ are not included in instance i. For tasks that are started, but not completed during shift $s = i - 1$, the task duration is updated and set equal to the remaining time of the task. If any preventive tasks are completed during shift $s = i - 1$, new preventive tasks are generated by the simulator for instance i, so that the number of preventive tasks is kept constant.

After the planning period, the locations of the AVs and the maintenance tasks are updated for instance i, shift and task dependent sets and parameters are updated. The instance is then solved by the mathematical model, and the schedules generated for the first shift of the planning period of iteration i is performed in shift $s = i$. This iterative process continues until all shifts of the planning period are solved, as long as $i \leq n$. For a more thorough study of the simulator, the reader is referred to the code of the simulator and the code of the implementation of the mathematical model enclosed with the report.

7.2 Numerical Example of the Simulator

To demonstrate a simulation a scenario of two wind farms is generated. The vessel fleet of the scenario consists of two vessels, one AV and one SES, and the planning period is set to three shifts. Three iterations of the simulation period are presented. The solutions are not described in detail, only the relevant parts for updating instances. The instances for iteration 1, 2 and 3 are presented in Figure 30, 31 and 32.

In the first iteration of the scenario there are a total of six corrective tasks, where four of them are triggered alarms. There are four possible preventive tasks to be performed, however, the energy production during the first shift is high, and it is therefore only desired to perform two preventive tasks during this shift. The AV is located at the depot when the planning period starts. Input data on shifts, tasks and the location of the AV for the first iteration are presented in Figure 30.

Shift data

Shift	1	2	3
Wind Speed [m/s]	13	5	8
Weather Window AV	0 – 12	1 – 12	0 – 12
Weather Window SES	0 – 12	1 – 12	0 – 12
Desirable to perform extra preventive maintenance	No	Yes	Yes

AV data

Location shift 1:

The depot

Shifts offshore: 0

Task data

Task number	1	2	3	4	5	6	7	8	9	10
Task duration	3	3	0.5	0.5	0.5	0.5	60	60	60	60
Time performed during first shift of planning period	3	3	0.5	0.5	0.5	0.5	0	0	8.6	8.6

Instance 1

Figure 30: Relevant input data of the planning period of iteration 1 of the numerical example that illustrates the simulator.

During shift $s = 1$ of the simulations, all corrective tasks are completed. All the four checked alarms result in new corrective tasks. Two of the preventive tasks, task 9 and task 10, are performed and the AV travels to wind farm 1. Figure 31 shows the updated instance for the second iteration. The planning period, and, hence, the weather windows, wind speeds and list of shifts of high energy production, are shifted by one shift. Shift $s = 1$ is deleted, and shift $s = 4$ is added. The tasks that are completed during shift $s = 1$ are deleted in the second instance, while the resulting tasks of the checked alarms are included. Five failures occur during shift $s = 1$, and the alarms corresponding to these are included in the second instance. The task durations of task 9 and task 10 are updated, as these tasks are performed, but not completed.

Shift data

Shift	1	2	3
Wind Speed [m/s]	5	8	11
Weather Window AV	1 – 12	0 – 12	0 – 12
Weather Window SES	1 – 12	0 – 12	0 – 12
Desirable to perform extra preventive maintenance	Yes	Yes	No

AV data

Location shift 1:

Wind Farm 1

Shifts offshore: 1

Task data

Task number	7	8	9	10	11	12	13	14	15	16	17	18	19
Task duration	60	60	51.4	51.4	7.5	7.5	3	3	0.5	0.5	0.5	0.5	0.5
Time performed during first shift of planning period	10.8	10.8	10	10	7.5	7.5	3	3	0.5	0.5	0.5	0.5	0.5

Instance 2

Figure 31: Relevant input data of the planning period of iteration 2 of the numerical example that illustrates the simulator.

Also during shift $s = 2$ of the simulations all corrective tasks are completed. For this iteration, one of the checked alarms are false, and only four of the five checked alarms result in new corrective tasks to be included in the third instance. As energy production is low during shift $s = 2$, all four preventive tasks are performed during this shift. The AV stays in wind farm 1. The updated instance of the third iteration is presented in Figure 32.

Shift data

Shift	1	2	3
Wind Speed [m/s]	8	11	7
Weather Window AV	0 – 12	0 – 12	0 – 12
Weather Window SES	0 – 12	0 – 12	0 – 12
Desirable to perform extra preventive maintenance	Yes	No	Yes

AV data

Location shift 1:

Wind Farm 1

Shifts offshore: 2

Task data

Task number	7	8	9	10	20	21	22	23	24	25	26
Task duration	49.2	49.2	41.4	41.4	3	7.5	3	3	0.5	0.5	0.5
Time performed during first shift of planning period	8.3	8.3	10.2	10.2	3	7.5	3	3	0.5	0.5	0.5

Instance 3

Figure 32: Relevant input data of the planning period of iteration 3 of the numerical example that illustrates the simulator.

7.3 Input Data of the Simulator

This section describes how scenarios to test in the simulator are generated in MATLAB, and how task and shift dependent data is generated during the simulations. In order to evaluate the mathematical model's applicability for real wind farms, scenarios are generated based on selected input data that aims to be as realistic as possible. This input data is used to create scenarios where the number and type of corrective maintenance and weather forecast for the planning period are generated randomly and varying for each scenario. How sets and parameters of the scenarios are generated are illustrated by Figure 33. In the following sections the generation of corrective maintenance and weather forecasts are studied in detailed, followed by a description of the cost parameters of the mathematical model. As described in Section 7.1, a scenario file includes data on all shifts from the first shift in the simulation period, shift $s = 1$, to the last shift of the planning period of the last shift in the simulation period, shift $s = n + |S| - 1$. When discussing sets and parameters that are generated for the simulation period throughout this section, this includes all shifts from $s = 1$ to $s = n + |S| - 1$. The reader is referred to the MATLAB code of the scenario generation and of the simulator enclosed with the report for a deeper study of how different sets and parameters are calculated and generated.

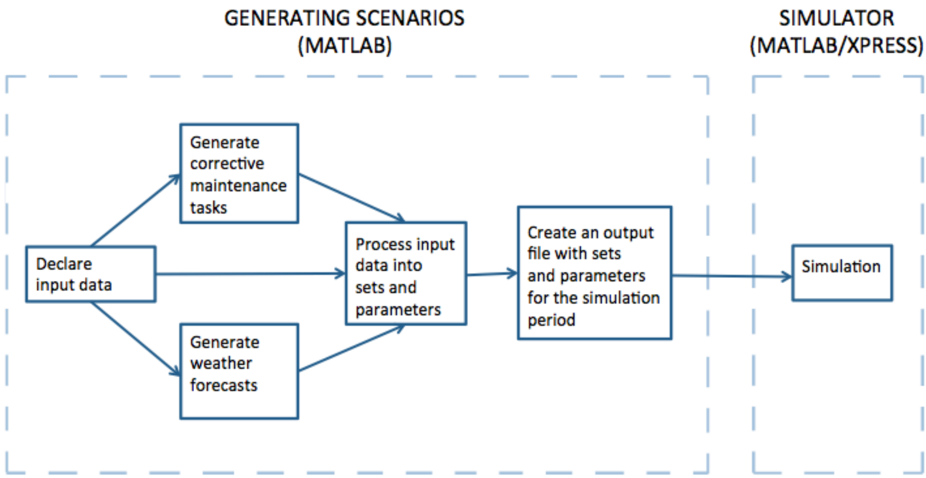


Figure 33: Illustration of the generation of random scenarios to test in the simulator.

7.3.1 Maintenance Tasks Generation

Maintenance tasks are divided into six categories; triggered alarms, manual resets, minor repairs, medium repairs, major repairs and preventive maintenance. As a simplification, it is assumed that the properties of tasks of the same category are identical. Maintenance tasks for an instance are generated based on the number of turbines in the wind farms. The maintenance tasks are then allocated to the different wind farms, and a set of which vessels that can perform the maintenance task is generated. The set of maintenance tasks are referred to as M in the model formulation, the set of which maintenance tasks that are located in wind farm i as M_i and the set of which vessels that can perform maintenance task m as V_m. Preventive maintenance tasks and corrective maintenance tasks are distinguished in the model and separated into two different sets. These two sets are generated differently in the scenario generator. For each different scenario for a specific set of wind farms simulated over the same season, the number of preventive tasks is constant. The number of corrective tasks is random and changes for different scenario.

It is assumed that all corrective tasks of the types manual reset, minor repair, medium repair or major repair are the results of triggered alarms, as described in Section 3. Alarms for each shift within the simulation period is generated using a binomial distribution for an alarm to be triggered (the combined failure rates of all other types of corrective tasks and false alarms) at a turbine and for no alarms to be triggered at the turbine. The number of triggered alarms is calculated based on the number of successes for n independent experiments, where n is the number of turbines. For each triggered alarm that occurs, a binomial distribution is used to decide if the alarm results in a corrective task, and if so, which type of corrective task it results in. The set of corrective maintenance tasks are referred to as M^C in the model formulation, where M^C includes both triggered alarms and other corrective tasks.

Preventive maintenance tasks generated are based on the yearly amount of preventive maintenance that is required by a turbine. The total hours of preventive tasks in the wind farm is then calculated, and this is used to calculate how many preventive tasks that must be performed during a shift to complete all preventive tasks during a year. It is favorable to perform preventive maintenance when energy production, and, hence, downtime costs, are low, and therefore the number of preventive tasks generated is seasonally dependent. Of the total number of yearly preventive tasks, the highest proportion of tasks is allocated to be performed during summer and the lowest during winter.

To allow for some flexibility in when to perform preventive maintenance, the number of total preventive tasks generated for the simulation period is higher than the demand. This allows for performing more preventive tasks when energy production is low. The number of desired preventive tasks for the planning period is set to be less than the actual demand, to β % of the actual demand. This allows for shifting some preventive maintenance from periods when energy production is high to later periods of lower production. The set of generated preventive maintenance tasks are referred to as M^P in the model formulation and the number of desired preventive tasks as B.

7.3.2 Weather Generation

The weather parameters of interest in the scenarios are wind speeds and wave heights for the shifts of the simulation period. Wind speeds are used to calculate downtime costs for the respective shifts, while wave heights are used to generate weather windows for the different vessel types for each shift. In practice, other wave parameters such as wave period, currents and wave direction, influence the accessibility of a wind turbine for a given vessel in addition to wave heights. A comparison of the availability and the O&M costs using a single-parameter wave criteria of wave height and using a multi-parameter wave criteria was conducted by Sperstad et al. in [72]. The results showed that these two approaches gave relatively similar outcomes. It is therefore chosen to base the weather windows of this problem on wave heights only.

The weather of the simulation period is generated randomly based on two input parameters. The first is the season of the simulation period. The second is a loaded data file containing wind speeds and wave heights of several years with an hourly resolution. A random year is chosen from the data file, and then a continuous period of the same length as the simulation period is randomly chosen within the given input season this year. The wind speeds and wave heights of the simulation period is set equal to the wind speeds and the wave heights of the period chosen from the data file. As a simplification in the model, it is assumed that the wind speed is constant within a shift. The wind speed is therefore changed to the average of these hourly values loaded from the data file for a shift.

Weather windows are generated based on the wave height loaded from the data file. A weather window for a vessel is the continuous time in a shift where the wave heights do not exceed the wave height limits of the vessel. If several weather windows exist in one shift, the longest weather window is chosen. In the model formulation the weather windows are given as lower bounds, L^W_{vs}, and upper bounds, U^W_{vs}, for when a vessel v can perform maintenance during shift s.

7.3.3 Calculation of Cost Parameters

The objective function of the mathematical model presented in Chapter 5 minimizes both real costs and penalty costs of the problem. In this section the cost parameters of both the real costs and the penalty costs are explained.

Transportation costs are split into costs of travelling between nodes (the depot and the wind farms) and of travelling between turbines within a wind farm. Transportation costs of travelling between nodes are calculated based on the distances between nodes and the transportation speeds and costs of different vessel types. They are referred to as C^T_{ijv} in the model formulation and are calculated as shown in Equation (76).

$$\begin{aligned}\text{Transportation Costs [EUR]} = &\\ &\frac{\text{Distance Between Nodes [km]}}{\text{Speed of Vessel [km/h]}}\\ &* \text{ Transportation Cost of Vessel [EUR/h]}\end{aligned} \tag{76}$$

As stated in the introduction of Chapter 5, internal turbine locations are ignored as the distances between the turbines are negligible compared to distances between nodes. To approximate the internal transportation costs, an internal cost parameter is added to each performed delivery task. When calculation this internal cost parameter it is attempted to capture the difference in fuel costs of a vessel lying still and waiting in the wind farm and the fuel costs of transporting technicians between turbines and transferring technicians to and from a turbine. It is assumed that when transporting technicians between turbines the vessels run on full speed. How the vessels transfer technicians to and from the turbines varies for different types of vessels. Smaller ships like CTVs and SESes keep their position by pressing against the turbine while larger ships such as AVs uses a dynamic positioning system that requires a lot of power. As a simplification it is assumed that all types of vessels run on approximately full power when transferring technicians. Vessels that wait in the wind farm keep their engines on, and, hence, fuels costs occur regardless if a vessel is transporting technicians or lies still, waiting for tasks to be performed. The fuel cost difference of lying still and transporting and transferring technicians is estimated to be 40 %.

The internal transportation costs are calculated as shown in Equation (77). The time of transporting technicians between turbines is negligible compared to the transfer time, and, hence, only the transfer time is used. The transfer time is included twice for each task performed, once for transferring technicians to the turbine, and once for transferring the technicians from the turbine. The time of transferring is then multiplied by 40 % of the transportation costs at full power. The internal transportation costs are referred to as C_v^{IT} in the model formulation.

$$\begin{aligned}&\text{Internal Transportation Costs [EUR/Task]} = \\ &\qquad \text{Time to Transfer Technicians [h]} * 2 \\ &\qquad * \; 40\ \% * \text{Transportation Cost of Vessel [EUR/h]}\end{aligned} \tag{77}$$

The costs of an AV to stay offshore during nights are simplified to 0 for the scenarios generated. This is because it is assumed that night costs such as salary for the crew, are not dependent on the AV being onshore or offshore at night. This cost parameter is referred to as C_v^{OUT} in the model formulation.

Downtime costs are calculated for each task during each shift. They are dependent on the power output of the corresponding turbine and the turbine output in percentage of maximum output given the wind speeds of the respective shifts. The relationship between the power produced and the wind speed is shown in

Figure 17 of Section 2.4. How downtime costs are calculated is shown in Equation (78). Downtime costs are referred to C_{ms}^{LP} in the model formulation.

$$\begin{aligned}
&\text{Downtime Costs [EUR/h]} = \\
&\qquad \text{Energy Price [EUR/MWh]} \\
&\qquad * \text{ Effect of Turbine [MW]} \\
&\qquad * \text{ (Turbine Efficiency Given Wind Speed) [-]}
\end{aligned} \tag{78}$$

The penalty cost of not completing a preventive task within a shift is included to force the model to perform preventive maintenance. As the turbines with preventive tasks are only shut down when the task is performed, downtime costs does not give incentive to perform preventive maintenance tasks, rather the opposite. To ensure that preventive tasks are given incentive to be completed, independent of which wind farms the tasks are located in, this penalty cost is calculated using the sum of the largest possible transportation costs and the largest possible downtime costs of the turbines during a shift. This is shown in Equation (79). The costs of an AV travelling to the wind farm furthest from the depot, including the internal transport costs, are used for the largest possible transportation costs. Using the largest possible transportation cost forces any free vessel to perform the tasks, regardless of the vessel type. The largest possible downtime costs are calculated using the maximum power output of the turbine of the highest capacity. The downtime costs are calculated for one hour longer than the time possible to perform maintenance during a shift. This is to ensure that the penalty costs are higher than the downtime costs of performing the task, even if the turbines are generating maximum power and the tasks are performed by an AV from the shift starts and during the entire shift. The penalty cost of of not completing a preventive task within a shift is referred to as C_m^{NP} in the model formulation.

The Penalty Cost of Not Completing a
Preventive Task Within a Shift [EUR/Task] =
Energy Price [EUR/MWh]
* Highest Effect of Turbines [MW]
* (Time Possible To Perform Task During Shift + 1 Hour) [h]
+ Transportation Costs for an AV to the Wind Farm
Furthest from the Depot [EUR]
+ Internal Transportation Costs for the AV [EUR] (79)

The model distinguishes between the number of desired preventive tasks to be completed in the planning period and extra preventive maintenance tasks to be performed when energy production is low. A parameter of which shifts it is desirable to perform extra preventive maintenance tasks is included in the model. This parameter is referred to as K_{ms} in the model formulation. It is given the value of 1 if it is desirable to perform extra preventive maintenance during shift s, and 0 if not, and it has the possibility to be task specific. The values of K_{ms} is depending on the wind speeds of the shifts. It is set to 1 when production is lower than a specified percentage of the maximum energy output possible. This percentage is hereby referred to as α. When a turbine produce less than α % of maximum power, it is more attractive to perform extra preventive tasks than generate power. The α is case specific, and should be determined based on evaluation of several factors. Examples of such factors are how many preventive tasks the user of the model wishes to perform during the planning period: the average demand for preventive tasks, above the average demand or below the average demand, or if there are an overriding target on electricity produced. The determination of α is also affected by how many preventive tasks to be performed during the year, the amount of the demand that are scheduled for each planning period, how many preventive tasks that have been performed during previous planning periods and the size of the vessel fleet.

The penalty cost of not completing a corrective task within a shift is included to force that corrective tasks are completed even in periods of low energy production where accumulated downtime costs are lower than transportation costs. This penalty cost is calculated by using the maximum downtime costs for one day of one turbine, as shown in Equation (80). The length of one day was decided by trials in MATLAB to get a penalty cost of corrective tasks guaranteed higher than the penalty cost of not doing desired preventive tasks. This gives an incentive to perform corrective tasks before preventive tasks. The penalty cost of not completing a corrective maintenance task within a shift is referred to as C_m^{NC} in the model formulation.

$$\begin{aligned}&\text{The Penalty Cost of Not Completing a}\\&\text{Corrective Task Within a Shift [EUR/Task]} =\\&\qquad\text{Energy Price [EUR/MWh]}\\&\qquad\text{* Highest Effect of Turbines [MW] * 24 [h]}\end{aligned} \tag{80}$$

The penalty costs of not starting a task that there is not enough time to complete within the planning period are included to give incentive to start performing tasks that are not completed until after the planning period ends. If these penalty costs are not included the model will not start performing a task that requires more time than available within the planning period and it may not perform tasks towards the end of the planning period. These penalty cost parameters are not directly included in the objective function, however, they affects the values of variables in the objective function, the variables c_m. The variables c_m are dependent on a penalty cost parameter and how many hours that are left of the tasks started, the more hours left, the higher value of c_m. These penalty cost parameters are referred to as C_m^{NC*} and C_m^{NP*} in the model formulation and are calculated as shown in Equation (81) and (82).

The penalty cost parameters of not starting tasks that are not completed are calculated per hour and then multiplied with the hours left of the tasks to give value to c_m. This is to give incentive to perform as many hours of the task as possible, not just incentive to start performing it. The penalty cost parameters are calculated using the downtime costs of one hour and an estimate for the transportation costs per hour. The downtime costs of a shift of maximal power output is used to ensure that incentives are given also on days of maximum energy production. It is not possible to calculate the accurate average hourly transportation costs, as the number of performed hours is not known in advance of solving the problem. As an estimate, the total transportation costs are divided on the minimum amount of preventive maintenance that must be performed consecutively. The cost parameter of corrective tasks is set incrementally higher than for preventive tasks to force the model to prioritize corrective tasks over preventive tasks in shifts with no downtime costs.

$$
\begin{aligned}
&\text{The Penalty Cost of Not Starting Corrective Tasks [EUR/h]} = \\
&\qquad \text{Energy Price [EUR/MWh]} \\
&\qquad * \text{ Highest Effect of Turbines [MW]} \\
&\qquad + \frac{\text{Transportation Costs [EUR]}}{\text{Minimum Time of Performing Preventive Tasks [h]}} \\
&\qquad + 1
\end{aligned} \tag{81}
$$

$$
\begin{aligned}
&\text{The Penalty Cost of Not Starting Preventive Tasks [EUR/h]} = \\
&\qquad \text{Energy Price [EUR/MWh]} \\
&\qquad * \text{ Highest Effect of Turbines [MW]} \\
&\qquad + \frac{\text{Transportation Costs [EUR]}}{\text{Minimum Time of Performing Preventive Tasks [h]}}
\end{aligned} \tag{82}
$$

8 Computational Study

In this chapter the results from a computational study of an exact implementation of the mathematical model presented in Chapter 5 and the two rolling horizon heuristics presented in Chapter 6 are presented. Implementation details of the tests are outlined in Section 8.1, and in Section 8.2 the input data of the scenarios used for testing is described. Tests of the static problem are performed to evaluate and compare the performance of the exact model and the two heuristics, and the results are presented in Section 8.3. The exact model and the best performing heuristic are then tested in a dynamic setting to adjust for technical aspects, and the results are presented in Section 8.4. In Section 8.5 the results of testing for different parameter values of the mathematical model are presented. Finally, in Section 8.6, it is illustrated how simulations of the problem using the mathematical model can provide valuable information when analyzing strategical aspects of O&M in offshore wind farms.

As both the rolling horizon heuristics and the simulations are solved iteratively, the use of the term iteration can cause some confusion. In this chapter, the terms iteration and iteratively are used for iterations of the heuristics. Throughout this section an iteration of the simulator is referred to as solving a planning period of the simulations.

Abbreviations are used in figures presented throughout the computational study. These abbreviations are presented in Table 4.

Table 4: List of abbreviations used in the figures of the computational study.

OV	Objective value
ST	Solution time
RC	Real costs
TC	Transportation costs
DC	Downtime costs
M	Number of hours of maintenance performed
CM	Number of hours of corrective maintenance performed
PM	Number of hours of preventive maintenance performed
RC/M	Real costs per hour of maintenance performed

8.1 Implementation of the Solution Methods

The computational study is based on implementation of the mathematical model in commercial optimization software. All the different solution methods are implemented using Xpress Mosel as the modelling language and solved using Xpress version 7.8.0. The implementations of the mathematical models are called from a simulator developed in MATLAB, version R2014a. Simulations are used for both static and dynamic tests of the models, however, for static tests the simulation period is set to one shift. Hence, only one planning period is solved in the static tests. A separate MATLAB code is developed to generate scenarios to simulate. Sets and parameters of the scenarios are written to MAT-files to load in the simulation code.

The aim of the rolling horizon heuristics is to find solutions of high quality within the chosen time limit. Also for the exact model it is more important to find a solution of high quality than to prove optimality, as the problem size and complexity can make the problem hard to solve within the specified time limit. To enhance the chance of finding high quality solutions, the automatic strategies for cuts and heuristics in Xpress are overruled for the implementation of both the exact model and the heuristics. The cut strategy is set to no cuts, 0, to avoid spending unnecessary time to improve the bound and instead focus on finding a better solution. For the heuristic strategy, an extensive heuristic strategy is chosen. Using an extensive search, more time is allocated at the beginning of the solving process to finding a good solution.

The tests of the computational study are performed on a HP DL 165 G6 computer with an AMD Opteron 2431 2,4 GHz processor, 24 GB of RAM and running on a Linux operating system. The implementations of the mathematical model, the simulator and the code for generating scenarios used for the computational study can be found in the enclosed digital attachments.

8.2 Input Data

This section outlines the input data that is used to generate scenarios to test in the simulations. In order to generate realistic scenarios, best practice for the offshore wind industry has been applied where possible. Various sources and expert opinions have been used to find different parameter data. Energy from offshore wind is a relatively new industry and access to input data is limited. Reasonable estimates has therefore been used when there is no data available. The input data that is used when generating scenarios is mainly based on a reference case created for verification of O&M simulation models for offshore wind farms by Dinwoodie et al. in [26] and on conversations with Bjørn Ivar Vold, asset management engineer in Wind Offshore in Statkraft.

Three types of vessels are included in the vessel fleet of the scenarios generated, AVs, regular CTVs and SESes. Speed, transportation costs, maximum offshore time, and wave height limits of the three vessel types are given in Table 5. The speed and wave height limits for regular CTVs and the speed of AVs are found in the reference case by Dinwoodie et al. in [26]. Wave height limits for AVs are based on the results of a computational study on wave limits from [72], while wave height limits for SESes are, together with the speed of SESes, taken from the vessel specifications of the SES Umoe Mandal WaveCraft [79]. Transportation costs for regular CTVs are given in [21]. As data for AVs and SESes are limited, costs of these vessels are chosen within a reasonable estimate compared to the costs of regular CTVs. Daily cost rates are given in [74].

Table 5: Vessel fleet input data used to generate scenarios.

	AV	SES	Regular CTV
Speed of vessel [knots]	12	45	20
Transportation costs [EUR/h]	1 125	383	225
Maximum offshore time	4 weeks	1 shift	1 shift
Wave height limits [m]	3.0	2.5	1.5
Daily cost rates [EUR/day]	6 950	16 700	2 360

Input data on different types of maintenance tasks are given in Table 6. Except for triggered alarms, these categories and the corresponding data are taken from the reference case by Dinwoodie et al. in [26]. The categories are based on types of maintenance tasks and their respective failure rates defined in the Reliawind project, a project that identified and analyzed critical failures of wind farms [87]. Data on triggered alarms are based on conversations with Bjørn Ivar Vold. It is assumed that a corrective task can only happen after an alarm is triggered, however not all triggered alarms result in maintenance tasks, some can be false alarms. The failure rate of a triggered alarm is therefore set to be equal to the total failure rate of a corrective task happening at the turbine and the rate of false alarms. The rate of false alarms is assumed to be approximately 10 % of the total triggered alarms.

Only tasks that can be performed by AVs, regular CTVs or SESes have been included in the data set, tasks that require jack-up barges, such as major replacements, are omitted. Task durations, yearly failure rates, what vessel types that can perform the tasks and what tasks that require the vessel to stay at the turbine when performed are given in Table 6.

Table 6: Maintenance task input data used to generate scenarios.

	Triggered alarms	Manual Reset	Minor Repair	Medium Repair	Major Repair	Preventive maintenance
Task duration [h]	0.5	3	7.5	22	26	60
Required technicians	2	2	2	3	4	3
Yearly failure rate	12	7.5	3.0	0.275	0.04	1
Vessel type	All	All	All	All	AV	All
Requires vessel to stay at turbine	No	No	No	No	Yes	No

The number of desired preventive tasks, β, is set to 70 % of the demand in the planning period. Of the total number of yearly preventive tasks, 50 % are allocated to be performed during summer, 25 % during spring and 25 % during fall. The power output level of when it is considered as more attractive to produce power than to perform additional preventive maintenance, α, is set to 25 % of the maximum power output. This corresponds to a wind speed just below 10 m/s, as can be calculated from Figure 17. Incentive to perform extra preventive tasks is then given when the wind speed is outside the range where a turbine produce more than 25 % of maximum output, i.e. when the wind speeds are below 10 m/s or above the cut off speed.

Weather forecasts for the scenarios generated are based on weather data collected from 2004–2012 at the offshore research platform FINO 1. This is the same weather data as used for the reference wind farm in [26]. FINO 1 is situated in the North Sea, approximately 45 km to the north of Borkum, Germany, and can be considered representative of Central North Sea conditions [34]. The price of energy is set to 90 EUR/MWh, including both the electricity selling price and subsidies.

For comparison purposes when analyzing the mathematical model, a reference case of two wind farms has been constructed to form a basis for the scenarios generated. Data such as capacity of turbines, length of shifts and vessel fleet are fixed for this reference case and apply to all scenarios tested if not otherwise stated. The time unit used in the scenarios generated is hours, and, hence, there are 24 time units in one day. The fixed input data are summarized in Table 7 and Table 8.

Table 7: General input data used to generate scenarios.

Number of wind farms	2
Distance between wind farms [km]	50
Number of AVs	1
Number of SESes	1
Number of regular CTVs	0
Length of shifts [h]	12
Time to transfer technicians from vessel to turbine [h]	0.5
Season	Summer

Table 8: Wind farm specific input data used to generate scenarios.

	Wind farm 1	Wind farm 2
Capacity of turbines [MW]	5	3.6
Distance from depot [km]	80	70
Distance between turbines [km]	1	1

8.3 Testing of the Solution Methods for the Static Problem

This section presents the results of testing the exact model and the two rolling horizon heuristics for the static problem, i.e. for one planning period. In Section 8.3.1 it is tested how large problems the exact model and the heuristics can solve. The performance of the three models are then evaluated by comparing solution time and solution quality in Section 8.3.2. Solution quality is compared in terms of the objective values. In Section 8.3.3, the effect of adding the symmetry breaking constraints presented in Section 6.2 are tested for the best performing heuristic.

For real problems, it is found sufficient if the model is solved within two hours. The upper limit on solution time of the exact model is therefore set to 7200 seconds. As the heuristics are tested for planning periods of up to three shifts, an upper limit on solution time for each iteration is set to 2000 seconds. With a solution time of 2000 seconds and three shifts in the planning period, and thus three iterations, the total solution time of the heuristics stays within two hours.

To obtain statistical significance of the tests performed in the computational study, several problems are solved for each test. Throughout the computational study, 95 % confidence intervals of the solutions of these problems are used for comparisons for each test performed. When comparing two different models, parameters of a model or length of the planning period, confidence intervals for the difference in solutions for each problem tested are used. Only problems where at least one solution is found for both the compared models are included in the confidence intervals.

8.3.1 Performance of Solution Methods

To test how large problems the exact model is able to solve, the exact model is tested for problems with different numbers of turbines and different lengths of the planning period. Each combination of number of turbines and length of planning period tested are referred to as a problem combination, and for each problem combination twenty problems are tested. An overview of the problem combinations tested for the exact model is given in Table 9.

Table 9: Results of problem combinations solved by the exact model: Number of problems in, range in number of tasks in, number of problems where at least one solution is found and number of problems solved to optimality for each problem combination.

	Range in no. of tasks of problem combination	No. of problems in problem combination	No. of problems with at least one solution	No. of problems solved to optimality
1 shift - 120 turbines	8 – 17	20	20	9
1 shift - 140 turbines	11 – 25	20	20	3
1 shift - 160 turbines	11 – 23	20	20	3
1 shift - 180 turbines	14 – 27	20	20	1
2 shift - 120 turbines	8 – 17	20	14	8
2 shift - 140 turbines	11 – 25	20	8	3
3 shift - 120 turbines	8 – 17	20	17	8
3 shift - 140 turbines	11 – 25	20	13	2
3 shift - 160 turbines	11 – 23	20	10	0

For all tested problems with a planning period of one shift at least one solution is found, however all problems are not solved to optimality. Figure 34 presents the 95 % confidence intervals of the gaps in the solutions of these problem combinations. As Table 9 and Figure 34 show, the exact model can solve realistic problems, both for current and future offshore wind farms sizes, within a reasonable gap in objective value for a planning period of one shift. The exact model struggles to solve larger problems for longer planning periods than one shift. For several of these problems tested, no solution is found within the memory capacity of the computer.

RHH-1 is tested for the problem combinations with planning periods of three shifts and RHH-2 is tested for the problem combinations with planning periods of two and three shifts. The results of testing RHH-1 and RHH-2 are presented in Table 10 and Table 11, respectively. The same twenty problems of the problem

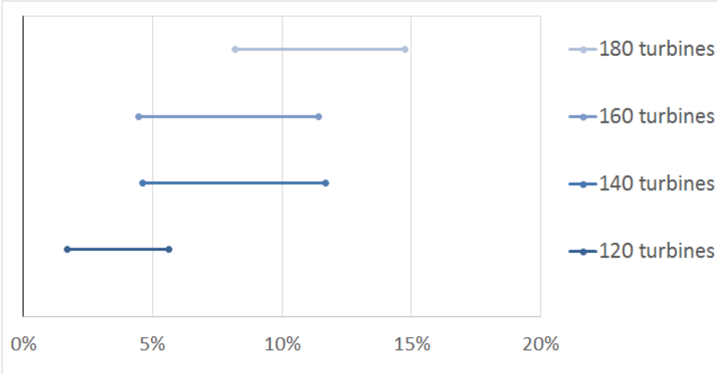


Figure 34: 95 % confidence interval for the gap of the solutions when solving the exact model for a planning period of one shift and different numbers of turbines.

combinations tested for the exact model are used to test RHH-2 and RHH-1. The heuristics are not tested for a planning period of one shift. Solving the heuristics with only one shift in the planning period means that only the free detailed time block, DTB, of the heuristic is active. There are no fixed DTB or aggregate time block, ATB, in this case. Hence, it is equivalent to solving the exact model for a planning period of one shift. As the tables show, RHH-1 and RHH-2 can solve problems of realistic wind farm sizes for current offshore wind farms with a planning period of more than one shift. However, when the number of turbines increases to realistic future wind farm sizes, both of the heuristics starts struggling to find solutions to all the problems tested.

Table 10: Number of problems tested for RHH-1 where at least one solution is found and number of problems tested for RHH-1 that obtain solutions equal to or better than the solutions of the exact model.

	No. of problems with at least one solution	No. of solutions equal to or better than the solutions of the exact model
3 shift - 120 turbines	18	14
3 shift - 140 turbines	16	11
3 shift - 160 turbines	13	9

Table 11: Number of problems tested for RHH-2 where at least one solution is found and number of problems tested for RHH-2 that obtain solutions equal to or better than the solutions of the exact model.

	No. of problems with at least one solution	No. of solutions equal to or better than the solutions of the exact model
2 shift - 120 turbines	20	17
2 shift - 140 turbines	20	19
3 shift - 120 turbines	20	14
3 shift - 140 turbines	20	10
3 shift - 160 turbines	17	13

8.3.2 Comparison of Solution Methods

From Table 9 – 11 it can be seen that RHH-1 and RHH-2 are able to solve larger problems than the exact model, and that the heuristics finds solution of equal or higher quality than the exact model for several of the problems tested. This is possible for the problems where the exact model is not solved to optimality or the exact model does not find any solution to the problem. 95 % confidence intervals of the difference in the performance of the three models are calculated and presented in Figure 35 – Figure 37. Figure 35 and Figure 36 show how RHH-1 and RHH-2 perform better than the exact model in terms of solution time. For RHH-2 the difference in objective value is relatively small, while for the RHH-1, the objective values are generally higher than for the exact model.

From Figure 37 it can be seen that the solutions of RHH-1 are in general more expensive than the solutions of RHH-2 for the problems tested. In addition, the confidence interval for the difference in RHH-1 and the exact model is much larger than for RHH-2 and the exact model. This means that RHH-2 provides solutions of less variable quality than RHH-1 and that the performance of RHH-2 is more stable than the performance of RHH-1.

Based on the results of testing the three models, RHH-2 is considered as the best performing model for planning periods of more than one shift. RHH-2 finds at least one solution to more problems than both the exact model and RHH-1, it provides solutions of high and stable quality and it has the lowest solution time for the problems tested. As RHH-2 performs better than RHH-1, this implies that that for this problem, fixing more decisions in the DTB is more efficient than keeping several variables free during later iterations. It seems that too much time is spent on re-assessing these variables, and that this prevents that

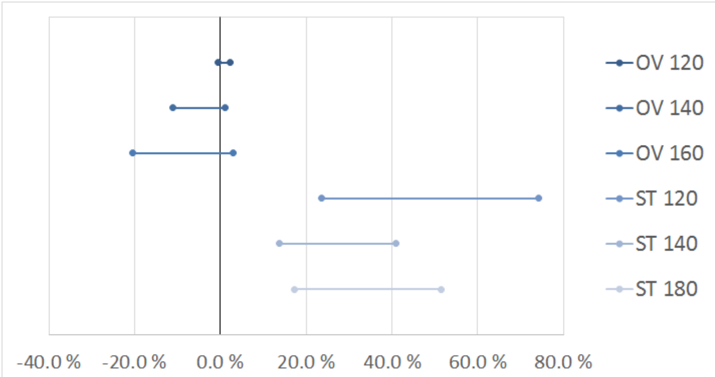


Figure 35: 95 % confidence interval for the difference in objective value and solution time for the exact model and RHH-1 for problems of 120, 140 and 160 turbines, with a planning period of three shifts. Positive differences mean that the values of the exact model are greater than for RHH-1.

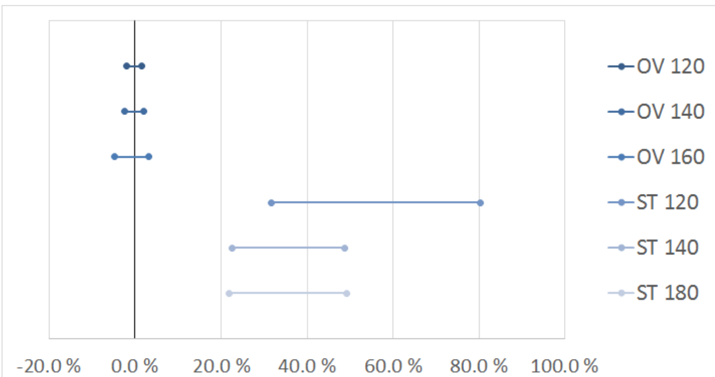


Figure 36: 95 % confidence interval for the difference in objective value and solution time for the exact model and RHH-2 for problems of 120, 140 and 160 turbines, with a planning period of three shifts. Positive differences mean that the values of the exact model are greater than for RHH-2.

solutions of higher qualities are found. RHH-1 is therefore discarded in favor of RHH-2 and not further tested.

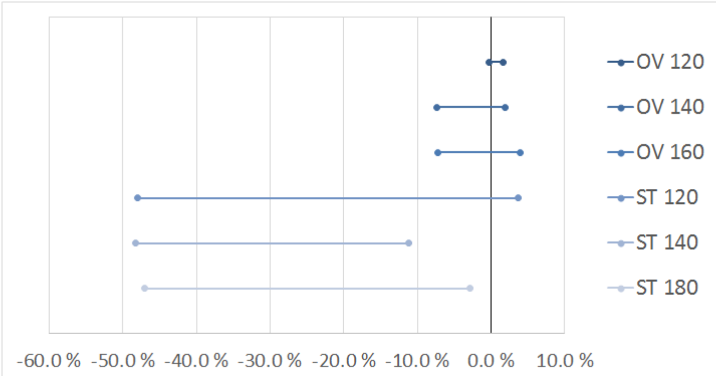


Figure 37: 95 % confidence interval for the difference in objective value and solution time for RHH-2 and RHH-1 for problems of 120, 140 and 160 turbines, with a planning period of three shifts. Positive differences mean that the values of RHH-2 are greater than for RHH-1.

8.3.3 The Effect of Symmetry Breaking Constraints on the Solution Methods

To increase the computational efficiency of the solution methods, symmetry breaking constraints are added to the model formulation. Symmetry breaking constraints can, however, cause some problems when they are applied to heuristics. When adding such constraints, particular solutions are eliminated from the solution space, and this may conflict with the search direction of the heuristic. Tests are therefore conducted to study how the added symmetry breaking constraints affect the solutions of RHH-2.

RHH-2 is tested without the symmetry breaking constraints for the twenty problems of the problem combinations with a planning period of three shifts and 120 and 140 turbines. From Table 12 and Figure 38, it seems that RHH-2 without the symmetry breaking constraints performs equal to or better than with the symmetry breaking constraints in terms of objective value. This implies that the added symmetry breaking constraints eliminate solutions of high quality. However, as the table shows, without the symmetry breaking constraints RHH-2 are not able to solve all the problems tested. In addition, the solution time increase significantly for several of the problems. As the solution quality is not reduced considerably, it is considered as more important to find good solutions to more problems, than better solutions to fewer problems. Hence, the symmetry breaking constraints are kept in RHH-2 for the further testing.

Table 12: Comparison of the solutions of RHH-2 with symmetry breaking constraints (SBC) and without SBC. The table includes the number of problems where at least one solution is found, the number of problems where RHH-2 with SBC found better solutions than without SBC (with SBC > without SBC), equal solutions (with SBC = without SBC), and worse solution (with SBC < without SBC).

	No. of problems where at least one solution is found without SBC	With SBC > without SBC	With SBC = without SBC	With SBC < without SBC
2 shifts - 120 turbines	19	7	5	8
2 shifts - 140 turbines	18	16	0	4

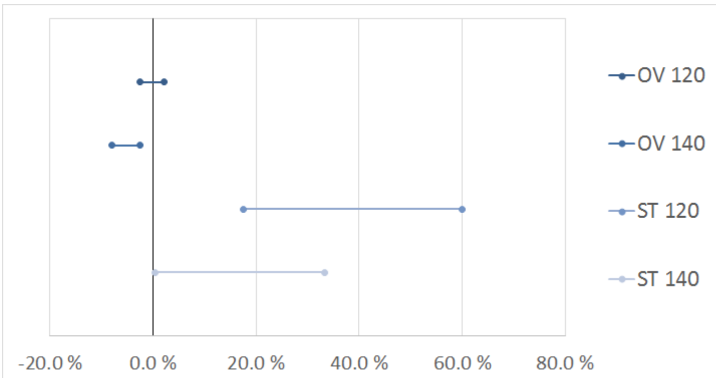


Figure 38: 95 % confidence interval for the difference in objective value and solution time for RHH-2 without and with symmetry breaking constraints. Positive differences mean that the values of RHH-2 without the symmetry breaking constraints are greater than with the symmetry breaking constraints.

8.4 Testing of the Solutions Methods in a Dynamic Setting

Specific technical aspects of the exact model and RHH-2 are further tested in a dynamic setting to improve the performance. These aspects include the length of the planning period, the number of iterations solved for a specific length of the planning period and the upper limit on the solution time of each iteration in the heuristic.

The models are tested dynamically by simulating the problem over a longer time period using the simulation framework presented in Chapter 7. For the tests of this section, a simulation period of seven shifts are used. When performing simulations the length of the simulation period can affect the results. The closer the length of the simulation period is to the length of the real problem horizon, the more accurate results the simulations yield. The results of a simulation can also be affected somewhat by some start and end effects of the simulation period. Unless a start-up situation is simulated, then the simulation can fail to capture the effect of decisions made in periods prior to the simulation period. Likewise, toward the end of the simulation period, lack of information on periods subsequent the simulation period can result in sub-optimal solutions for the last iterations of the simulation. To minimize these effects it is important to choose a sufficiently long simulation period. For the tests of the computational study, two measures are included to reduce start and end effects. Corrective tasks which symbolizes the result of checked alarms in the shift prior to the first shift of the simulation period are generated and included in the simulations. This is done to capture some of the decisions made in earlier periods and, which will reduce the start effects. To reduce the end effects of the simulations, input data (or information) of all shifts in the planning period of the last shift in the simulations are included. This means that if the length of the simulation period is n and the length of the planning period is $|S|$, then information on all shifts from shift 1 in the simulation period to shift $n + |S| - 1$ is included in the simulations. This is illustrated in Figure 27 of Section 7.1. The amount of information when solving for the last shifts of the simulation period is then equal to the amount of information when solving for any other shift.

To evaluate the different aspects of the models studied in each test, solution time and solution quality are compared. Solution quality is evaluated based on real costs and the number of hours of maintenance performed. To compare the number of hours of maintenance, the sum of all hours of work during the entire simulation period is used. This means the sum of all hours of maintenance performed during the first shift of each iteration of the simulations. The same apply to the real costs, when comparing real costs, the sum of the real costs for all shifts of the simulation period is compared. Real costs consists of the variable costs that are dependent on the schedules generated; the transportation costs and the downtime costs. Daily fixed costs, such as daily vessel rates, are not included, as these occur for each shift regardless of the schedules generated. The number of hours of maintenance performed includes both corrective and preventive maintenance, unless otherwise stated. For the dynamic tests solution time is evaluated in terms of the solution time of solving one planning period in the simulations.

8.4.1 Length of the Planning Period

Changing the length of the planning period is tested to see if the value of additional information from including more shifts in the planning period improve the solution quality. To test the planning period length, ten scenarios with 120 turbines are tested for planning periods of one, two and three shifts.

Figure 39 presents the results of comparing RHH-2 solved for planning periods of two and three shifts. The results of comparing RHH-2 solved for a planning period of two shifts and the exact model solved for one shift are presented in Figure 40. The upper time limit of the exact model is reduced to the time that is allocated to solve each iteration of the heuristic, to 2000 seconds.

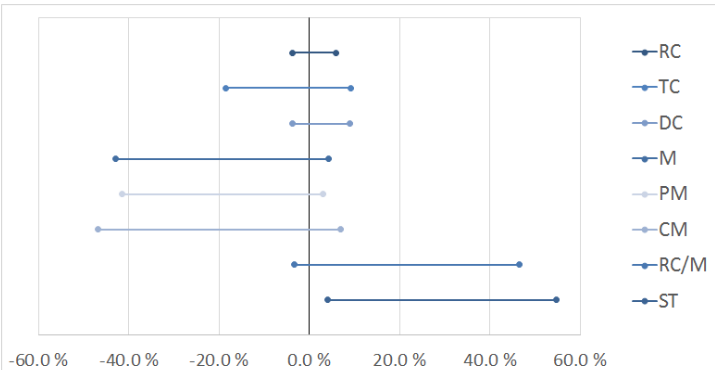


Figure 39: 95 % confidence interval for the difference in solution time and solution quality for RHH-2 with a planning period of two and three shifts. Positive differences mean that the values of a planning period of three shifts are greater than for a planning period of two shifts.

The figures show that by reducing the length of the planning period, the solution time is reduced. This is especially due to reduction in the number of iterations. Reducing the length of the planning period also improves the solution quality, generally the real costs are reduced and more maintenance is performed. It appears that the heuristic puts too little emphasis on the first shift of the planning period and that it uses too much computational effort on solving later shifts. Reducing the length of the planning period therefore reduces the computational effort needed to solve the problem. These results imply that the value of including information on additional shifts in the planning period is lower than the decrease in solution quality caused by the extra computational effort needed, hence, a greedy approach is favorable for the problem studied in this thesis.

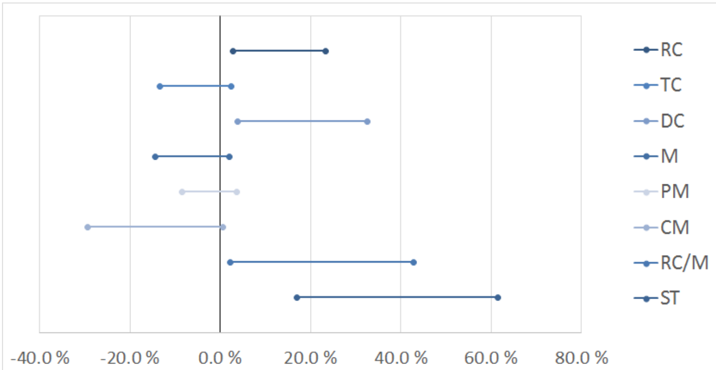


Figure 40: 95 % confidence interval for the difference in solution time and solution quality of RHH-2 with a planning period of two shifts and the exact model with a planning period of one shift. Positive differences mean that the values of a planning period of RHH-2 with two shifts are greater than for the exact model with one shift.

One of the reasons that the value of additional information of later shifts is limited can be that it is favorable to perform most maintenance task during the first shifts, regardless of the weather forecasts of later shifts. For corrective tasks this applies due to the running downtime costs, it is never more favorable to perform a corrective task in a later shift if there is enough capacity to perform it during the first shifts. As preventive tasks are of a relatively long duration and the penalty costs give incentive based on the hours of performed maintenance, it is also favorable to perform preventive tasks in earlier shifts, as long as the electricity production is lower than a specified limit.

8.4.2 Number of Iterations Performed in RHH-2

This test evaluates the effects of reducing the number of iterations of RHH-2 to see if this can improve the heuristic, and if it can perform better than the exact model solved for a planning period of one shift.

When the number of iterations in RHH-2 is reduced, the heuristic only gives MIP-solutions for the shifts included in the DTBs of the performed iterations, while the solutions of the remaining shifts remain LP-relaxed. Scenarios of 120 turbines with a planning period of two shifts are studied and compared to the same scenarios solved by the exact model with a planning period of one shift. The results are presented in Figure 41 and Figure 42.

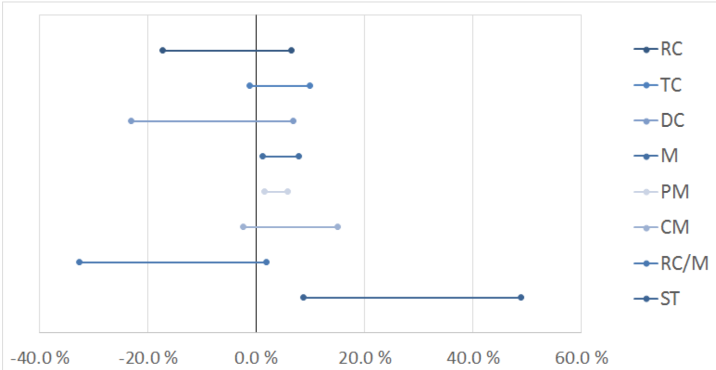


Figure 41: 95 % confidence interval for the difference in solution time and solution quality for solving one and two iterations of RHH-2 with a planning period two shifts. Positive differences mean that the values of solving two iterations are greater than for solving one iteration.

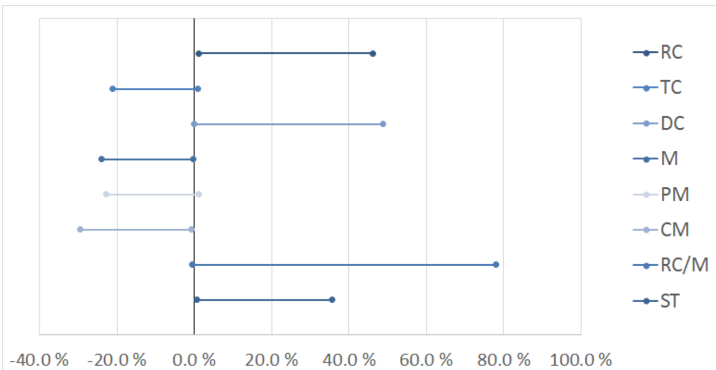


Figure 42: 95 % confidence interval for the difference in solution time and solution quality for solving the exact model with a planning period of one shift and for solving one iteration of RHH-2 with a planning period of two shifts. Positive differences mean that the values of solving RRH-2 are greater than for solving the exact model.

These results show that reducing the number of iterations for RHH-2 reduces the solution time, but at the expense of the solution quality. Compared to the exact model with one planning period, RHH-2 with one iteration reduces the solution time, however, the solution quality of the exact model is significantly higher. The exact model with one planning period is therefore considered as better than RHH-2 with a planning period of two shifts solved for one iteration.

8.4.3 Upper Limit on Solution Time of Each Iteration in RHH-2

In this test it is examined if an increase in the upper limit on the solution time of each iteration performed in RHH-2 can increase the solution quality. As mentioned, it is found sufficient if the model is solved within two hours for real problems. For the tests performed, the upper limit on the solution time of each iteration of RHH-2 is set to 2000 seconds. When reducing the number of shifts in the planning period to two shifts, this allows for an upper limit of 3600 seconds for each iteration. Figure 43 presents the results of comparing RHH-2 with a planning period of two shifts and a time limit of 3600 second for each iterations with the exact model with one planning period and solved within 2000 seconds. The difference of the solution quality of the two models are not substantial, however, the exact model provides somewhat better solutions than RHH-2. The solution time of the exact model significantly lower, due to that the total solution limit of the exact model is set significantly lower.

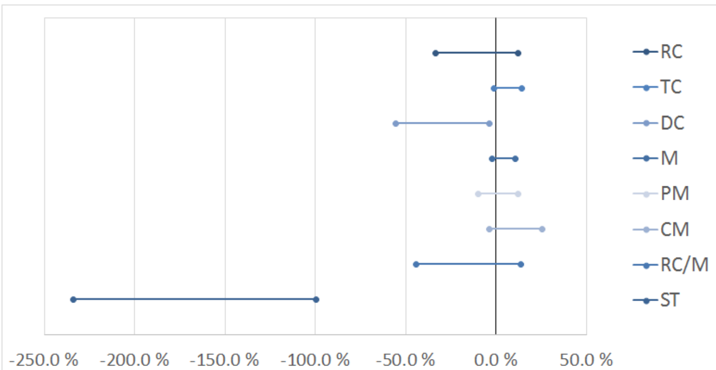


Figure 43: 95 % confidence interval for the difference in solution time and solution quality for solving the exact model with a planning period of one shift and for RHH-2 with a planning period of two shifts and an upper limit on solution time of each iteration of 3600 seconds. Positive differences mean that the values of solving the exact model are greater than for solving RHH-2.

Based on the results of testing different aspects of the exact model and RHH-2, it is chosen to use the exact model, solved for a planning period of one shift and with an upper limit on the solution time of 2000 seconds, for further testing in the computational study. The exact model solved for a planning period of one shift is tested dynamically for the symmetry breaking constraints presented in Section 6.2 as the effect of these are model specific. The results are similar to the results of testing the symmetry constraint for RHH-2 for the static problem. The solution quality is slightly higher without the symmetry breaking constraints, however, the difference is not significant and the solution time is reduced significantly. It is therefore chosen to keep the symmetry breaking constraints.

8.5 Testing of Parameter Values that Affect Preventive Maintenance

In this section the amount of preventive maintenance that is performed when adjusting the values of different model parameters is studied. The amount of preventive maintenance that is scheduled to be performed by the mathematical model depends on two factors; the value of the penalty cost parameters for not performing and not completing preventive tasks, and the chosen α, the power output level where it is considered as more favorable to produce power than perform additional preventive maintenance. As there are no downtime costs related to preventive tasks that are not performed, the penalty costs are needed to give incentive to perform preventive maintenance. The α then adjusts the number of preventive tasks performed based on the wind speeds and the corresponding power outputs of the planning period, as described in Section 7.3.3. There is no correct answer on the amount of preventive tasks that should be scheduled. This depends on the preventive maintenance strategy chosen by the user of the model.

To test the effect of adjusting the values of the penalty cost parameters and the value of α, the problem is simulated for a period of fourteen shifts. Two different sets of values of the penalty cost parameters are tested, and each of these sets are tested for five different values of α.

The penalty cost parameters are calculated as described in Section 7.3.3. The two different penalty cost parameters compared are based on the transportation costs of AVs and of CTVs. As described in Section 7.3.3, using the transportation costs of AVs forces any free vessel to perform preventive maintenance in case of free vessel capacity. Based on the input data presented in Section 8.2, CTVs are more expensive to use than SESes. The transportation costs of CTVs are therefore chosen to force both CTVs and SESes, but not AVs, to perform preventive maintenance if there are free vessel capacity. The values of α tested are the power output levels corresponding to the wind speeds 8, 9, 10, 11 and 13 m/s. This give α equal to 11 %, 19 %, 25 %, 34 % and 86 %, respectively. Ten different scenarios are tested for each of the ten different scenario groups, and the scenario groups are referred to as AV-8, AV-9, AV-10, AV-11 and AV-13, and CTV-8, CTV-9, CTV-10, CTV-11 and CTV-13. It should be noted that for all the scenarios tested, changing the values of the penalty cost parameters and the α does not affect the amount of corrective maintenance performed.

Figure 44 shows that the number of hours of preventive tasks performed are dependent on both the value of the penalty cost parameters, and the value of α. When solving a problem, the values of these parameters should therefore be adjusted to fit the preventive maintenance strategy chosen for the specific problem, to ensure that enough preventive maintenance is performed.

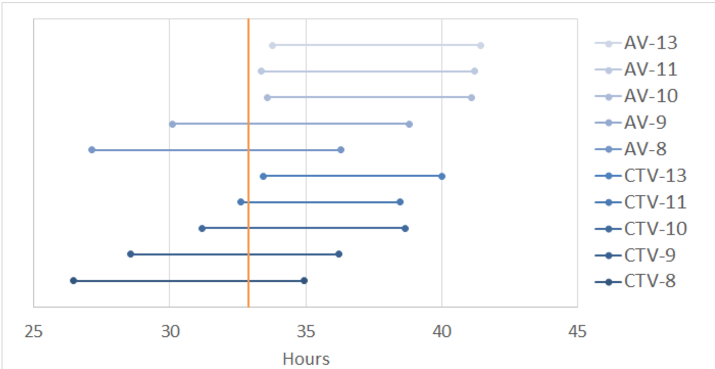


Figure 44: 95 % confidence intervals for the number of hours of preventive maintenance performed during one shift for the ten scenario groups tested. The orange line represents the average hours of preventive maintenance that must be performed during a shift in order to complete all yearly preventive tasks.

From Figure 45, it can be seen how also the real costs of the scenarios are affected by changing these parameter values. The number of hours of preventive maintenance performed and the real costs does not increase linearly. From this figure it may seem like the real costs per hour of preventive maintenance performed decrease with increasing values of α to a certain point, and after this point increasing the value of α increase the real costs per hour preventive maintenance performed. For the penalty cost parameters based on AV costs, this point is at the value of α that corresponds to 10 m/s. For CTV costs, it is at the value of α corresponding to 11 m/s. Figure 45 only shows the average values for each scenario groups, however, the figure still illustrates how the real costs and number of hours of preventive maintenance performed change for the different scenario groups tested. In addition, these results are supported by calculated confidence intervals of the difference in real costs per hour of maintenance performed for all the combinations of adjacent values of α.

When deciding which parameter values to use in the strategic analyzes, it is assumed that the preventive maintenance strategy entails to perform at least 50 % of the yearly preventive maintenance during summer. To obtain this, the average number of hours that is required to be performed during each shift is

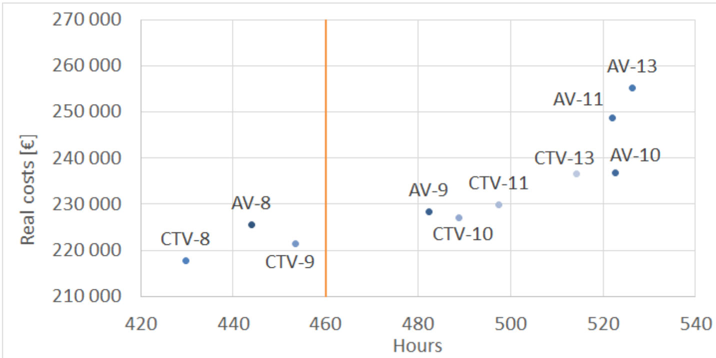


Figure 45: Average value of total real costs of and total number of hours of preventive maintenance performed during the simulation period for the ten scenario groups tested. The orange line represents the average hours of preventive maintenance that must be performed during fourteen shift in order to complete all yearly preventive tasks.

calculated. It is further assumed that it is desired to perform at least this many hours of preventive maintenance. Looking at the confidence intervals in Figure 44, this excludes the combinations AV-8, AV-9, CTV-8, CTV-9 and CTV-10. Of the remaining combinations it can be seen from Figure 45 that on average, lower real costs per hour of preventive maintenance performed are obtained for CTV-11 than for CTV-13 and for AV-10 than for AV-11 and AV-13. These are therefore discarded in favor of AV-10 and CTV-11. The real costs of AV-10 and CTV-11 are compared in Figure 46, and CTV-11 has lower real costs for most of the scenarios tested. The combination of penalty cost parameters based on CTV costs and an α-value corresponding to the power output with a wind speed of 11 m/s is therefore used in the strategic analyzes.

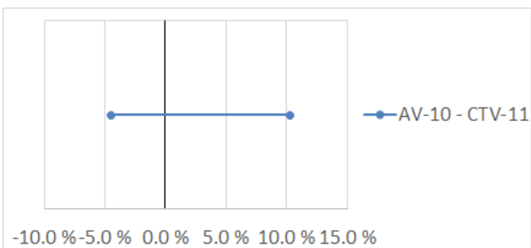


Figure 46: 95 % confidence interval of the difference in real costs of AV-10 and CTV-13.

8.6 Analysis of Strategic Decisions

Simulating the problem can provide valuable information when analyzing strategical aspects of O&M in offshore wind farms. The simulations can show how the different strategical decisions affect the performance on an operational level. To illustrate this, this section presents the results of analyzing the vessel fleet size and mix and the synergy effects of a joint vessel fleet for two wind farms compared to separate vessel fleets. The different strategic decision options are simulated for fourteen shifts and their effect on the operational performance are compared in terms of real costs and hours of maintenance performed.

8.6.1 Vessel Fleet Size and Mix

Three different vessel fleets, presented in Table 13, are analyzed for ten scenarios with two wind farms and a total of 100 turbines.

Table 13: The three different vessel fleets compared.

	AV	SES	CTV
Fleet 1	1	1	0
Fleet 2	0	2	0
Fleet 3	0	3	0

The confidence interval of the number of hours of preventive tasks performed for the ten scenarios tested for each of the three vessel fleets are presented in Figure 47. The results of the figure indicate that the technician capacity of Fleet 1 and Fleet 3 is sufficient, as they both have capacity to perform more preventive maintenance than the average hours required during the simulation period in order to complete all yearly preventive tasks. This does not apply for Fleet 2, which implies that the technician capacity of Fleet 2 is too small. The amount of preventive maintenance performed by Fleet 3 might be higher than the user of the model desires. This illustrates that adjusting the values of the penalty cost parameters of not performing or completing preventive maintenance and of α, as discussed in Section 8.5, should be performed also for different vessel fleets.

The effect of changing the fleet capacity by replacing an AV with a SES is presented in Figure 48. AVs has twice the capacity of SESes and CTVs, hence, an AV has a relatively large impact on the total technician capacity of the fleet. These results shows that Fleet 2 performs better than Fleet 1 in terms of costs. This is linked to higher transportation costs of Fleet 1, as AVs has significantly higher transportation costs than SESes. Fleet 2 has however higher downtime

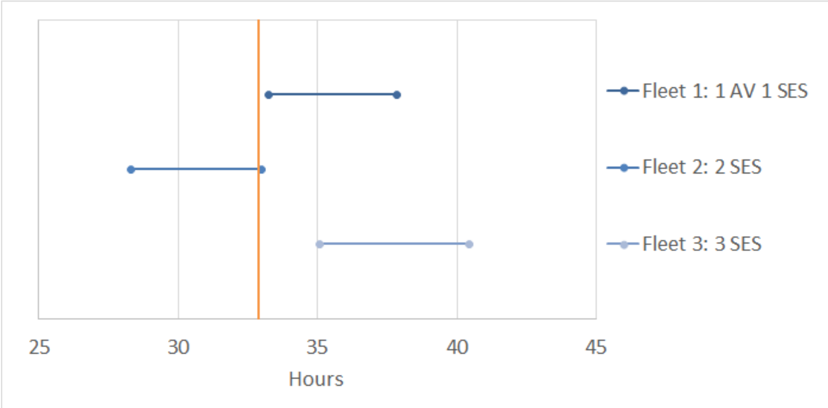


Figure 47: 95 % confidence intervals of the hours of preventive maintenance performed during the simulation period by the three different vessel fleets. The orange line represents the average hours of preventive maintenance that must be performed during the simulation period in order to complete all yearly preventive tasks.

costs. This is due to that the lower capacity of vessel Fleet 2 causes that some corrective maintenance tasks must be delayed until technicians are available, and the turbines are therefore shut down for a longer time period.

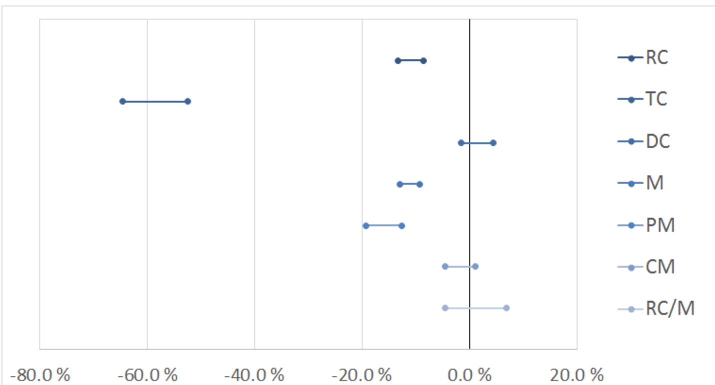


Figure 48: 95 % confidence intervals of the difference in real costs, hours of maintenance performed, real costs per hour maintenance performed and vessel capacity for Fleet 1 and Fleet 2. Positive differences mean that the values of Fleet 2 are greater than for Fleet 1.

By comparing the capacity of Fleet 1 and Fleet 2 with the hours of maintenance they perform, it can be seen that Fleet 1 has 1.5 times the capacity of Fleet 2, however, Fleet 1 only performs 10 to 15 % more hours of maintenance. As can be seen from Figure 47, Fleet 1 performs sufficient preventive maintenance, and one reason that there are unused capacity in Fleet 1 can therefore be that Fleet 1 has overcapacity. Another reason for this unused capacity can be the relatively long time it takes to transfer technicians to and from the turbines, as this puts a ceiling on the number of maintenance tasks a vessel can perform during a shift. Fleet 1 is therefore compared to a third fleet, Fleet 3, that has equal technician capacity, but a larger ceiling on how many tasks that can be performed during a shift as it consists of an additional vessel.

The results of comparing Fleet 1 and Fleet 3 are presented in Figure 49. Even when adding an additional SES, the transportation costs of Fleet 1 is considerably higher than for fleets of only SESes. Fleet 3 performs more preventive maintenance than Fleet 1, which implies that the amount of maintenance performed by Fleet 1 is restricted by the ceiling on how many tasks that could be performed during a shift.

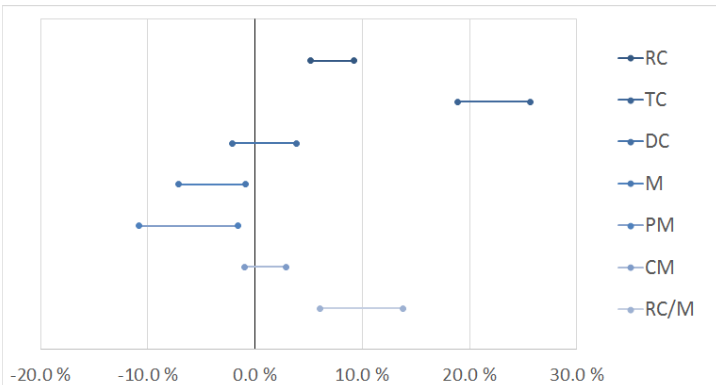


Figure 49: 95 % confidence intervals of the difference in real costs, hours of maintenance performed, real costs per hour maintenance performed and vessel capacity for Fleet 1 and Fleet 3. Positive differences mean that the values of Fleet 1 are greater than for Fleet 3.

From looking at the results of simulating the three vessel fleets for fourteen shifts, it is seen how the simulations can provide valuable information on the operational performance from different strategic decisions. The simulations give an impression of the vessel fleet capacity needed, and can contribute in comparing operational costs of different fleets. The results show that a vessel fleet with a technician capacity that is too small increases the downtime costs due to corrective tasks being delayed. It also reduces the amount of preventive maintenance performed. The simulations show how including an AV in the vessel fleet increases the transportation costs significantly. However, it should be noted that some types of tasks can only be performed by AVs. The costs of renting a vessel to perform these tasks, and the possible extra downtime costs for delaying the performance of these tasks until an AV is rented, should therefore be taken into account when considering vessel fleets of only SESes and CTVs.

When comparing the operational performance of the different vessel fleets in the above analysis, only variable costs related to the schedules generated are compared. When making strategic decisions on what vessel fleet to acquire, the fixed costs associated with the fleets, the daily vessel rates, should be taken into account. Daily cost rates include capital expenditures and operational expenditures such as maintenance of the vessel and salary for the vessel crew.

By calculating confidence intervals that include both the daily rates and the real costs of the simulations of the different vessel fleets, it is found that for the simulation period Fleet 1 is approximately 10 % more expensive than Fleet 3 for the ten scenarios tested. However, Fleet 1 is not dependent on renting an AV if tasks requiring AVs occur. Fleet 3 are therefore less expensive than Fleet 1 only if the costs related to the maintenance tasks requiring an AV do not increase the total costs by more than 10 %.

8.6.2 Synergy Effects of a Joint Vessel fleet

In this section the synergy effects of having a joint vessel fleet for two wind farms compared to having two separate vessel fleets are examined. Two different scenario groups of vessel fleets are studied, these are presented in Table 14. For the first of these scenario groups it is tested to see if the synergy effects are influenced by the distance between the wind farms. Ten scenarios are tested for each scenario group, and the same scenarios are used to test the joint fleet and to test the two separate fleets for each scenario group.

Table 14: The two different joint and separate vessel fleets tested.

	Scenario group 1	Scenario group 2
Joint Vessel Fleet	1 AV + 1 SES	3 SES
Vessel Fleet Wind Farm 1	1 AV + 1 SES	2 SES
Vessel Fleet Wind Farm 2	1 AV + 1 SES	2 SES

The results of testing the scenarios of the first scenario group are presented in Figure 50 and Figure 51. It can be seen from Figure 51 that both the joint vessel fleet and the two separate vessel fleets perform more preventive maintenance than necessary in order to perform all yearly preventive tasks. For the α-value corresponding to 11 m/s, the separate fleets perform significantly more preventive maintenance than the joint vessel fleet. To better compare the downtime costs for the joint fleet and the two separate fleets,the α-value of the two separate fleets is revised downwards to the α-value corresponding to 10 m/s. The results presented in Figure 50 and Figure 51, are the results of an α-value corresponding to 10 m/s for the separate fleets.

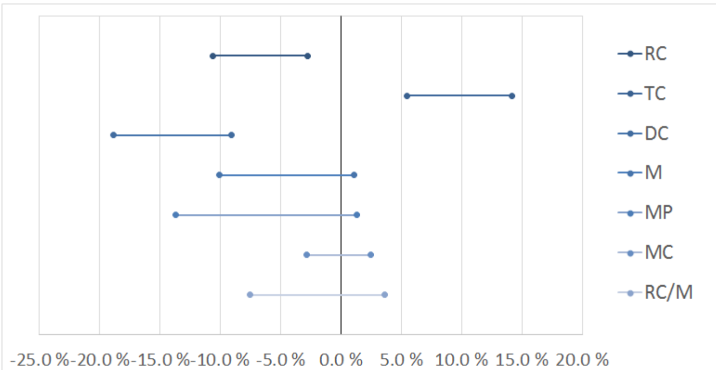


Figure 50: 95 % confidence intervals of the difference in real costs, hours of maintenance performed, real costs per hour maintenance performed and vessel capacity for the joint vessel fleet and the two separate vessel fleets combined for scenario group 1. Positive differences mean that the values of the joint vessel fleet are greater than for the combined separate fleets.

The total real costs of the joint vessel fleet are higher than the combined total real costs of the two separate fleets. The reason for this is that downtime costs are lower as there are more capacity to perform corrective tasks sooner with two separate vessel fleets. For the scenarios tested the transportation costs of the joint vessel fleet are higher than of the two separate fleets combined. This is because the vessel capacity per maintenance task is higher for the two separate fleets, so the AV is used less frequently than for the joint vessel fleet. The joint vessel fleet and the two separate vessel fleets are also compared in terms of total costs. Total costs include the real costs of the schedules generated and the daily vessel rates for the entire simulation period. 95 % confidence interval of the difference between total costs of the joint fleet and the separate fleets combined are calculated, and these show that the two separate vessel fleets are 62 % to 65 % more expensive than the joint fleet. This shows that AVs are very expensive investments for small, single wind farms, and that AVs might be a better option

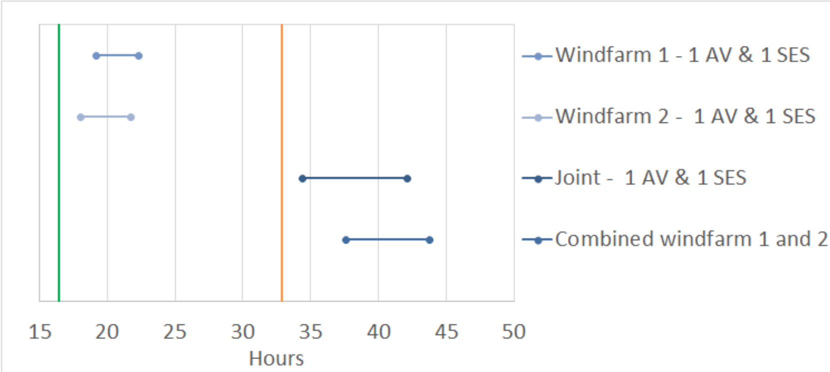


Figure 51: 95 % confidence interval of the number of hours of preventive maintenance performed during a shift by the joint vessel fleet and the separate vessel fleets of scenario group 1. The orange line represents the average hours of preventive maintenance that must be performed in both wind farms during a shift in order to complete all yearly preventive tasks. The green line represents the average hours of preventive tasks that must be performed in each wind farm during a shift.

for joint vessel fleets of multiple wind farms due to economies of scale.

The vessel fleets of the first scenario group are also tested for two wind farms where the distance between them is double the length of the wind farms of Figure 50 and Figure 51. It should be noted that the distance between wind farms only affects the synergy effects of the joint fleet if it is possible for vessels to travel between wind farms. The 95 % confidence interval of the difference between total costs of the joint fleet and the separate fleets combined, ranges from the separate fleets being 47 % to 66 % more expensive than the joint fleet. These results show that there are considerably positive synergy effects of a joint vessel fleet containing an AV also for wind farms located further away from each other. However, it also demonstrates that there are larger variations in the synergy effects of a joint vessel fleet for wind farms located further away from each other. This is because the reduction in costs to a greater extent is dependent on the location of the AV since the cost of travelling between the wind farms increases considerably.

To examine if there exists positive synergy effects for vessel fleets without AVs, a joint vessel fleet of three SESes is compared to two separate vessel fleets of two SESes. For the same reasons as for the first scenario group tested, the α-value of the separate fleets is revised downwards to the α-value corresponding to 10 m/s. As for the first scenario group, the joint vessel fleet has higher real costs due to higher downtime cost than the two separate vessel fleets combined for the scenarios of the second scenario group. However, for the scenarios of the second scenario group, the joint vessel fleet and the separate vessel fleets perform approximately the same amount of maintenance, as shown in Figure 52. Comparing the total costs of the joint vessel fleet and the two separate fleets, the two separate fleets are 18 % to 33 % more expensive than the joint fleet. These results clearly show the synergy effects of a joint vessel fleet. For the joint vessel fleet, the number of vessels can be reduced by one without compromising the amount of maintenance performed.

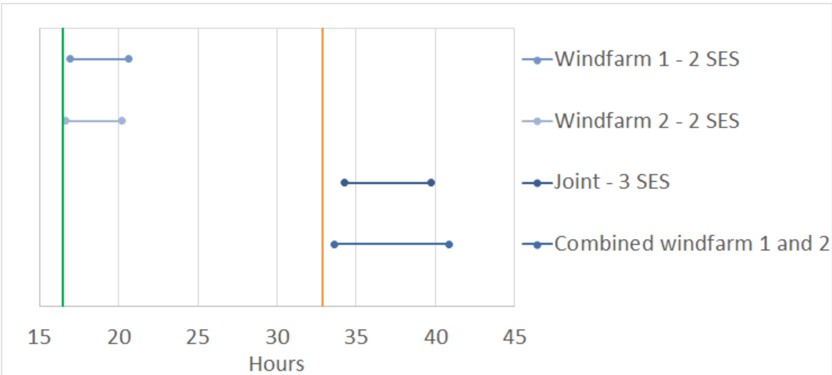


Figure 52: 95 % confidence interval of the number of hours of preventive maintenance performed during a shift by the joint vessel fleet and the separate vessel fleets of scenario group 2. The orange line represents the average hours of preventive maintenance that must be performed in both wind farms during a shift in order to complete all yearly preventive tasks. The green line represents the average hours of preventive tasks that must be performed in each wind farm during a shift.

9 Concluding Remarks

This thesis addresses one aspect of how to reduce the O&M costs of offshore wind energy. A static, deterministic model, that utilizes weather forecasts to create cost efficient schedules for multiple wind farms with a joint vessel fleet is presented. Two different rolling horizon heuristics for solving the problem, RHH-1 and RHH-2, are developed. The difference between RHH-1 and RHH-2 are the number of decisions that are fixed in each iteration of the heuristics.

RHH-1, RHH-2 and an exact model for solving the problem are compared in terms of solution time and solution quality by performing static tests of one planning period. The results show that the heuristics are able to solve problems of larger sizes than the exact model when solving for planning periods of more than one shift. Applying the heuristics decreases the solution time, often significantly, and the solutions found are often of equal or better quality than the solutions of the exact model. For the two heuristics, the heuristic with the most rigorous fixing strategy, RHH-2, performs the best.

Simulations of the exact model and RHH-2 over a longer time period show that the exact model solved for a planning period of one shift performs better, both in terms of solution time and solution quality, than RHH-2 solved for planning periods longer than one shift. This implies that the value of including information on additional shifts in the planning period is lower than the decrease in solution quality caused by the extra computational effort needed to solve the problem for a longer planning period. Even reducing the number of iterations in the heuristic or increasing the time limit of each iteration in RHH-2 does not offset the delay with finding a solution of the same quality as solving the exact model for a planning period of one shift. Hence, a greedy solution method is favorable for this problem. Including symmetry breaking constraints for the models reduce both the solution time and the solution quality, however, the solution time is reduced significantly and the reduction in solution quality is relatively low and within acceptable limits.

The amount of preventive maintenance that is scheduled depends on the value of different penalty parameters. It is shown how the value of these parameters are problem specific, and that they should be adjusted for different problems to fit the number of turbines, the vessel fleet and the chosen preventive maintenance strategy of the problem solved.

The exact model solved for a planning period of one shift and RHH-2 solved for longer planning periods are able to solve the operational problem of generating maintenance schedules for realistic scenarios, both for current and future sizes of offshore wind farms. Simulations of the problem can also contribute with valuable information when making strategic decisions. By evaluating different vessel fleets it is shown that a vessel fleet with a capacity that is too small increases downtime costs due to delayed completion of corrective tasks and reduces the amount of preventive maintenance performed. Including an AV in the vessel fleet increases the capacity considerably, however it also increases the transportation costs significantly. Comparing joint vessel fleets for two wind farms with two separate vessel fleets shows that a joint vessel fleet can reduce the combined vessel capacity needed for the wind farms, and that the reduction in fixed costs are greater than the increase in operational costs. This demonstrates that there are positive synergy effects of a joint vessel fleet for multiple wind farms.

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