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Determining the Optimal Vessel Fleet for Maintenance of Offshore Wind Farms

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Preface

This master thesis is a part of the Master of Science degree within Managerial Economics and Operations Research at the Department of Industrial Economics and Technology Management at the Norwegian University of Science and Technology (NTNU).

I would like to thank my supervisors Professor Lars Magnus Hvattum (Department of Industrial Economics and Technology Management, NTNU), and PhD student at Department of Industrial Economics and Technology Management and Analyst at MARINTEK, Magnus Stålhane, for thorough guidance through the semester.

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Abstract

Today the offshore wind energy industry needs financial support to be profitable. For offshore wind farms to be more competitive against other energy sources, the costs must be reduced, and this may be achieved by increasing the efficiency of operation and maintenance. In this thesis operations research is used to develop both a deterministic and stochastic strategic model to determine the optimal fleet size and mix for doing maintenance, by taking stepwise development into account.

The results show that the deterministic model can solve problems of realistic size for a planning horizon of 25 years in less than 23 minutes. The stochastic model takes uncertainties in number of failures and weather conditions into account. The computational study shows that a stepwise development of wind farms influence the optimal fleet and is therefore important to take into consideration. The value of the stochastic solution is significant and there is a benefit of having a stochastic model compared to a deterministic one. The problem solver uses the Branch & Bound method as solution strategy to solve the mixed integer programming problem, and the Branch & Bound tree grows rapidly in size. An integer solution is found fast, but it takes some time to prove that the optimal solution is found, due to a flat solution landscape.

Sammendrag

I dag mottar havvindparkene økonomisk støtte for å være lønnsomme. For at havvindmøller skal være konkurransedyktige mot andre energikilder er det viktig å få redusert kostnadene, og dette kan oppnås ved å øke effektiviteten til drift og vedlikehold. I denne masteroppgaven er operasjonsanalyse brukt for å utvikle både en deterministisk og en stokastisk modell for langsiktig planlegging, med hensikt å bestemme den optimale vedlikeholdsflåten. Modellene tar hensyn til stegvis utbygging av vindparker.

Resultatene viser at den deterministiske modellen kan løse problemer av realistisk størrelse med planleggingshorisont på 25 år i løpet av mindre enn 23 minutter. Den stokastiske modellen tar hensyn til usikkerhet i antall feil og værforhold. Analysene viser at stegvis utbygging av vindparker påvirker flåtebeslutningen og er derfor viktig å ta hensyn til. Verdien av den stokastiske løsningen er betydelig og det viser at det er en verdi i å ha en stokastisk modell framfor en deterministisk. Problemløseren benytter Branch & Bound for å løse heltallsproblemet, og Branch & Bound-treet vokser raskt i størrelse. Det tar kort tid å finne en heltallsløsning, men det tar tid å påvise at optimal løsning er funnet, fordi løsningsrommet er flatt.

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Chapter 1

Introduction

The electricity demand is increasing in the world, and will continue to grow for the next 20 years, according to World Energy Outlook 2012 by IEA (2012*b*). In 2035 the demand is expected to have increased with 35 % from the 2010 level, as shown in Figure 1.1. This figure shows that the energy demand is increasing in all parts of the world, but most rapidly in the third world. The rising living standard in China, India and the Middle East is the biggest reason for the dramatic increase. As a consequence, the IEA expect that CO_2 emissions will rise with 19 % in the time period from 2011 to 2035. This will lead to an estimated average temperature increase of 3.6 °C (IEA, 2012*a*).

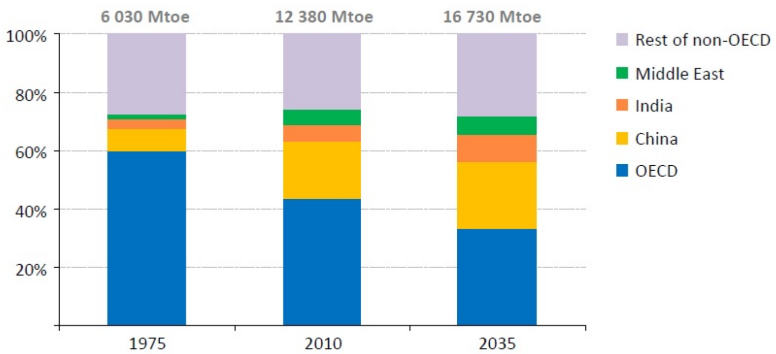


Figure 1.1: Distribution of world energy demand. Mtoe is the short for Million tonnes of oil equivalent. 1 toe is equal to 11.63 MWh. Source: IEA (2012*b*).

The Kyoto Protocol is an international contract which sets binding commitments for many industrialized countries, and one goal is to reduce the greenhouse gases, which CO_2 is a part of. To be able to fulfill the commitment there is a big focus on renewable energy production. IEA expect that renewable sources will constitute 31 % of the electricity generation by 2035. In the industrialized countries the growth in electricity production is expected to come from renewable sources, and at the same time the production from polluting sources such as coal is expected to decrease, as shown in Figure 1.2. To fulfill the targets of reducing greenhouse gas emissions, the focus on renewable energy sources is crucial.

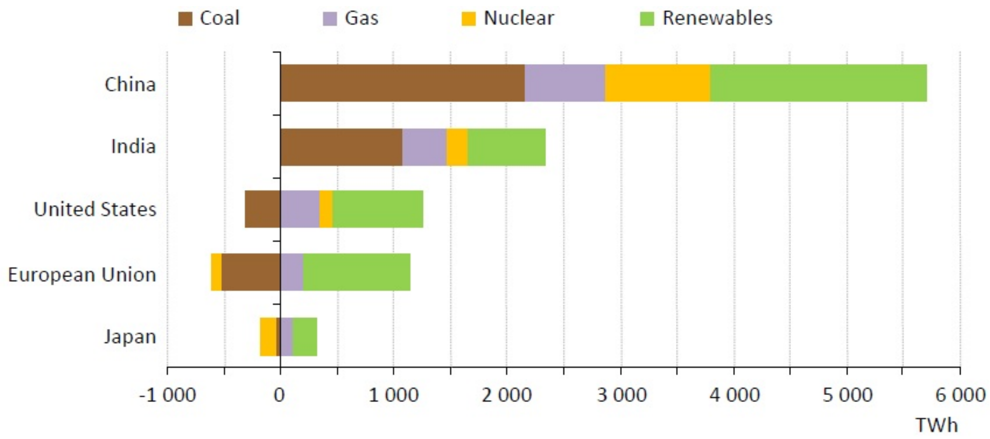


Figure 1.2: Change in power production 2010 – 2035. Source: IEA (2012*b*).

One fast growing renewable energy source is wind energy. The annual installed capacity in wind energy has increased in the past 15 years, as shown in Figure 1.3. According to the annual market update 2011 from the Global Wind Energy Council (GWEC, 2012), the market grew by 6 % in 2011 compared to the previous year. One interesting remark is that the majority of wind power installations were outside of the OECD, and this is a trend which is likely to strengthen even further in the near future. China, USA and India are the top three nations in annual installed capacity in 2011. In the next places are the European countries such as Germany, UK, Spain, Italy, France and Sweden. In Europe, the increase in annual installed wind production has been almost zero since 2009, but the cumulative installed capacity in offshore wind energy is still increasing.

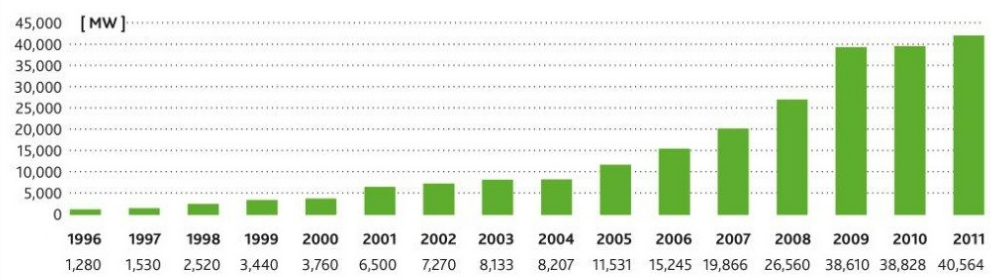


Figure 1.3: Global annual installed wind capacity from 1996 to 2011. Source: GWEC (2012).

The offshore wind industry is younger than the land based, and may be improved in several areas. Compared to the land based wind industry, offshore wind is much smaller. Offshore wind constitutes only 2.5 % of the annual wind market in the world. While China is the main driver of growth in the land based wind market, Europe is in a clear lead in the offshore wind market. More than 90 % of the world's offshore wind power is currently installed outside northern Europe, in the North, Baltic and Irish Seas, and in the English Channel (GWEC, 2012). Offshore wind has a big potential because the wind resource is generally much better offshore, and large scale development is possible. Since offshore wind is a relatively new technology, there is significant potential for cost reduction and technological innovations (GWEC, 2012).

In addition to fulfill the Kyoto Protocol the European Union has made their own 20-20-20 targets. These three targets state that greenhouse gas emissions should be 20 % lower than 1990, 20 % of the energy production must be from renewable energy sources, and there should be a 20 % increase in energy efficiency (European Commission, 2011). To be able to fulfill these targets an increase in renewable energy is crucial, and one essential component is offshore wind. In Europe there has been a steady growth in cumulative installed offshore wind capacity, from nearly zero in 2000 to nearly 4 GW in 2011, as shown in Figure 1.4.

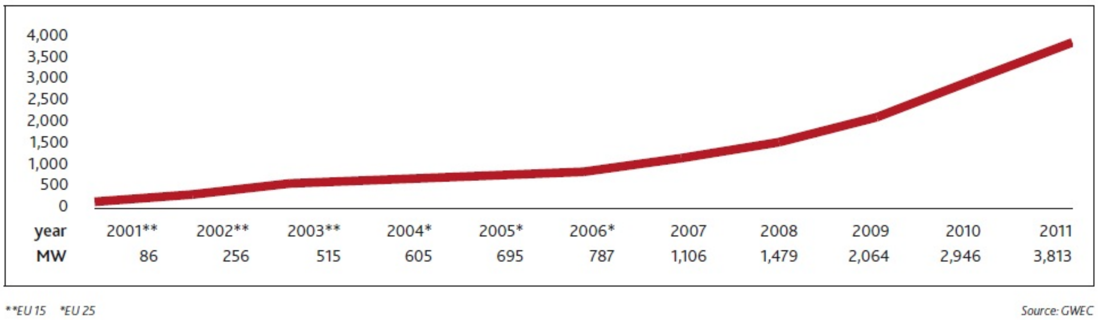


Figure 1.4: European cumulative installed offshore wind capacity. Source: GWEC (2012).

An important factor to make offshore wind more attractive is to reduce the costs. Today, the offshore wind energy industry needs financial support to be profitable, in UK the producers receive approximately 100 EUR per MWh power produced in support (Ofgem, 2011). When the investment is done, the biggest cost is due to operation and maintenance (O&M) of the offshore wind farms. Compared to onshore wind farms, O&M costs make up a larger proportion of the total cost. Several papers have quantified how big this cost is; Fingersh et al. (2006) state that the O&M costs for a single 3 MW wind turbine in shallow water could be \$215 000 per year and Marsh (2007) believes the cost of offshore wind farm O&M

could be anywhere between GBP 50 000 and GBP 100 000 per turbine. They agree that the sum is depending on a range of factors including location, machine size and how well the O&M function is organized. As a general remark O&M costs is between 20–25 % of the total costs for an offshore wind turbine (Snyder and Kaiser, 2009). A reduction in O&M costs may lead to a more competitive price for offshore wind farms compared to other energy sources. To reduce the costs, it is important to decide the optimal fleet for doing O&M. In this thesis a model for solving this problem will be developed with use of Operations Research (OR).

1.1 The Maintenance Activities

To be able to determine the optimal fleet of vessels for maintenance of offshore wind farms it is necessary to know the types of maintenance tasks to perform on an offshore wind turbine. The maintenance activities can be divided into three groups; preventive maintenance, condition based maintenance and corrective maintenance.

1.1.1 Preventive Maintenance

Preventive maintenance consists of planned maintenance performed in order to prevent a component failure. Preventive maintenance is planned to be performed on fixed time intervals (Obdam et al., 2007). Typical maintenance tasks could be visual inspection, changes of consumables, (greasing, lubrication, oil filters), oil sampling and tightening of the bolts (Besnard et al., 2009). Some guidelines about how often the preventive maintenance should be done are often given by the producer. The costs of preventive maintenance is due to transportation and revenue loss from production stops. In order to reduce the loss in revenue the preventive maintenance should be done on days with low production.

1.1.2 Condition Based Maintenance

Condition based maintenance is based on the actual health of the system (Obdam et al., 2007). These are the maintenance tasks that are neither preventive nor corrective maintenance. Measuring equipment is installed on the wind farms and when they are reporting odd values, the crew need to go out and check the health of the system. These maintenance tasks do not need to be done immediately, unlike the corrective maintenance, as there has been no failure yet. As long as no failure has occurred there is no loss in revenue due to production stops. By waiting too long, the component may fail and the costs will increase due to production loss. Therefore the condition based maintenance is not a part of a long term plan, which is used for the preventive maintenance.

1.1.3 Corrective Maintenance

Corrective maintenance is all the unplanned maintenance that is necessary to do after an unexpected failure of a system or a component (Obdam et al., 2007). Corrective maintenance should be done immediately to reduce revenue loss due to production stops. When and how often the corrective maintenance tasks need to be done is uncertain, however based on historical data it is possible to estimate how often it occurs. The failure rates typically follow a bath tub curve which indicates that most failures will occur in the beginning and in the end of the wind turbine's lifetime (Allwood and Sharp, 2006). In the middle part of the lifetime the failure rates will be approximately constant.

When determining the number of outage days per year, it is important to consider both how often the failures occur and how many days the wind turbine is out of order for each type of failure. An accident on a gearbox is quite rare, as it happens with 13 out of 100 wind turbines, but each failure takes on average 6.3 days to fix (Milborrow, 2010). Combining the number of failures with the number of days the turbine is out of order provides an estimate of the average loss of productivity (Milborrow, 2010). Figure 1.5 is based on a research done on 1500 land based turbines in Germany over ten years (1997-2006) by the German Wind Energy Measurement Program.

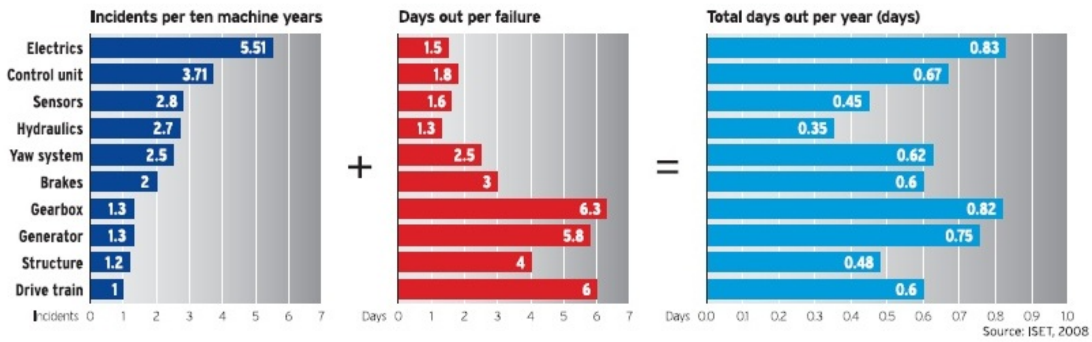


Figure 1.5: Failure rates and outage time (Milborrow, 2010).

A study done by Van Bussel and Schöntag (1997), where wind turbines located along the German coast in the state of Schleswig-Holstein were studied, classified failures in 6 classes as shown in Table 1.1. The only failure class that requires a crane vessel is failures on blades. The table states that failures requiring an external crane have an event rate of 0.44 per year (Van Bussel and Schöntag, 1997).

The total costs of corrective maintenance is the sum of transportation costs, the loss in revenue due to production stops, the cost of the crew and the equipment. Compared to preventive maintenance, the cost associated with loss in revenue is

Table 1.1: Type of failures (Van Bussel and Schöntag, 1997). MBTF stand for mean times between failure.

Class	Failure	Events/year	MTBF[hours]
1	Blades	0.44	19923
2	Gearbox / Generator / Yaw	0.14	62614
3	Electronics / Control system	0.29	30227
4	Hydraulic	0.22	39845
5	Electric	0.37	23692
6	Others	0.33	26564
	Total	1.79	4897

more important for the corrective maintenance. For preventive maintenance the time without production is the same whenever the maintenance is done, but for corrective maintenance it is really important to do the tasks as soon as possible after the failure occurs.

1.1.4 Government regulations

The government for the actual country may put on some regulations about how the maintenance should be performed. It may be a regulation stating how often a wind turbine needs to be visited, and how often preventive maintenance should be executed. The main goal for the government is to take care of the public and avoid dangerous situations. Regulations according to Health, Safety and Environment (HSE) for the workers will also apply. They may state how long response time a helicopter can have and how far away from workers at a wind turbine the vessel can be. Safety restrictions on wave height for the different vessels may also apply.

1.2 Maintenance Fleet Composition

To find the best fleet, it is necessary to know which vessels to choose between. Many possible concepts are relevant, such as catamaran, supply vessel, crane vessel, mother ship, helicopters and a Dutch harbor at sea. Large ships have the advantage that they can carry more personnel and equipment, and probably withstand significant wave heights better than smaller ships. Small ships, however, are more mobile and cheaper both to purchase and operate.

1.2.1 Supply Vessels

When only personnel and small equipment is needed, a supply vessel can be used. In Figure 1.6 some examples of supply vessels are given.

(a) Wind server. Photo:Fjellstrand

(b) Fob Swath. Photo: *http://www.odfjellwind.com/*

(c) Wind Cat. Photo: *http://www.windcatworkboats.com/*

Figure 1.6: Supply vessel examples.

Odfjellwind's Fob Swath is shown in Figure 1.6b and is used as a service vessel for offshore wind farms, and has space up to 24 or 36 passengers. It can stay safe against the turbine in up to 2.5 meters significant wave heights. Fjellstrand's Wind Server is shown in Figure 1.6a and comes in two sizes, one with space for 12 passengers and one for 24 passengers, both with a speed of 25 knots. Wind Server is a new concept developed in 2012 in cooperation with Carbon Trust, a British organization to help reducing CO_2 emissions and saving energy. In Figure 1.6c the Wind Cat is shown. This vessel is used to transport a maximum of 12 passengers and equipment below 2 tonnes, and can do safe transfers in waves up to 2 meters.

These are three examples of supply vessels, but there are many more in the market, examples are Fob Lady and SWATH Tender and catamarans. The Wind Cat is an example of a small supply vessel, while Fob Swath is an example of a larger supply vessel. For intermediate sized components like main bearing and yaw drive, a larger supply vessel is required for transportation (Gardner et al., 2009). For preventive maintenance, only personnel and small equipment is needed. The most favorable way is therefore to use small supply vessels (Van Bussel and Schöntag, 1997).

1.2.2 Crane Vessel and Jack-Up Barge

To change large components like the blades or the generator, a crane vessel is necessary. Cranes for offshore work are available in several types and sizes, and some examples are shown in Fiugre 1.7.

(a) An example of a crane vessel. Photo: classifieds.justlanded.com

(b) HOCHTIEFS's Thor jack-up platform. Photo: hochtief-construction.com

(c) The Windcarrier jack-up vessel by Fred. Olsen. Photo: Windcarrier.com

Figure 1.7: Examples of crane vessel and jack-up vessel.

HOCHTIEF's Thor jack-up platform is shown in Figure 1.7b and can be used in waters up to 50 meters deep. Fred. Olsen Windcarrier's jack-up vessel is shown in Figure 1.7c and is a self-elevating vessel. Usually the weight of wind turbine components is not a limiting factor. The lifting height as well as the water depth can be a limit to the deployment of certain types of cranes (Van Bussel and Schöntag, 1997).

1.2.3 Helicopters

For preventive maintenance and condition based maintenance, which just need personnel, helicopter is an alternative. In Figure 1.8 an example can be seen of using a helicopter for doing maintenance of a wind turbine. The benefit of using a helicopter is the high speed which leads to shorter travel time. The short travel time lead to shorter time windows needed and possibly shorter production stops. The helicopter can land on a jack-up vessel if needed, for example when immediate assistance is needed. The helicopter has limitations in use due to strong winds and dense fog, but are not limited by wave height.

Figure 1.8: Helicopter used for maintenance tasks at an offshore wind turbine. Photo: Bond Aviation Services

1.2.4 Mother Ship

Offshore station concepts, like a mother ship, become more relevant as the planned offshore wind farms are getting bigger and moving further out from shore. The long distance to the closest shore makes it necessary to have long time windows for doing maintenance tasks. The mother ship can stay on-site, providing accommodation for the personnel and has capacity for multiple catamaran work boats to transfer personnel out to the wind turbines (Gundegjerde and Halvorsen, 2012).

Two possible mother ship concepts are the Sea Wind maintenance vessel, see Figure 1.9a (Renewable Energy Focus, 2011) proposed by Offshore Ship Designers. Another is the Ulstein's X-bow concept, see Figure 1.9b designed for Sea Energy PLC (The Maritime Executive, 2012). These solutions also support helicopter operations including transport of personnel to and from shore.

1.2.5 Dutch Harbor at Sea

The Netherlands has plans for 6 GW of offshore wind power production in 2020 in the North Sea (HEDEN, 2011). They are planning to build out IJmuiden area, laying 80 km from shore. This long distance implies higher costs due to longer

(a) The Sea-Wind WMV is an example of a mother ship. Photo: renewableenergyfocus.com

(b) X-Bow Hull Mother Ship designed for Sea Energy PLC. Photo: Norsk Skipsfarts Forum.

Figure 1.9: Mother ship examples.

shipping time for construction and maintenance and longer cables for the electric connection. Therefore they have come up with the idea of an offshore port on an artificial island, see Figure 1.10. By using the island they do not need long time windows and do the long travel from shore to perform maintenance tasks. The island, which will be 1000 m in diameter, will consist of landing sites, sites for storage and assembly and commissioning wind turbines, hotel, substation, etc.

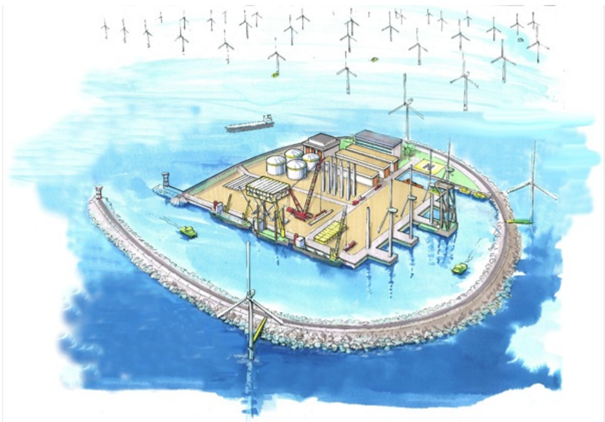


Figure 1.10: An example of how a Dutch Harbor at Sea can look like (HEDEN, 2011).

1.3 Location of Offshore Wind Farms

Up until now, offshore wind farms have been located close to the shore. The rapidly increasing amount of offshore wind energy, force the developers to move farther away from shore. One example from Great Britain is the Dogger Bank Zone in the North Sea, located between 125 km and 290 km from shore (Forewind, 2011), and will be one of the wind farms farthest out to sea. The Dogger Bank will also be the biggest offshore wind farm, with an agreed target capacity of 9 GW and with a potential for approximately 13 GW (Forewind, 2011). This will indicate many hundreds of wind turbines, and all of them will not be built simultaneously. Therefore the development of the largest wind farms will be stepwise, and takes several years to complete.

When the number of offshore wind farms are growing, the number of wind farms close to another is increasing. For big and expensive ships such as multi-purpose vessels and jack-up rigs, sharing of vessels between several wind farms can be profitable. This is called pooling and means that a pool of vessels is shared between two or more farm owners, and is used by the owners. The bigger wind farms with many more wind turbines can utilize the economies of scale, where a cost advantage can be achieved and the O&M costs per wind turbine can be reduced.

1.4 Contents of this Thesis

In Chapter 2 the problem description will be presented. The literature review which contains relevant literature for this problem can be found in Chapter 3. A deterministic mathematical model to solve the problem is presented in Chapter 4, and in Chapter 5 the stochastic model is presented. The computational study on both the deterministic and stochastic model is presented in Chapter 6. The conclusion is found in Chapter 7.

Chapter 2

Problem Description

The purpose of this thesis is to develop models and solution methods to determine an optimal fleet size and mix to be used in the execution of operations and maintenance in the offshore wind industry. The main focus will be on developing models that scale well and can be used for any realistic size. The models will also deal with gradual expansion over time. The models will then be analyzed to evaluate different aspects of the solutions and the models.

2.1 Time Aspects

It takes many years from winning the rights to develop the offshore wind farms and to the wind farm is ready to produce power. To plan and build an offshore wind farm takes several years. The biggest wind farms are developed stepwise. The optimal fleet may change as a consequence of the building times of each wind farm. It may be profitable to purchase vessels instead of renting vessels when knowing that the demand will increase in the future. To build an artificial island or a mother ship is a huge investment, and will not be profitable for just one small wind farm. But with the knowledge that other wind farms will come soon and can share this offshore station, it may be profitable to build it from the beginning.

To take care of the time aspects discussed above, the strategic planning horizon should have the same length as a normal life cycle of a wind turbine, which is said to be between 20 and 25 years. The variations between seasons should also be taken into consideration. The preventive maintenance tasks will normally be performed only during summer, because of the weather conditions. Corrective and condition based maintenance tasks need to be performed during the whole year. To have vessels which can handle big wave heights are more crucial in the winter than in summer, because of rougher weather conditions during the winter.

2.2 Location

An aspect when determining the optimal vessel fleet is to take into account where the wind farm is located. The weather is different in the Baltic Sea compared to the North Sea, and the weather is often rougher far from shore. The location influence the decision in two ways, i.e. by the weather condition and the distance to shore. The distance to shore affect the traveling time for each vessel. The weather conditions influence the wave heights and limit the number of hours a vessel can operate per year. These factors are important to take into consideration when determining the optimal fleet, because it influences the decision on which vessels to invest in.

The farther the offshore wind farm is from shore, the more valuable is the speed of the vessel. A helicopter is faster than the ships and is more likely to be purchased when the distance increases. The investment in an offshore station is also more likely to occur when the distance from shore is increasing.

The wave heights influence which vessels to invest in. A vessel that can handle higher waves is more crucial when the offshore wind farm is located in the North Sea compared to the Baltic Sea. Buying a more expensive vessel which can handle a half meter higher waves is very profitable if it leads to more operating hours. To buy a cheap vessel which nearly never can sail is wasted money.

Both the increasing distance to shore and the rough weather conditions increase the likelihood of investing in an offshore station. An offshore station will decrease both the traveling distance and the length of necessary weather windows, and leads to longer operating times for each vessel. This means each vessel can operate more hours per year and may lead to investments in fewer vessels in total.

There are two main strategies for operating the vessels. The vessels can either return to a harbor on shore or to an offshore station after performing the maintenance tasks.

2.3 Adjustment of the Fleet

The time from ordering a vessel to it is ready to operate takes some time, so it is important to have a long term plan for acquiring vessels. For rental contracts, it is possible to rent vessels on the spot market. But especially in the summer months the demand may exceed the supply, and the offshore wind operators seek to make contracts some months before. The model developed in this thesis will suggest when vessels should be acquired and rented, and thus make it possible to plan the acquiring and renting contracts in good time.

2.4 Uncertainty

A lot of uncertain parameters need to be taken into consideration. The prices for purchasing, selling, chartering in and chartering out are all uncertain and hard to predict for a long time period of 20–25 years. It is hard to predict when a fault may occur on a wind turbine. The same for the weather conditions, which is not possible to predict perfectly for a long time horizon. Especially, the weather conditions is of great importance for determining the optimal fleet.

Chapter 3

Literature Review

This thesis focuses on finding the optimal fleet of vessels for performing maintenance on offshore wind farms. The aim is to develop a model deciding how many vessels of each type is optimal for an offshore wind farm's operator. This is a kind of a maritime vessel fleet size and mix problem (MFSMP), which in its basic version is a problem that consists of deciding how many ships of each type to use in order to meet the demand (Pantuso et al., 2012). In this thesis, both a deterministic and a stochastic model is developed, so this literature review will contain publications representing both versions of the problem. This thesis is directed towards maintenance of offshore wind farms, and an own section containing publications on this topic is added.

3.1 Ship Routing and Scheduling

One of the first surveys in ship routing and scheduling, Ronen (1983), dates back to 1983 and conclude that relatively little work has been done in ship routing and scheduling compared to vehicle scheduling. Ten years later, Ronen (1993) published a second review on ship scheduling from 1982 to 1992. Where he sees that the increasing availability of microcomputers and their rapidly increasing computer power has made some changes in the literature. More realistic problems are addressed with their optimal solutions. He concludes that both breadth and depth of application of OR tools to ship scheduling have increased during the last decade. Christiansen et al. (2004) published a survey on ship routing and scheduling from 1993 to 2003. They divide the literature into the different planning horizons; strategic, tactical and operational planning, and see an increased interest and focus on ship routing and scheduling. The review presented include almost 60 references, which is twice as many as the review Ronen (1993) published for the preceding decade. Hoff et al. (2010) published a survey considering both maritime and land-based transportation, focusing on industrials aspects. The survey focus on OR that combines fleet composition and vehicle routing, and found in total 95 scientific papers that address this combination. Pantuso et al. (2012) states it is a difference between land-based and maritime FSP. Christiansen et al. (2004) and Hoff et al. (2010) point out the main differences between ships and trucks in their surveys; ships have higher travel times, higher uncertainty and higher cost per ship. Even when considering the total fleet, capital binding is generally much higher in maritime transportation. Another difference is the highly standardized manufacturing of trucks compared to the individual design of a ship.

3.1.1 Maritime Fleet Size and Mix Problem

The first contribution on maritime fleet size problems was Dantzig and Fulkerson (1954). The authors applied a linear programming (LP) model to determine the minimum number of tankers in order to guarantee a shipping service with a fixed schedule.

Fagerholt (1999) has made a model to solve the problem of deciding an optimal fleet in a real liner shipping problem. The chosen solution method consists of three phases. In phase 1 all feasible routes are generated, then in phase 2 single routes are combined into multiple routes and finally a set partitioning problem, where the columns are the routes generated in phase 1 and 2, are used.

There has been developed models for supply to oil and gas installations on the Norwegian continental shelf. One of them is presented in Fagerholt and Lindstad (2000), where a solution to the real problem of determining an efficient policy for a supply operation in the Norwegian Sea. The model is developed at a tactical planning level. Many similarities can be seen to the offshore wind farms, as it both needs to take the rough weather conditions into account, and has a depot on the coast.

Another model is presented in Halvorsen-Weare et al. (2012) to decide the optimal fleet composition and periodic routing of offshore vessels. The problem solved consists of determining the optimal fleet composition of offshore supply vessels and their corresponding weekly voyages. The supply vessel planning problem is to find the optimal fleet composition, and accordingly minimizing the costs while maintaining a reliable supply service. The solution method is a voyage-based approach, where all candidate voyages are generated a priori.

To take some uncertainty into consideration Halvorsen-Weare and Fagerholt (2011) created robust schedules to the supply vessel planning problem. The problem was to supply offshore installations with goods, and they realized that the weather conditions have a big impact on the execution of a schedule. Different approaches were tested, and revealed that adding robustness criteria to the optimizing procedures gives lower predicted cost.

Fagerholt (2001) presented a new optimization based approach for a multi-ship pickup and delivery problem with soft time windows (m-PDPSTW). He concludes that soft time windows are advantageous over hard time windows, as long as a proper cost is set for the violation of the time window.

Zeng and Yang (2007) made a model to determine the types of ships, the number of each type, and the ship routing. This was done to improve the efficiency of coal shipping and the results conclude that the method can decrease the unit shipping cost. They presented an integrated fleet design and ship routing model, in order to solve the two problems simultaneously. A two-phase tabu search algorithm was used to solve the problem.

Pesenti (1995) has made a hierarchical resource planning model, to decide the purchase and use of ships in order to satisfy customers' demands. At the strategic planning level, which is planning for 3 – 5 years, decisions on the purchase or sale of ships and on the routes to be followed are made.

Much of the above literature contains detailed routing planning aspects. Hoff et al. (2010) states that in strategic fleet management decision models, it will typically not make sense to include routing aspects at a very detailed level.

As stated in the survey by Hoff et al. (2010) one of the major critiques of today's research is the lack of treatment of stochastic aspects, together with concepts of risk and robustness. The next section will present the literature which take uncertainty into account through stochastic programming.

3.1.2 Planning Under Uncertainty

The number of publications containing uncertainties in ship scheduling and routing is scarce. As Verderame et al. (2010) states: 'there is a great potential for future contributions within the area of scheduling under uncertainty, especially with regard to ship routing.' Most publications treat deterministic ship scheduling and routing problems, as discussed in Section 3.1.1.

Stochastic programming (SP) traces its roots to Dantzig (1955), where the recourse model is first introduced. Since that time, tremendous progress has been made toward an understanding of properties of SP models and the design of algorithmic approaches for solving them (Higle, 2005).

List et al. (2006) address a fleet sizing problem for disposition of radioactive wastes. They use robust optimization to explore the effects of uncertainty on the equipment acquisition strategy. They have included two separate risk variables: one related to financial risk and a second related to delayed and deferred shipments. The results show a trade off between the risks and the importance of taking risk into account when deciding the overall level of equipment acquisition.

For strategic planning problems, the paper by Alvarez et al. (2011) is one of few papers which explicitly treats uncertainty. They developed a robust optimization model to solve a maritime fleet renewal problem (MFRP) with random variations in the selling and purchasing prices of ships. The problem was transformed into a mixed integer problem (MIP) in order to solve it.

Bakkehaug et al. (2012) have also studied the strategic MFRP problem. They developed a new multi-stage stochastic programming model for the strategic MFRP, which take the uncertainty of future parameters such as demand, freight rates and vessel prices into consideration. The results suggest that significant savings are possible when accounting for the uncertainty.

Dong and Song (2009) have studied the container fleet sizing and empty repositioning in liner shipping systems. They made a simulation-based optimization tool to find the optimal container fleet size in order to minimize the expected total costs.

The papers reported here give a brief overview of the fact that few papers take uncertainty into account in the strategic planning of the FSMP. Some papers use average values or extreme values to consider uncertainty, but not many articles use stochastic programming to find the optimal solution with uncertainty.

3.2 Operation and Maintenance of Offshore Wind Farms

The literature described above considers maritime fleet size and mix problems. Here, literature considering the offshore wind farm industry will be presented. The number of papers using OR to study the fleet needed for performing maintenance of offshore wind farms is scarce.

Andrawus et al. (2007) have studied two quantitative maintenance optimization (QMO) techniques, the Delay-Time Maintenance Model (DTMM) and Modeling System Failure (MSF) with use of Monte Carlo simulation. The purpose is to find the best maintenance strategy when both costs and benefits of maintenance are quantified.

At the Energy research Centre of the Netherlands (ECN) they have developed an O&M Cost Estimator (OMCE), which is a simulation program in MATLAB. With use of this simulation tool they try to find the optimal maintenance strategy as described in Van de Pieterman et al. (2011). They conclude that long waiting times for suitable weather windows is a major contributor to the wind farm downtime, leading to high revenue losses. For a closer description of OMCE and the OMCE calculator, see Obdam et al. (2007). This O&M tool is also described in Rademakers et al. (2008).

Van Bussel and Schöntag (1997) have made a Monte Carlo simulation model which shows that the availability level is very poor and that a redesign for offshore application is inevitable. This model was further developed to decide the offshore wind farm availability and the related O&M costs, as described in Van Bussel (1999).

Dekker (1996) has published an overview of several maintenance optimization models with use of OR from different industries. He concludes that the case studies published show that mathematical models are a good means to achieve both effective and efficient maintenance. Besnard et al. (2009) have used OR to perform preventive maintenance optimization. They have developed a linear integer optimization model to minimize the total cost of performing preventive maintenance. They conclude that in their example 43 % of the cost to perform preventive maintenance could be saved.

Gundegjerde and Halvorsen (2012) have developed a combined routing and scheduling model for deciding the optimal fleet for performing maintenance at offshore wind farms. They have developed a strategic planning model which use one year as an example year with the assumption that all the other years in the planning horizon are identical. All the wind turbines are there from the beginning of the planning horizon. They have limitations with a maximum of two wind farms. Their thesis has been used as a motivation to make a strategic model with a planning horizon of 20-25 years. The model developed in this thesis can handle more than two wind farms and take into account a stepwise building of the farms.

Chapter 4

Deterministic Mathematical Model

The deterministic model has been formulated as a MIP. This chapter describes the mathematical model and the assumptions in more detail.

Throughout the rest of this thesis the word ‘vessel’ is used as a collective term for both vessel and helicopter. The word ‘rent’ is used for chartering in vessels, and ‘hiring out’ is often used instead of chartering out vessels. This is because these words start with different letters and can be used when modeling. The words ‘activities’ and ‘tasks’ will both be used, meaning the same: maintenance tasks and maintenance activities.

4.1 Assumptions

It is difficult to describe the real world with a mathematical model, some assumptions need to be done, as described in this section.

4.1.1 Uncertainty

In this deterministic model all the uncertain parameters are assumed to be known. Uncertain parameters include prices, weather conditions and unforeseen failures. Perfect knowledge about the weather conditions would give an accurate number of hours a given vessel would be able to operate at a wind farm during a time period. If all failures were foreseeable, the exact number of maintenance tasks to perform during a time period would be known.

The preventive, the condition based and the corrective maintenance activities are modeled in the same way, because all maintenance activities are known in this deterministic model.

4.1.2 Time

The main purpose of this strategic model for long term planning is to decide the optimal fleet size and mix for O&M tasks on offshore wind farms. There are mainly two questions the model will answer: What kind of vessels are needed, and when shall the vessels be bought or rented?

The time aspect of the model is important and the model will be divided into time periods. The length of a time period can be fixed or vary during the planning horizon. In the beginning of the planning period the length of a time period may be short. Further into the future, longer time periods may be used. All maintenance activities need to be done during the given time period. Therefore no activities can be postponed to the next time period.

Each vessel type's capacity to perform maintenance tasks is described by two time parameters. One time parameter will give the total amount of time a vessel can operate during a time period. The other time parameter will give how many hours a vessel of a given type will use to do a maintenance activity of a given type, on a given wind farm. The travel time, which is the time a vessel uses from shore or an offshore station to the wind farm, is included in the latter time parameter. It is assumed that a vessel is visiting only one wind farm on each trip. The distances between wind turbines in the same wind farm is negligible. The actual routing of the vessels will not be included in detail to avoid that the problem gets too big. Vessels connected to an offshore station will use shorter time to perform a maintenance activity compared to a vessel with base on land. Each travel to the wind farm and each performance of a maintenance task will not be modeled in detail, so average times will be used.

For big vessels with space enough for two or more working teams, it is assumed the teams will work in parallel on several wind turbines on the same wind farm, when possible. The time a big vessel uses for a maintenance activity of a given type is therefore reduced, compared to a smaller vessel from the same station.

The purchasing, selling, renting and hiring out decisions will be made in the beginning of each time period. This means it will not be possible to sell any vessels in time period 1, because it is assumed that in the beginning there are no vessels. It is also assumed that the vessels rented or hired out will apply for the whole time period. This assumption leads to integer boundaries on these variables. To be able to rent or hire out vessels for a part of the period, continuous variables may be used.

4.1.3 Costs

The main purpose is to minimize the total costs of the vessel fleet for doing O&M. The costs of purchasing a vessel is divided into investment costs, fixed costs and

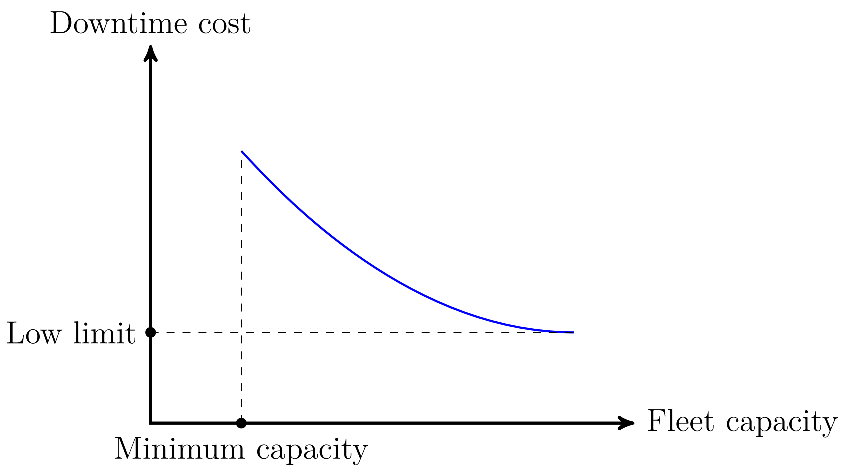


Figure 4.1: Downtime cost as a function of fleet capacity.

variable costs. The investment cost is the cost of goods sold and is a non-recurring transaction. The fixed cost is equal to the sum of depreciation, insurance and other costs attached to own a vessel. The variable costs are the costs associated with operating the vessel, here mainly fuel costs. The total cost is the net present value. All the costs will be discounted to todays value. This is important because of the long planning horizon.

The downtime cost is the loss in revenue due to production stops. The downtime cost for performing preventive maintenance tasks are influenced by the spot price and possible wind energy production, but the time the wind turbine needs to be stopped is constant. This cost is neglected in this model, because it will be small compared to the other costs. The downtime cost for unforeseen failures is taken into consideration, because it can affect the decision on the fleet composition. The downtime cost will be reduced with higher fleet capacity, as illustrated in Figure 4.1. If the fleet capacity is just high enough to cover the demand, then it has minimum capacity. Increasing fleet capacity will reduce the loss in revenue due to production stop in peak maintenance periods, as illustrated in Figure 4.2. To increase the fleet capacity beyond the demand in peak hours, will have no effect.

The curve showed in 4.1 is linearized to make the model linear. The curve is steepest in the beginning and then flattened out. The curve is divided in k line segments, where the slope will decrease for each line segment.

4.1.4 Stepwise Development of Wind Farms

To model that a big wind farm is being developed stepwise, each step can be seen as the addition of a new wind farm, to the ones already existing. In this way, the

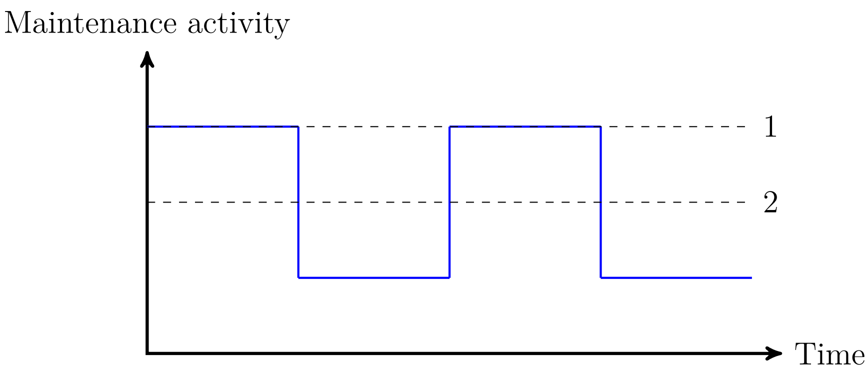


Figure 4.2: Maintenance activity demand as a function of time. The dashed line numbered 1 is illustrating the minimum downtime cost. The dashed line numbered 2 is illustrating the minimum capacity of the fleet.

big wind farm is seen as a cluster of smaller wind farms, with no distance between them. The model can also use separate wind farms with unequal distances to the same harbor. This gives the possibility for wind farm operators to consider sharing of vessels by pooling.

4.2 Definitions

Lower case letters will be used to represent indices and variables, and capital letters represent sets and constants.

Indices

f	Wind farm.
i	Type of maintenance activity.
k	Line segment.
p	Time period.
v	Type of vessel.
w	Type of offshore station, e.g. artificial island or mother ship.

Sets

F	Set of wind farms $F : \{1, ..., \|F\|\}$.
P	Set of time periods in the given time horizon.
V	Set of vessel types.
W	Set of offshore stations.
A	Set of maintenance activities.
K_i	Set of line segments for maintenance activity i.
V_w^W	Set of vessel types relevant for use to offshore station w, where $V_w^W \subseteq V$.
V_i	Set of vessel types which can perform maintenance activity of type i, where $V_i \subseteq V$.
A_v	Set of maintenance activities which can be performed by vessel of type v, where $A_v \subseteq A$.

Constants

C_{pv}^I	Investment cost of acquiring vessel of type v in time period p.
C_{pv}^F	Fixed cost of having vessel of type v in time period p.
C_{pv}^V	Variable cost of vessel of type v per hour in operation in time period p.
C_{pv}^R	Cost of renting vessel of type v in time period p. The vessel must be rented for the whole time period.
C_{pw}^I	Cost of acquiring an offshore station of type w in time period p.
C_{pw}^F	Cost of having an offshore station of type w in time period p.
C_{fikp}^D	Reduction in downtime cost because of additional capacity.
C_p^B	The budget limit for investing in vessels and/or offshore station in time period p.
R_{pv}^S	The revenue of selling a vessel of type v in time period p.
R_{pv}^H	The revenue of hiring out the vessel of type v in time period p. The vessel must be hired out for the whole time period.
T_{pv}^O	Operation time in hours for vessel of type v in time period p.
T_{fipv}^M	Number of hours vessel v need for maintenance activity i on wind farm f in time period p.
N_{fip}	Number of maintenance activities of type i needed to be done in time period p on wind farm f.
M_w	Maximum capacity at offshore station of type w.
G_{vw}	Amount of capacity one vessel of type v will occupy on an offshore station of type w.
E_{ki}	Maximum limit of the variable u_{fikp}.
R_v^V	The residual value of the vessel of type v in the end of planning horizon.

Decision Variables

x_{pv}	Number of vessels of type v owned in time period p.
x^J_{pv}	Number of new vessels of type v joining the fleet in time period p.
x^L_{pv}	Number of vessels of type v leaving the fleet in time period p.
y^R_{pv}	Number of vessels of type v rented in time period p.
y^H_{pv}	Number of vessels of type v hiring out in time period p.
z^J_{pw}	Number of offshore station(s) of type w acquired in time period p.
z_{pw}	Number of offshore station(s) of type w in time period p.
t_{fipv}	How many hours a vessel of type v operate on wind farm f in time period p on maintenance activity of type i.
u_{fikp}	The amount of extra capacity of the fleet used in time period p on wind farm f of doing maintenance activity of type i on line segment k.

4.3 Mathematical Model

The deterministic model will be explained in detail, starting with the objective function and continuing with the constraints.

4.3.1 Objective Function

The objective function

$$
\begin{aligned}
\min Z = \quad & \sum_{p\in P}\sum_{v\in V} C^I_{pv} x^J_{pv} + \sum_{p\in P}\sum_{v\in V} C^F_{pv} x_{pv} && \text{(4.1a)}\\
& + \sum_{p\in P}\sum_{w\in W} C^I_{pw} z^J_{pw} + \sum_{p\in P}\sum_{w\in W} C^F_{pw} z_{pw} && \text{(4.1b)}\\
& - \sum_{v\in V} R^R_v x_{|P|v} - \sum_{p\in P}\sum_{v\in V} R^S_{pv} x^L_{pv} && \text{(4.1c)}\\
& + \sum_{p\in P}\sum_{v\in V} C^R_{pv} y^R_{pv} - \sum_{p\in P}\sum_{v\in V} R^H_{pv} y^H_{pv} && \text{(4.1d)}\\
& + \sum_{f\in F}\sum_{i\in A}\sum_{p\in P}\sum_{v\in V} C^V_{pv} t_{fipv} - \sum_{f\in F}\sum_{i\in A}\sum_{k\in K}\sum_{p\in P} C^D_{fikp} u_{fikp}, && \text{(4.1e)}
\end{aligned}
$$

is to minimize the total costs for maintenance activities. The first part is the sum of the investment cost of purchasing a vessel and the fixed costs of having a vessel, as shown in (4.1a). The first term of (4.1b) is the investment costs in offshore stations and the second term is the fixed costs of having an offshore station. The first term of (4.1c) is the residual value, which is the value of the fleet in the end of the planning horizon. This term is included to avoid vessels to be sold in the time period prior to the last one. The second term is the revenue of selling a vessel.

The minus sign is because this is a revenue, which is the same as a negative cost. The first term of (4.1d) is the sum of all costs of renting a vessel, which is the rent expenditure, and the second term is the revenue for hiring out vessels. The first term of (4.1e) shows the variable costs for both the rented and the purchased vessels. This is typically fuel costs and payment for personnel. The last part of (4.1e) is reduction in revenue loss due to production stops, resulting from increased capacity of the fleet.

4.3.2 Constraints

All the maintenance activities need to be done in the given time period. The fleet of vessels needs to have sufficient capacity to perform all the activities within the time period. The ratio between the number of hours a given vessel operates and the number of hours the vessel needs for doing a maintenance activity, must be greater than the number of activities to be done. Stated mathematically,

$$\sum_{v \in V_i} \frac{t_{fipv}}{T^M_{fipv}} \geq N_{fip} + \sum_{k \in K_i} u_{fikp}, \qquad f \in F, \quad i \in A, \quad p \in P. \tag{4.2}$$

Here the constraints are given with a greater or equal sign, but this can be replaced with an equal sign. The constraint will often be fulfilled with an equal sign, because the variable u_{fikp} give a reduction in the objective function, and will be as high as possible to reduce the total cost.

The time a vessel is in operation must be smaller then the maximum number of hours a vessel can operate in a time period. The sum of vessels in a given time period, is the number of purchased vessels plus the number of rented vessels minus the number of vessels hired out:

$$\sum_{f \in F} \sum_{i \in A_v} t_{fipv} \leq T^O_{pv} \left(x_{pv} + y^R_{pv} - y^H_{pv} \right), \qquad p \in P, \qquad v \in V. \tag{4.3}$$

When purchasing a vessel belonging to an offshore station, the offshore station also needs to be purchased:

$$M_w z_{pw} \geq \sum_{v \in V^W_w} G_{vw} \left(x_{pv} + y^R_{pv} \right), \qquad p \in P, \quad w \in W. \tag{4.4}$$

These constraints also provide the maximum capacity limit at the offshore station. As different types of vessels take different amount of space, the parameter G_{vw} is included. As an example, a mother ship can have 10 small catamarans attached, but only 3 bigger vessels.

The number of vessels in the fleet in a certain time period are the number in the previous period plus the number of vessels joining the fleet minus the number of vessels leaving the fleet:

$$x_{pv} - x_{p-1,v} = x^J_{pv} - x^L_{pv}, \qquad p \in P \setminus \{1\}, \qquad v \in V. \tag{4.5}$$

For the first period the number of vessels in the fleet is equal to the number of vessels joining the fleet in this period:

$$x_{pv} = x^J_{pv}, \qquad p = 1, \qquad v \in V. \tag{4.6}$$

The number of offshore stations are equal to the number in the previous period plus the number of offshore stations built:

$$z_{pw} = z_{p-1,w} + z^J_{pw}, \qquad p \in P \setminus \{1\}, \qquad w \in W. \tag{4.7}$$

Once an offshore station is built, it is not possible to sell at it a later time. A mother ship can in theory be sold, but an island can not. For the first period the number of offshore stations is equal to the number built in this period:

$$z_{pw} = z^J_{pw}, \qquad p = 1, \qquad w \in W. \tag{4.8}$$

The total investments in offshore stations and vessels, minus the sales revenue, are lower than the budget limit:

$$\sum_{p=1}^{p'} \sum_{v \in V} C^I_{pv} x^J_{pv} + \sum_{p=1}^{p'} \sum_{w \in W} C^I_{pw} z^J_{pw} - \sum_{p=1}^{p'} \sum_{v \in V} C^S_{pv} x^L_{pv} \leq C^B_p, \qquad p' \in P. \tag{4.9}$$

The maximum value of the variable u_{fikp} must be restricted:

$$u_{fikp} \leq E_k, \qquad f \in F, \quad i \in A, \quad k \in K, \quad p \in P, \tag{4.10}$$

as it will only give a reduction in the objective value to have extra fleet capacity up to a level decided by the peak hours. The extra capacity of the fleet is more valuable for the first extra capacity, then the curve flattens. This ensure that u_{fikp} will reach E_1 before E_2.

Finally, constraints (4.11) – (4.19) define the domain of the decision variables.

$$x_{pv} \in \mathbb{Z}^+, \qquad p \in P, \quad v \in V, \tag{4.11}$$
$$x^J_{pv} \in \mathbb{Z}^+, \qquad p \in P, \quad v \in V, \tag{4.12}$$
$$x^L_{pv} \in \mathbb{Z}^+, \qquad p \in P, \quad v \in V, \tag{4.13}$$
$$z_{pw} \in \mathbb{Z}^+, \qquad p \in P, \quad w \in W, \tag{4.14}$$
$$z^J_{pw} \in \mathbb{Z}^+, \qquad p \in P, \quad w \in W, \tag{4.15}$$
$$y^R_{pv} \in \mathbb{Z}^+, \qquad p \in P, \quad v \in V, \tag{4.16}$$
$$y^H_{pv} \in \mathbb{Z}^+, \qquad p \in P, \quad v \in V, \tag{4.17}$$
$$t_{fipv} \geq 0, \qquad f \in F, \quad i \in A, \quad p \in P, \quad v \in V, \tag{4.18}$$
$$u_{fikp} \geq 0, \qquad f \in F, \quad i \in A, \quad k \in K, \quad p \in P. \tag{4.19}$$

Chapter 5

Stochastic Mathematical Model

This chapter describes a mathematical model which takes some of the uncertainty into consideration. In the deterministic model described in Chapter 4, all the input data are assumed deterministic and known. In reality, all parameters are not known and therefore a stochastic model has been developed.

5.1 Assumptions

The assumptions made for the deterministic model described in Section 4.1, will also be valid for this model, except some of the deterministic assumptions.

5.1.1 Uncertainty

The main uncertain parameters attached to this problem are the prices, the number of failures and the weather conditions. The number of failures influence the demand of vessels and by that the optimal fleet. The weather conditions influence the length of the time windows and is an important factor affecting the number of hours a vessel can sail in a given time period. The wind speed and the corresponding wave height are the most important factors affecting the decision of determining the optimal fleet. The prices for acquiring and renting vessels are also uncertain. Comparing with other markets, the market for vessels used for performing maintenance at offshore wind farms is more predictable, because the demand depends on the number of wind farms. The number of wind farms is known in advance, and the demand is therefore more predictable than in other markets. The small changes in prices will not have a big influence on determining the optimal fleet. The general tendencies in prices are more important and are also easier to predict. The uncertainties in prices are therefore not taken into consideration in this model. The model presented in this chapter takes into account uncertainties in weather conditions and turbine failures requiring corrective maintenance.

5.1.2 Number of Stages

To decide the number of stages it is important to think of the timing of the decisions relative to the resolution to be made. The most obvious is to have one time period as a stage. Because this is a strategic planning model with a long time horizon, and therefore many time periods, this will increase the size of the problem rapidly. With only 20 time periods and two possible outcomes in each time period this will produce 2^{20} scenarios. This will take long time to solve and the optimal solution may be hard to find.

Another approach is to state that the time periods in the second stage are approximately independent of each other, both when looking at the number of failures which require corrective maintenance, and when looking at the weather which determines the total operation time in each time period. The decision regarding chartering in and out vessel is independent from one period to another. This independence in the second stage will make it possible to solve all time periods in parallel and have a two-stage recourse model.

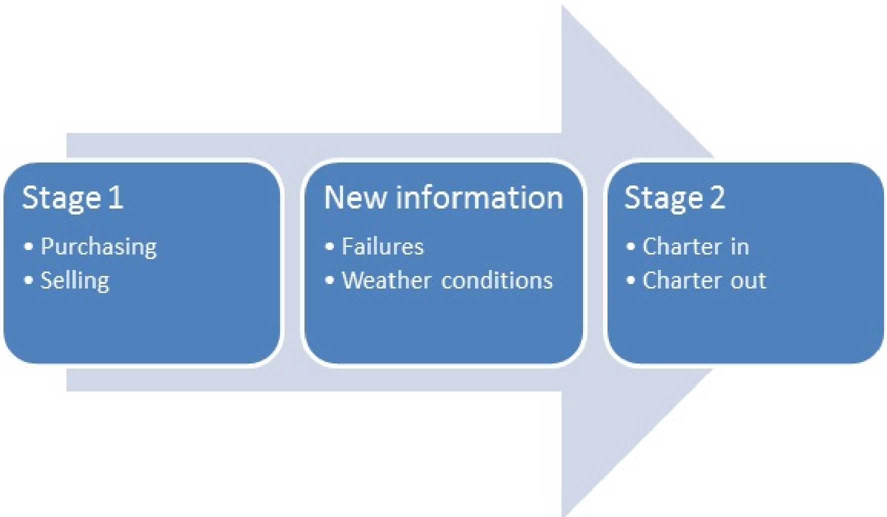


Figure 5.1: Illustration of when decisions and new information are received.

In the first stage, determination of how many vessels should enter and leave the fleet, and how many offshore stations should be built, for the whole planning horizon, will be decided. This is illustrated in Figure 5.1, where the big arrow illustrate how the different decisions are to be made in time. The first stage problem will be to decide the fleet in every time period. The exact demand for the

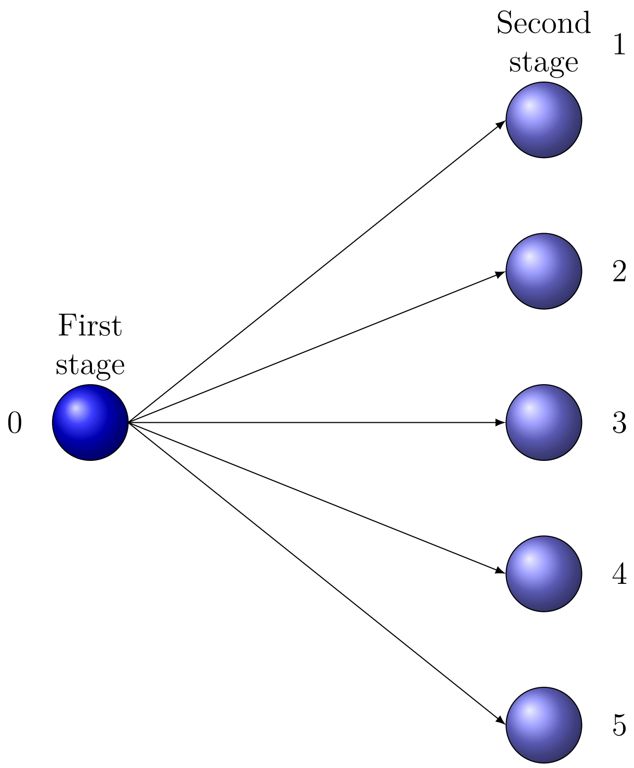


Figure 5.2: Scenario tree for 5 scenarios.

fleet is not known yet, neither how often corrective maintenance need to be done nor how long operation time each vessel has in the given time period.

After the first stage, new information about the number of corrective maintenance tasks and weather conditions will be received. Based on the new information it is possible to charter in and out vessels to ensure that every maintenance task will be performed in the given time period, as illustrated in Figure 5.1.

A principal sketch of how the scenario tree will look like is shown in Figure 5.2. This is an example with 5 scenarios in stage two. Node 0 represents the decisions made in the first stage, and the nodes numbered 1–5 represent each of the possible scenarios in stage two.

5.1.3 New Sets and Variables

The decision variables containing buying and selling vessels and offshore stations are the same as for the deterministic model. The decision variables for chartering in and out, for extra capacity of the fleet and the time each vessel operates, has an extra subscript s added to separate the decisions made for each scenario. A new set S is added, containing the different scenarios.

5.1.4 Constraints and Stages

The first stage constraints involve all the constraints associated with buying and selling vessels and helicopters, and buying offshore stations. These constraints are the same as for the deterministic case. The second stage constraints differ from the deterministic model, as one constraint is needed for each scenario.

5.2 Definitions

The same notation as in the deterministic model described in Section 4.2 is used. The sets, variables, and constants, which are dependent on the scenarios in stage two, have an extra index, s, which represents the scenario. The indices, sets, parameters and decision variables, which are the same in both the deterministic and stochastic model, will not be repeated here, see Section 4.2.

Indices

s Scenario number.

Stochastic parameters

B_s The probability of scenario s.

Sets

S Set of scenarios.

Constants

T^O_{pvs} Operation time in hours for vessel of type v in time period p in scenario s.

N_{fips} Number of maintenance activities i needed to be done in time period p on wind farm f in scenario s.

Decision Variables

y^R_{pvs}	Number of vessels of type v rented in time period p in scenario s.
y^H_{pvs}	Number of vessels of type v hiring out in time period p in scenario s.
t_{fipvs}	Number of hours a vessel of type v operate on wind farm f in time period p on maintenance activity of type i in scenario s.
u_{fikps}	The amount of additional capacity of the fleet, used in time period p on wind farm f, doing maintenance activity of type i in scenario s, to make the fleet more efficient.

5.3 Mathematical Model

The stochastic model consists of the objective function, and the constraints in the stage and second stage.

5.3.1 Objective Function

The main purpose of the objective function

$$\min Z = \sum_{p\in P}\sum_{v\in V} C^I_{pv} x^J_{pv} + \sum_{p\in P}\sum_{v\in V} C^F_{pv} x_{pv} \tag{5.1a}$$

$$+ \sum_{p\in P}\sum_{w\in W} C^I_{pw} z^J_{pw} + \sum_{p\in P}\sum_{w\in W} C^F_{pw} z_{pw} \tag{5.1b}$$

$$- \sum_{v\in V} R^R_v x_{|P|v} - \sum_{p\in P}\sum_{v\in V} R^S_{pv} x^L_{pv} \tag{5.1c}$$

$$+ \sum_{s\in S} B_s \left[\sum_{p\in P}\sum_{v\in V} C^R_{pv} y^R_{spv} - \sum_{p\in P}\sum_{v\in V} R^H_{pv} y^H_{spv} \right. \tag{5.1d}$$

$$\left. + \sum_{f\in F}\sum_{i\in A}\sum_{p\in P}\sum_{v\in V} C^V_{pv} t_{sfipv} - \sum_{f\in F}\sum_{i\in A}\sum_{k\in K}\sum_{p\in P} C^D_{fikp} u_{sfikp} \right], \tag{5.1e}$$

is to reduce the expected value of the total costs. The terms (5.1a) – (5.1c) are the same as for the deterministic case. The terms inside the square bracket are nearly the same as for the deterministic model, and is multiplied with the probability that the scenario will occur, which give the expected cost. The variables connected to chartering in and out, time of operating the vessel and amount of extra capacity, have an extra subscript s, to tell which scenario it is associated with.

5.3.2 First Stage Constraints

The constraints summarized here are the same as for the deterministic model. Here, the equations are just listed, as the explanation is already given in Section 4.3.2.

$$x_{pv} - x_{p-1,v} = x^J_{pv} - x^L_{pv}, \qquad p \in P \setminus \{1\}, \qquad v \in V, \tag{5.2}$$

$$x_{pv} = x^J_{pv}, \qquad p = 1, \qquad v \in V, \tag{5.3}$$

$$z_{pw} = z_{p-1,w} + z^J_{pw}, \qquad p \in P \setminus \{1\}, \qquad w \in W, \tag{5.4}$$

$$z_{pw} = z^J_{pw}, \qquad p = 1, \qquad w \in W, \tag{5.5}$$

$$\sum_{p=1}^{p'} \sum_{v \in V} C^I_{pv} x^J_{pv} + \sum_{p=1}^{p'} \sum_{w \in W} C^I_{pw} z^J_{pw} - \sum_{p=1}^{p'} \sum_{v \in V} C^S_{pv} x^L_{pv} \leq C^B_p, \qquad p' \in P. \tag{5.6}$$

Constraints (5.2) – (5.6) are equivalent to (4.5) – (4.9).

$$x_{pv} \in \mathbb{Z}^+, \qquad p \in P, \quad v \in V, \tag{5.7}$$
$$x^J_{pv} \in \mathbb{Z}^+, \qquad p \in P, \quad v \in V, \tag{5.8}$$
$$x^L_{pv} \in \mathbb{Z}^+, \qquad p \in P, \quad v \in V, \tag{5.9}$$
$$z_{pw} \in \mathbb{Z}^+, \qquad p \in P, \quad w \in W, \tag{5.10}$$
$$z^J_{pw} \in \mathbb{Z}^+, \qquad p \in P, \quad w \in W. \tag{5.11}$$

Constraints (5.7) – (5.11) are equivalent to (4.11) – (4.15).

5.3.3 Second Stage Constraints

The second stage problem will be solved for each scenario. The constraints are changed to take the different scenarios into account.

The constraints

$$M_w z_{pw} \geq \sum_{v \in V^W_w} G_{vw} \left(x_{pv} + y^R_{pvs} \right), \qquad p \in P, \quad w \in W, \quad s \in S, \tag{5.12}$$

are modified versions of constraints (4.4) from the deterministic model. These constraints ensure that the number of vessels added to an offshore station are less than the capacity of the station and that the station is built. These constraints can be moved to first stage constraints if it is forbidden to rent vessels for an offshore station. If only purchased vessel can be a part of the offshore station, these constraints can be reduced by deleting the variable y_{pvs}^{R} and be a part of the first stage problem.

The constraints

$$\sum_{v \in V_i} \frac{t_{fipvs}}{T_{fipv}^{M}} \geq N_{fips} + \sum_{k \in K_i} u_{fikps}, \qquad f \in F, \quad i \in A, \quad p \in P, \quad s \in S, \tag{5.13}$$

are the modified editions of the constraints (4.2) in the deterministic model. The change is due to s which represents the different scenarios in the second stage.

The constraints

$$\sum_{f \in F} \sum_{i \in A_v} t_{fipvs} \leq T_{pvs}^{O} \left(x_{pv} + y_{pvs}^{R} - y_{pvs}^{H} \right), \qquad p \in P, \quad v \in V, \quad s \in S, \tag{5.14}$$

are the modified versions of the corresponding constraints (4.3) in the deterministic model. The change is due to introduction of s which represent the different possible outcomes in second stage.

The constraints

$$u_{fikps} \leq E_k, \qquad f \in F, \quad i \in A, \quad k \in K, \quad p \in P, \quad s \in S, \tag{5.15}$$

are the edited versions of constraints (4.10) from the deterministic model. The constraint set an upper limit for the decision variable u_{fikps}.

The following constraints set the requirements of the decision variables to be non-negative and have integer values (5.16 and 5.17), and impose non-negativity properties (5.18 and 5.19).

$$y_{pvs}^{R} \in \mathbb{Z}^{+}, \qquad p \in P, \quad v \in V, \quad s \in S, \tag{5.16}$$

$$y_{pvs}^{H} \in \mathbb{Z}^{+}, \qquad p \in P, \quad v \in V, \quad s \in S, \tag{5.17}$$

$$t_{fipvs} \geq 0, \qquad f \in F, \quad i \in A, \quad p \in P, \quad v \in V, \quad s \in S, \tag{5.18}$$

$$u_{fikps} \geq 0, \qquad f \in F, \quad i \in A, \quad k \in K, \quad p \in P, \quad s \in S. \tag{5.19}$$

Chapter 6

Computational Study

This section describes the choice of critical input parameters, the preprocessing of data in Excel and the instance generator implemented in C++. The results and analysis from the computational study will also be presented in this chapter. A potential offshore wind farm, located in the North Sea, together with a number of different vessel types, helicopters and offshore stations have been used as a basis for the test cases.

6.1 Selection Of Critical Input Data

Input data for the model is based on the research done by Gundegjerde and Halvorsen (2012). They have pursued the best practice for the offshore wind industry where possible, in order to generate realistic scenarios. The data has been aggregated to fit the model explained in Chapters 4 and 5. The main purpose of the computational study has not been to analyze the costs themselves, but to determine how the model can be used.

6.1.1 Vessels and Offshore Stations

The model has been developed to handle various types of vessels and offshore stations. The data regarding vessels and offshore stations are based on Gundegjerde and Halvorsen (2012) and Kaiser and Snyder (2010). The data about helicopters are based on Conklin and de Decker (2011) and Gundegjerde and Halvorsen (2012). The costs are estimated, but an offshore wind farm operator will have access to all the data. Therefore the cost data is not given here, see the attached files for further details. Some relevant characteristics for the vessels are described in Table 6.1.

The costs are chosen such that renting a vessel for a period is much higher than the fixed costs of owning a vessel. The price for renting in vessels is higher in the summer, when the demand is high. The preventive maintenance tasks are mainly performed in the summer, because of the weather conditions, and therefore the demand for vessels are higher in the summer. In the same way, the revenue of hiring out vessels in the winter is lower. The operational cost is cost per hour and is the same for both rented and bought vessels. The residual value in the last period is set equal to the selling price in the time period prior to the last one. When a vessel is needed for many consecutive periods, a purchase is cost saving. The revenue of selling a vessel is set to be less than the cost of purchasing, to avoid an artificial selling. If the cost of selling a vessel is equal to the price of purchasing the vessel back, several identical solutions will be possible, and may cause a longer solution time.

Table 6.1: Characteristic of the vessels and helicopters.

Vessel number	Vessel type	Personnel amount	Wave restriction [m]	Lift capacity [Metric tons]
1	CTV(small)	12	1.5	0
2	CTV(large)	24	2.0	0
3	CTV(small)	12	1.5	0
4	Supply vessel (small)	40	2.5	0
5	Supply vessel (large)	70	2.5	0
6	Helicopter1	7	-	0
7	Helicopter2	9	-	0
8	Multi-purpose vessel	100	2.0	250
9	Jack-up rig	150	2.5	400

Offshore wind is a relatively new technology and is developing. The model can handle various vessel and offshore station concepts. Because the concepts are relatively new, it is difficult to find exact data, especially for offshore station concepts. Some of the data used for the offshore stations in this computational study are shown in Table 6.2, for further details see the attached files.

In this study, 9 types of vessels and 2 offshore station concepts are considered. The model can handle that some concepts are not available from the beginning of the planning horizon, but will be available at a later time. In this computational study, all the vessels are available from the beginning of the planning horizon.

6.1.2 Maintenance Activities

Preventive maintenance is done two times a year on each wind turbine. Because of difficult weather conditions in the North Sea during the winter, this will be

Table 6.2: The characteristics for the offshore stations used in the computational study.

Offshore station number	Offshore station type	Belonging vessel type	Vessel capacity
1	Mother ship	1 and 7	4 and 2
2	Artificial island	1 and 7	8 and 4

Table 6.3: The probability of different maintenance activities.

Type of maintenance	Operation type	Failure rate
Preventive maintenance	General maintenance	-
Corrective maintenance	Gearbox	0.13
Corrective maintenance	Hydraulic	0.27
Corrective maintenance	Electric	0.55
Corrective maintenance	Brakes	0.20

done in the summer. Random failures, such as corrective and condition based maintenance, have been merged into corrective maintenance and divided into four groups, as shown in Table 6.3.

Each maintenance activity type requires different amounts of personnel and lifting capacity. For corrective maintenance both human interaction, lifting capacity and transport activity restrict which vessels can be chosen. Only a failure of the gearbox will require lifting capacity. For performing preventive maintenance all vessels can be used, because it requires only personnel resources. For vessels with space for more personnel, the time used for this activity will be reduced as a consequence of personnel working in parallel. There is an upper limit to how many persons can work in parallel due to safety restrictions.

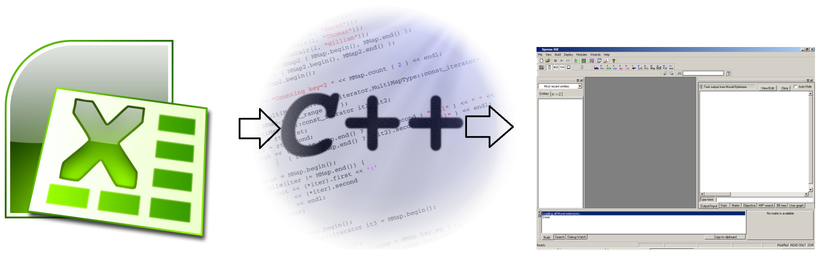
6.1.3 Other Input Data

Wind and wave conditions are based on downloaded data for Ekofisk from eklima.met.no. The weather on this offshore platform in the North Sea will represent the expected weather condition on an offshore wind farm in the North Sea. The weather data is used to count the number of hours a vessel can operate in each time period. Time periods can vary in length, but in this computational study it is chosen to fix the time period to three months, which means that a year consists of four time periods, and wind farms with an expected lifetime of 25 years consists of 100 periods.

Time value of money is important to take into consideration in a strategic planning model with a long planning horizon. The costs will therefore be depreciated with a rate of 3 % each year. The budget limit is set extremely high, to avoid the budget to be a limiting factor and a binding constraint. The number of wind farms are varying for different test cases. Each wind farms open up on different time, has different amount of wind turbines and different length to shore. For test cases with few wind farms, the wind farms farthest from shore are chosen.

6.2 Pre-Processing of Input Data

The input data is preprocessed with use of Excel and C++ before being input to the optimization software. In Excel, tables of costs for the first time period are made. Based on the data from the Ekofisk field, the number of hours a vessel can be used is determined. The data is read in to a C++ program where the generation of input files to Xpress is done. In the C++ program, the discounting of the cost is done and the number of failures are drawn. A random generator is used, and draw an integer number between 0 and 100. If the drawn number is below the probability for a maintenance task to occur, a corrective maintenance activity of that type needs to be executed in that period. The step by step process with input data, via the generator and into the optimization software is illustrated in Figure 6.1.



(a) Input data in Excel.

(b) Scenario generation in C++.

(c) Xpress-MP implementation.

Figure 6.1: The interaction between input data, the generator and the optimization software.

6.3 Implementation of the Models

The models have been implemented in the MOSEL language and the solver package used is FICO^{TM} Xpress Optimization Suite by Dash Optimization. The tests of the models are performed on a computer with an AMD Opteron 2431 CPU 2,4

GHz and 24 GB RAM. See the attached files for the model implementation. The presolve was skipped for the EV and EEV problems, because presolve allows illegal solutions in some of the test cases.

6.4 Computational Study of the Deterministic Model

The deterministic model will be investigated and analyzed. First the test cases will be described, then the results will be presented and analyzed.

6.4.1 Test Cases

For all test cases the number of types of activities is 5 and is shown in Table 6.3. The number of vessels is 9 and is described in Table 6.1. The number of offshore stations is 2 and described in Table 6.2. The number of wind farms, and the number of time periods changes. The corresponding number of wind farms, wind turbines and time periods are given in Table 6.4. One year is divided in 4 time periods, which consists of 3 months. The number of years indicate the length of the planning horizon.

6.4.2 Results and Analysis

The results of the test cases are presented in Table 6.4. Solving time is the time in seconds the model uses to solve the problem. The number of Branch & Bound (B&B) nodes says how big the B&B tree is for proving that the optimal solution is found.

The deterministic model is fast for solving big problems. The biggest test case in this study consists of 1140 wind turbines divided on 13 wind farms developed stepwise over the first four years of the planning horizon. The planning horizon is 25 years and the solution time is less than 23 minutes.

The results from these test cases show that large CTV's and small supply vessels will be bought early in the planning horizon. Vessels with lifting capacity are not needed in every time period, and are therefore rented in when needed. These are big vessels with huge investment costs and are best to rent. Just three of the test cases recommend a vessel being sold, and it happens in the second to last time period. This is a deterministic model and in cases with few corrective maintenance in the last period, it can be profitable to sell vessels, and can be interpreted as end-effects. In none of the test cases it is profitable to build an offshore station. A reduction on the investment cost will make it more likely to invest. In neither of the test cases a helicopter is rented or bought. The number of

Table 6.4: Test cases and solving times for the deterministic model.

Test case	Number of wind farms	Number of wind turbines	Number of years	Solving time [s]	Number of B&B nodes
1	1	40	1	0	1
2	1	40	2	0	1
3	1	40	3	0	1
4	5	300	3	0	11
5	5	300	4	1	27
6	5	300	5	0	31
7	10	850	5	1	23
8	10	850	7.5	2	43
9	10	850	10	4	396
10	10	850	12.5	4	54
11	10	850	15	5	175
12	10	850	17.5	13	1116
13	10	850	20	56	8390
14	10	850	22.5	69	5790
15	10	850	25	28	1750
16	13	1140	25	1338	106833

purchased vessels are as expected strongly related to the number of wind turbines. With planning horizons shorter than 2 years, there will be no investment in vessels, as it is cheaper to rent.

The different types of vessels are input to the model, and two vessels with identical properties should not be separated as two types of vessel. For instance, if two vessels have the same investment costs, the same fixed costs and just a small difference in variable cost, it should be just one type of vessel in the model. Two vessels with similar properties may lead to identical solutions, and cause longer solution times.

In Table 6.5 the number of purchased, rented, hired out and sold vessels are presented. The number presented in column 'number of rented vessels' and 'number of hired out' vessels is the average number for each time period. The amount of chartered in and out vessels differ not much from one test case to another. In average, 1 or 2 vessels are being rented each time period. The reason why these vessels are rented and not bought, is because different types are needed in different seasons. In the summer, small vessels are supplying the fleet to perform preventive maintenance, and additionally, corrective maintenance requires crane capacity. In the winter, some of the vessels are hired out, especially the CTVs which are used to perform preventive maintenance in the summer.

Table 6.5: Results from the computational study, number of vessels in each test case and the distribution between purchased, rented, hired out and sold vessels.

Test case number	Number of purchased vessels	Number of rented vessels	Number of hired out vessels	Number of sold vessels	Number of offshore stations
1	0	2.00	0.00	0	0
2	3	0.88	0.50	0	0
3	3	0.58	0.67	0	0
4	22	1.17	5.00	0	0
5	22	1.19	6.25	0	0
6	22	1.25	7.00	0	0
7	62	1.30	15.40	0	0
8	62	1.40	21.33	0	0
9	62	1.38	19.45	0	0
10	62	1.32	23.56	0	0
11	63	1.32	23.48	0	0
12	63	1.39	24.96	1	0
13	62	1.41	24.08	1	0
14	63	1.38	24.91	1	0
15	63	1.32	25.19	0	0
16	97	1.98	38.46	0	0

Realistic Size

The size of the problem depends on the number of wind turbines, the number of wind farms, the length of the planning horizon and the number of scenarios. The deterministic model has solved problems with 13 wind farms, 1140 wind turbines and with a planning horizon of 25 years in less than 23 minutes. This shows that the deterministic model can solve problems of realistic size.

6.5 Computational Study of the Stochastic Model

Here the scenario generation will be presented together with the result and analysis of the stochastic model. For the input data which is the same for both the stochastic and deterministic case, see Section 6.1.

6.5.1 Scenario Generation

The method used for scenario generation for the stochastic model is presented here. This applies for the weather scenarios, which are Weibull distributed, and the number of maintenance tasks attached to each scenario.

Weather Scenario Generation

The weather is one of the uncertainties the stochastic model will consider. The wind speed and wave height are the most important parameters which influence the availability of the vessels and the helicopters. The wave height will affect the accessibility of the vessels, and the wind speed will mainly affect the accessibility of the helicopters. The wind speed is also crucial for the production at the wind farms.

To model the wind speed in this computational study, a two-parameter Weibull distribution is used. In Weibull distribution, two important parameters, k and c, need to be estimated. k is the dimensionless shape parameter, and c is the scale parameter in (m/s) (Vallée et al., 2007). The cumulative Weibull distribution function of the wind speed v is

$$F(v; c, k) = 1 - e^{-(v/c)^k}, \tag{6.1}$$

and the Weibull probability density function for $v \geq 0$ is

$$f(v; c, k) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} e^{-(v/c)^k}. \tag{6.2}$$

Spahic et al. (2009) have done a study based on data from the North Sea, and they conclude that the wind speed can be approximated by the Weibull shape parameter $k = 2.17$. Bhattacharya and Bhattacharjee (2009) conclude that a good estimate of the parameters are:

$$c = 1.128\bar{v} \quad | \quad 1.4 \leq k \leq 4. \tag{6.3}$$

Based on these two studies, the selection of shape parameter is $k = 2.17$, and the scale parameter c is based on Equation (6.3). $\bar{v}$ is found with use of the historical data for the last ten years for the Ekofisk field in the North Sea derived from Norwegian Meteorological Institute (2012), and is the average wind speed per day. Excel is used to generate random numbers for wind speed with use of

$$v = c[-\ln(1 - RAND())]^{\frac{1}{k}}, \tag{6.4}$$

from (Gedam and Beaudet, 2000).

Based on historical wind speed data and wave height data from Ekofisk, a high correlation between wind speed and wave height can be observed. In this computational study, this correlation is assumed to be 1. This makes it sufficient to generate different wind scenarios, and then divide with the correlation factor $\bar{d}$ to estimate the corresponding wave heights. Based on historical data, the mean division factor has been calculated to $\bar{d} = 4.3$.

Failure Scenarios

The other crucial uncertainty parameter is the number of maintenance tasks which needs to be performed in each time period. To generate different number of failures on each wind farm, the same random number generator as described in Section 6.2. is used. The difference from the deterministic case is that the generator generate a new number of failures for each scenario.

6.5.2 Evaluation of the Stochastic Model

A stochastic model is often difficult to solve and often special purpose methods are used to solve the stochastic problems. The number of decision variables increase with the number of scenarios, and may lead to longer solving times. The expected value of perfect information and the value of stochastic solution, will be described and measured.

Expected Value of Perfect Information

Expected value of perfect information (EVPI) in stochastic programming measures the maximum amount a decision maker would be willing to pay for complete and accurate information about the future (Birge and Louveaux, 1997). It is not

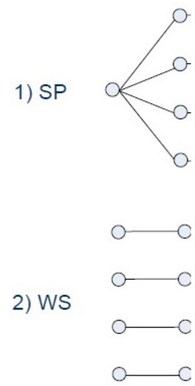


Figure 6.2: Illustration showing the difference between stochastic problem (SP) and the wait-and-see problem (WS). The expected value of perfect information (EVPI) is equal to the difference between SP and WS. Source: Lecture in 'Managerial Economics and Operations Research, Specialization Course', NTNU.

realistic to buy perfect information about weather in the future, but EVPI is a measure that says something about how much it is worth to pay for this kind of information. In this computational study, EVPI will be a theoretical value, because it is not possible to predict the weather and when failures happen. The concept of EVPI was first developed in the context of decision analysis and can be found in Raiffa and Schlaifer (1961).

To find EVPI, the stochastic problem (SP) is solved first. Secondly the wait-and-see problem (WS) is solved, which means that each scenario will be solved individually as a deterministic problem. The difference between SP and WS is

$$EVPI = SP - WS, \tag{6.5}$$

and is illustrated in Figure 6.2. The inequality

$$0 \leq EVPI, \tag{6.6}$$

is valid for any minimization stochastic program, which means that the value of the wait-and-see problem is always less than the value of the stochastic problem. Hence EVPI will always be positive.

Value of Stochastic Solution

The value of the stochastic solution (VSS) is the expected value of using a stochastic model for planning, instead of a deterministic model. To decide the value of a stochastic solution, it is necessary to compute the value of the expected value problem (EV), where the uncertain parameters are changed to their expected value.

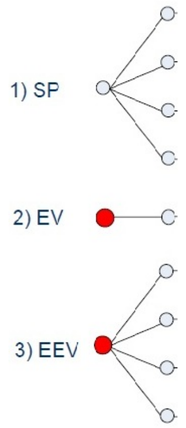


Figure 6.3: Illustration of VSS. The red dots indicate that EEV is solved with the fixed first stage variables from the EV problem. Source: Lecture in 'Managerial Economics and Operations Research, Specialization Course', NTNU.

Then the second-stage decisions in the stochastic problem is solved to optimality, with fixed first stage variables from the EV, and the result is the solution of the expected value of the EV problem (EEV). When a minimization problem is considered, the VSS is equal to

$$VSS = EEV - SP, \tag{6.7}$$

and is illustrated in Figure 6.3. The red dots indicating the same first stage solution in EV and EVV. They are fixed after solving the EV problem and used in EEV. The inequality

$$0 \leq VSS, \tag{6.8}$$

is valid for any stochastic program, which means that for a minimization problem the value of the stochastic solution will be lower and better than the solution of the EEV problem, and therefore the VSS will always be positive.

6.5.3 Test Cases

Different test cases have been generated with use of the instance generator in C++, with a different number of wind farms, number of wind turbines, number of steps in stepwise development, length of planning horizon and number of scenarios. For more information about vessels, offshore station concepts and maintenance activities, see Section 6.1.

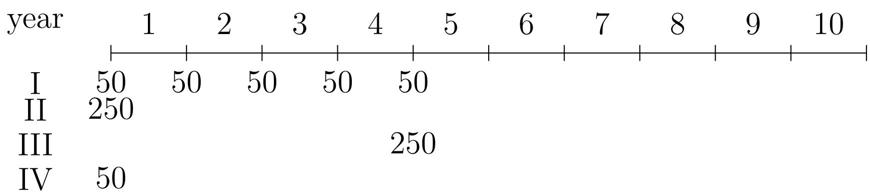


Figure 6.4: Timeline for stepwise development, showing when and how many wind turbines appear.

6.5.4 Stepwise Development

One of the goals with this model is to consider how the fleet differs resulting from stepwise development of wind farms. A planning period of 10 years is considered and the stepwise development is illustrated in Figure 6.4. The test cases have been named I–IV, with different steps. Test case I has 5 steps, installing 50 wind turbines in the beginning of each year the first 5 years. In test case II, 250 wind turbines stand there from the beginning of the planning period. In test case III, 250 wind turbines are all being installed at the same time, in beginning of year 5. In test case IV, 50 wind turbines are there from the beginning of the planning horizon.

The results show that test cases I–III all have the same fleet after 5 years. The total number of vessels is five and consist of three small CTVs, one small supply vessel and one multi-purpose vessel. In test case II and III all the 5 vessels are bought at the same time, right after the 250 wind turbines are installed. But in test case I the vessels are bought over time, as shown in Figure 6.5. The last test case IV, shows that the same decision will be made in the first time period as in test case I, namely investment in two vessels, one CTV and one multi-purpose vessel.

The results from these test cases show that the model with use of stepwise development for wind farms are very useful and cost-saving. At the end, the test cases I–III have the same fleet. Test cases I and IV have the same fleet after one year. Without this model it is hard to know when it is the right time for buying new vessels.

6.5.5 Computational Time

The solver use the B&B method as solution strategy to solve the integer programming problems. This is an implicit enumeration method. The feasible region is split into smaller regions, and a relaxed problem is solved in each subproblem (Lundgren et al., 2010). Solving the relaxed problem gives an optimistic bound, here called 'best bound', of the optimal objective function value. When generating

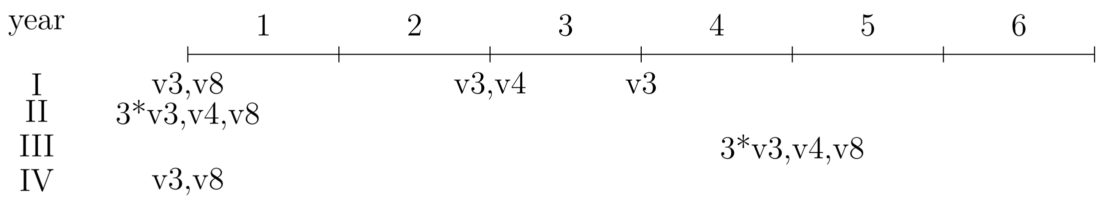


Figure 6.5: Timeline showing when to buy the different vessels for the test cases. v3 = small CTV, v4 = small supply vessel, v8 = multi-purpose vessel.

feasible solutions to the original problem, a pessimistic bound of the optimal objective function value is found. The best solution found after a given time, is in a minimization problem, the lowest pessimistic bound. The optimal solution could be equal to this pessimistic bound, or it could be lower, but never lower than the optimistic bound. The gap (G) is given in percent and is equal to the difference between best bound (BB) and best solution (BS), divided on the best solution:

$$G = \frac{BS - BB}{BS}. \tag{6.9}$$

The computational study has shown that the B&B tree grows rapidly in size. An integer solution is found fast, but it takes time to prove that the optimal solution is found. Many nodes and edges need to be solved, and the size of the tree for solving stochastic problems are as an example 13.9 Gb after 4000 seconds. In one test case the B&B tree for the EEV problem is above 18.6 Gb. The limiting factor for the model is not the solution time itself, but the memory capacity of the computer, which quickly runs out of memory. A solution time of only one or two hours should be considered short for this kind of strategic planning tool, with a planning horizon of 20–25 years. The landscape of the solutions is relatively flat, and is the main reason why the tree gets so big.

Different strategies have been tried to reduce the size of the B&B tree in proving that the optimal solution is found. One test case with 150 wind turbines divided on three wind farms, with a planning horizon of four years and 35 scenarios, has been solved with different strategies. There has been added some helping variables to sum over the scenarios for both renting and hiring out vessels, and then branching on these helping variables. Aggressive cutting strategy has also been tried and the default presolve function in Xpress has been turned on and off. The results shown in Table 6.6, indicate that the implementation of the helping variables and the aggressive cutting strategy do not lead to any improvement. The biggest changes are due to whether presolve is used or not. A better solution was found when the presolve was turned off, but a higher best bound was found by using the presolve.

By comparing the results from this test case, the best solution found is 113.54 MEUR and the best bound is 112.83 MEUR, which gives a gap of 0.6 %. This is significantly lower than the gap from any of the separate test cases. By combining the results from when the presolve is used and when it is not used, the gap decreases and the it can be proven that the solution is closer to the optimal one.

Table 6.6: Computational time.

	1	2	3	4	5	6
Presolve	no	no	no	yes	yes	yes
Helping variables	no	yes	no	no	yes	no
Aggressive cut strategy	no	no	yes	no	no	yes
Best solution [MEUR]	113.54	113.71	113.54	114.15	114.15	114.15
Best bound [MEUR]	112.14	111.92	112.14	112.83	112.83	112.83
Gap [%]	1.23 %	1.57 %	1.23 %	1.16 %	1.16 %	1.16 %
Solution time [s]	3198	3601	3000	3600	3600	3600

6.5.6 Evaluating the Stochastic Model

The EVPI compares the value of the wait-and-see problem with the stochastic solution. Complete information about weather conditions and number of failures is not possible and make the EVPI a theoretical value in these test cases. The VSS calculate the expected value of having a stochastic model compared to a deterministic one. The number of wind farms is fixed to 1 and contains 40 wind turbines. The planning horizon, given in years, and the number of scenarios, are increasing. The input data concerning vessels, offshore stations, and maintenance activities are as explained in Section 6.1. The stochastic problem in the test cases is solved to an optimality gap below 0.3 % and the biggest test case, number 10, took an hour to solve. The EV and EEV problems are solved to optimality, with a gap below 0.01 %. The test cases and their results are shown in Table 6.7.

The VSS and EVPI are positive in all test cases, and this is expected according to Equations (6.6) and (6.8). EVPI has a slow increasing tendency when the planning horizon and the number of scenarios increase. The VSS is considerably higher both in absolute value and in % compared with EVPI. The VSS is increasing with both number of scenarios and the length of the planning horizon. The increasing tendency in value of VSS shows there is a benefit of using the stochastic model compared with the deterministic.

When looking further into the solutions of the EV, EEV and SP problems the value of the VSS can be explained. The EV solution has a tendency to purchase a large CTV, while the SP solution invest in a small supply vessel instead. The stochastic model choose a bigger vessel with space for more personnel and with higher wave restriction. By this the stochastic model search for a more robust fleet

Table 6.7: EVPI and VSS results for the different test cases.

Test case	Number of years	Number of scenarios	EVPI [EUR]	EVPI [%]	VSS [EUR]	VSS [%]
1	2	1	-	0.00 %	-	0.0 %
2	2	2	3 315	0.01 %	2 253 796	7.7 %
3	4	20	202 183	0.35 %	4 817 962	8.4 %
4	4	30	252 795	0.47 %	6 109 295	11.4 %
5	8	16	256 327	0.30 %	12 171 392	14.3 %
6	8	32	154 012	0.19 %	13 358 137	16.3 %
7	10	32	198 439	0.21 %	14 490 218	15.2 %
8	10	40	223 930	0.24 %	15 095 814	16.2 %
9	12.5	40	241 187	0.23 %	17 041 649	16.4 %
10	12.5	50	339 916	0.33 %	17 373 865	17.0 %

compared to the expected value problem. As a consequence of the decision in the expected value problem, the EEV problem needs to charter in this supply vessel often.

Based on the results from this test, the conclusion is that there is a significant benefit of using the stochastic model compared to a deterministic model. The willingness to pay for perfect information is relative low.

6.5.7 Investments in Vessels and Offshore Stations

In neither of the test cases any offshore station concepts are purchased and built, because the benefits from having an offshore station does not make up for the costs used. The investment cost is an input parameter and is uncertain in this computational study, but the offshore wind farm operators will have access to more accurate data. If the investment cost is reduced, there will be investments in offshore stations. This model aggregates the time windows and in this way may reduce the benefit of having an offshore station. Offshore stations let vessels operate in shorter time windows, because of the reduction in transport distance and time.

In none of the test cases any vessel is sold. When a wind farm first has been built, it will never disappear, and the need for the already purchased vessels is therefore not reduced. The most attractive vessels are the supply vessel and the CTV. The supply vessel can handle higher waves compared to a CTV. In none of the test cases a helicopter is purchased.

6.5.8 Continuous Variables in Second Stage

The B&B tree grows rapidly in size as described in Section 6.5.5. The flat solution landscape leads to these big trees. The main reason is the integer boundaries on the decision variables in the second stage. In this section a discussion about what happens if the integer decision variables in the second stage are replaced with continuous variables. These are the variables concerning renting in and hiring out vessels. The continuous case can be seen as the vessel is not chartered for the whole period, but as a part of the period. In practice this is possible.

24 test cases have been solved with both continuous and integer second stage decision variables. One of the biggest test cases with 390 wind turbines divided on 6 wind farms developed stepwise, with 50 scenarios and a planning horizon of 6 years, is solved to optimality in less than one minute with continuous variables. The solution time is improving dramatically compared to the case with integer variables in second stage, where the the gap between the best solution and the best bound was 1.59 % after 30 minutes.

Neither in the integer nor continuous case an investment in an offshore station is taking place. Neither is any helicopter bought, nor any vessels sold in any of the test cases. The total number of bought vessels are the same for the integer and continuous case for 22 of the 24 test cases. In the two last cases, the continuous case choose to buy one more vessel than the integer case. The difference between the continuous and the integer case is the type of vessels bought. There is not possible to see a clear tendency, but there is a difference, and it depends on the test case.

As expected, the total number of chartered in vessels are lower in the continuous case. Especially expensive vessels, as the multi-purpose vessel and the rig, is only chartered in for a very short time period in the continuous case. These vessels are needed when maintenance of a gearbox need to take place, and it is just profitable to use the vessel to perform this maintenance task. The number of hired out vessels is as expected higher in the continuous case, because it is allowed to hire out a vessel for a part of the period.

The change from integer boundaries to continuous leads to a huge reduction in objective function value, as it is reduced by almost 50 % compared to the integer case. Based on these test cases it has been shown that continuous decision variables on renting in and hiring out vessels reduce the solution time significantly. By using continuous decision variables in the second stage, may cause different solutions in the first stage.

6.5.9 Realistic Size

The size of the problem depends on the number of wind turbines, the number of wind farms, the length of the planning horizon and the number of scenarios. For the stochastic model the biggest problem solved include 50 time periods. In this test case the year was split into 4 time periods for the whole planning period. A possibility is to increase the length of the time period towards the end of the planning horizon. A planning horizon of 25 years can be considered with use of 50 time periods, e.g. if the first 5 years consist of time periods of 3 months, the next 10 years consist of time periods of 6 months and the last 10 years consist of time periods of 12 months. The biggest problem solved with the stochastic model include 6 wind farms developed stepwise. This can be seen as a model that can be used for any realistic size of the offshore wind farm. By changing from integer boundaries to continuous decision variables in second stage, even bigger problems can be solved.

Chapter 7

Conclusion

In this thesis operations research is used to determine the optimal fleet for performing maintenance on offshore wind farms. Both a deterministic and a stochastic model is developed.

The computational study shows that the deterministic model has solved problems with 13 wind farms, 1140 wind turbines and with a planning horizon of 25 years in less than 23 minutes. This shows that the deterministic model can solve problems of realistic size in short time.

The computational study of the stochastic model shows that the stepwise development affect the fleet, and that the model developed in this thesis can be cost-saving when doing strategic planning for offshore wind farms developing stepwise. The computational time is less than an hour, but the Branch & Bound tree increases rapidly in size due to a flat solution landscape. An integer solution is found fast, but it takes some time to prove that the optimal solution is found. Different branching strategies have been tried without success.

The computational study shows that the value of stochastic solution compared to the deterministic can be as high as 17 %. This indicates that the number of failures and weather condition have significant impact on determining the optimal fleet. The willingness for paying for perfect information is low.

By allowing continuous variables in second stage, the solving time reduced significantly. A test case with 390 wind turbines divided on 6 wind farms, with a planning horizon of 6 years and 50 scenarios, is solved in less than 1 minute.

Compared to the FSMPOW model developed by Gundegjerde and Halvorsen (2012), the model in this thesis takes into consideration when the offshore wind farms are developed, and shows that the stepwise development has an impact on the optimal fleet. Both the model developed in this thesis and by Gundegjerde and Halvorsen (2012) can solve problems of realistic size. While FSMPOW computes with one example year, and assume that the rest of the years in the planning horizon are equal to the example year, the model developed in this thesis computes every year in the planning horizon. The models in this thesis have a more aggregated routing aspect than the FSMPOW.

One possible further work option is to make a short term planning model which take routing more into consideration. The number of vessels will be taken from the model developed in this thesis and then the operational planning model will find the best route and strategy for maintenance planning.

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