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Optimizing the Vessel Fleet Used to Install an Offshore Wind Farm

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Submission date: June 2017
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Problem Description

The purpose of this thesis is to study the fleet size and mix problem for the installation phase of an offshore wind farm. The strategic problem of finding the optimal vessel fleet is addressed and two deterministic models are formulated. Different solution methods are investigated in order to solve realistic sized test instances and thereby be able to use the model as a decision tool in order to support the decision maker with valuable insight.

Preface

This master thesis is the concluding part of our Master of Science at the Department of Industrial Economics and Technology Management, at the Norwegian University of Science and Technology (NTNU). The thesis is written within the field of Applied Economics and Operation Research, and studies a fleet size and mix problem for the installation phase of an offshore wind farm. The thesis is a continuation of our Project Thesis written during fall 2016.

We would like to give a special thanks to our supervisors Associate Professor Magnus Stålhane at the Department of Industrial Economics and Technology Management and Elin Espeland Halvorsen-Weare from SINTEF MARINTEK for their thorough and valuable guidance throughout the semester.

Trondheim, June 9th 2017

Abstract

Today, offshore wind is not a profitable source of energy compared to other energy sources. To increase the profitability of the offshore wind industry the life time costs of an offshore wind farm need to be reduced. Among others, this can be achieved by increasing the efficiency of the installation phase. Currently the vessel fleet is one of the largest cost contributors for the installation phase, and a small reduction in the vessel fleet cost can greatly improve the profitability of the offshore wind industry.

Two mathematical formulations of the fleet size and mix problem for the installation phase of an offshore wind farm are proposed: one original model and one reformulated pattern based model. The models are designed as strategic decision tools which is run years in advance of the actual installation in order to support the decision maker with valuable insight. The two models consider a given weather data and suggest which vessels to charter, the charter period for each vessel, and their respective installation schedules. The objective is to find the cost optimal fleet for the installation phase of an offshore wind farm. The models are solved with exact solution methods. To solve the pattern based model we propose three pattern generation methods. One exact method where all feasible patterns are generated, and two heuristic methods where only subsets of the most promising patterns are generated.

The proposed mathematical models are tested on several test instances. Due to the complexity of the problem the original model is not sufficient to solve test instances of realistic size. The pattern based model performs much better, and testing show that the model is able to solve test instances with five to ten vessels and 30-110 turbines, which is considered realistic. To further improve the solutions, different improvement measures are implemented. The computational tests show that the performance of the pattern based model is improved by restricting the start times, adding symmetry breaking inequalities, guiding the Branch and Bound search, and heuristically generate patterns. Heuristic pattern generation combined with restricting start times yields near optimal solutions with a great improvement in CPU time.

Sammendrag

Offshore vindindustrien er i vekst, men er per i dag ikke en konkurransedyktig og lønnsom energikilde sammenliknet med andre energikilder. Et kostnadskutt er påkrevd, og én måte å oppnå dette på er ved å effektivisere installasjonsfasen av en vindpark. Per i dag er kostnadene knyttet til installasjonsflåten ev av de største kostnadsleddene i installasjonsfasen, og et kutt i denne kostnaden vil kunne bedre lønnsomheten betraktelig.

To matematiske modeller er foreslått for å løse flåtestørrelse- og flåtesammensetningsproblemet (fleet size and mix problem) for installasjonsfasen av en offshore vindpark; en original modell og en reformulert modell basert på rundturer mellom havnen og vindparken (pattern basert modell). Modellene er utviklet som et beslutningsstøtteverktøy for strategiske beslutninger som skal tas måneder og år i forkant av et installasjonsprosjekt. De to modellene vurderer været i en gitt periode for å bestemme hvilke skip som skal benyttes, når skipene skal leies inn og for å lage timeplaner for hvert av de aktuelle skipene. Målet er å minimere leiekostnadene knyttet til flåten og dermed bidra til å redusere installasjonskostnadene. For å løse den pattern baserte modellen er det foreslått tre ulike metoder for å generere rundturer a priori, en eksakt metode som genererer alle mulige rundturer, og to heuristiske metoder som kun genererer et subsett av rundturer.

Flere tester er gjennomført på modellene, men på grunn av kompleksiteten i problemet klarer ikke den originale modellen å løse realistiske testinstanser. Den pattern baserte modellen gir mye bedre resultater og klarer å løse instanser med fem til ti skip og 30-110 turbiner. For å ytterligere forbedre den pattern baserte modellen er det implementert flere mulige tiltak. Testing viser at ved å legge til restriksjoner på mulige starttidspunkt, symmetribrytende ulikheter, guide søket i "Branch and Bound"-treet og å benytte heuristiske rundturgenereringsmetoder, oppnår vi nært optimale løsninger for alle instanser med store forbedringer i kjøretid.

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Chapter 1

Introduction

Today, there are more than 7 billion humans living on earth, and we are using electricity like never before (Our World in Data, n.d.). Roughly 80% of all households globally have access to electricity and the global average electricity consumption per household was approximately 3 500 kWh in 2010. Adding an increasing global population, which will reach approximately 9.2 billions in 2040, and the fact that more and more households gain access to the electricity grid due to urbanization, global electricity demand and consumption will increase rapidly in the years to come (The World Bank, n.d.). Global electricity consumption is expected to increase by 48% from 2012 to 2040. Currently, fossil fuel constitutes the largest share of the global electricity production, however environmental trends and governmental goals of increased use of renewable energy are helping to create a changeover in this distribution (World Energy Council, 2016).

The European Union (EU) has set goals of smart, sustainable, and inclusive growth by 2020 with three key targets; a 20% improvement in energy efficiency, a 20% cut in greenhouse gas emission compared to the 1990 levels, and that 20% of EU energy consumption shall be from renewable energy sources. These EU 20-20-20 goals aim to increase the focus on green energy and wind energy is becoming one of the main focus areas. A distinction is made between onshore wind production and offshore wind production, where the former is currently the most profitable. However, energy from offshore wind benefit from stronger and more stable wind and production per turbine is thus greater compared to the onshore counterpart (Mikkelsen & Kirkeby, 2016). To take advantage of this, the offshore wind industry focuses on reducing cost to improve profitability. As of today, the offshore wind industry receives governmental subsidies as a measure to promote further investment in the industry, but these subsidies will expire within the near future (Reuters, 2017). This creates an additional motivation for the industry to find more cost efficient solutions.

The total global installed capacity of offshore wind turbines is 14 384 MW and in 2017 Europe has scheduled installation of new offshore wind farms which alone will increase the global capacity by more than 3 000 MW (Global Wind Energy Council, n.d.). However, the high costs related to installation and operation and maintenance (O&M) of an offshore wind farm make the offshore wind industry less profitable and less competitive compared to industries based on other non-fossil energy sources. To improve the profitability of the offshore wind industry the life time costs need to be reduced, and one way to achieve this is by reducing the costs related to the installation phase of offshore wind farms.

The high installation costs are due to several factors including, but not limited to, challenging sea and weather conditions, high vessel charter rates, and high costs of subsea cables, turbines and foundations. The costs related to cables, turbines, and foundations, which account for approximately 60% of total installation costs, are hard to reduce due to the technical requirements imposed on these components in order to withstand the harsh weather conditions offshore. The costs related to the installation vessels are the second largest cost contributor and accounts for approximately 20% of total installation costs. According to the International Renewable Energy Agency (IRENA), a key opportunity to reduce construction and installation costs lies in reducing the amount of time required to install each megawatt of offshore wind energy, due to the high daily charter rates for offshore installation vessels (IRENA, 2016). Installation vessels have associated fixed costs in the range from £2.5 to £5.2 million, and an installation vessel fleet normally consists of 5-10 different vessels (Irawan et al., 2015). By a more efficient utilization of each vessel, this cost can be reduced and only a small improvement in utilization can have a great impact on the overall installation costs.

A more efficient use of vessel resources is essential and one way to achieve this is by improving the planning and scheduling of the installation phase. However, planning and scheduling of the installation phase is hard due to the strict weather requirements on vessel operation and the high amount of uncertainty related to the weather. Since the planning often takes place several years in advance of the installation, the weather forecasts are highly uncertain. The weather conditions at a specific site, wave height and wind speed in particular, will have a great impact on the choice of vessels. Due to the challenges related to a better utilization of the vessel resources, optimization of offshore wind farm logistics and installation concepts are of increasing interest for companies involved in the installation phase of offshore wind farms.

An offshore wind farm consists of multiple offshore wind turbines which again is composed of several components. These components need to be transported to the offshore site and installed by special designed vessels with the right capabilities. A vessel has a given capacity which limits the number of components transported per trip and weather requirements for performing activities offshore. The vessel capacity and the weather requirements above influence the installation schedules and will hence affect the total cost related to the installation and the vessel fleet. The purpose of the vessel fleet is to install the offshore wind farm as cost effective as possible and at the same time minimize the total installation time. To achieve this, we need to determine which vessel to charter, when to charter each vessel, and what activities each vessel is to perform.

This thesis is based on the work by Hansen & Siljan (2016) who model the fleet size and mix problem for the installation phase. However, Hansen and Siljan conclude that the proposed model can only be solved to optimality for small test instances and thus lack relevance for the offshore wind industry. Two time discrete and deterministic mathematical models for the fleet size and mix problem for the installation phase of an offshore wind farm (FSMPIOW) are formulated and presented in this thesis; one original model and one reformulated pattern based model which generates patterns a priori before finding the best pattern configuration. There are proposed three methods to generate patterns a priori; one exact method and two heuristic methods. The objective of the two models is to minimize the total vessel charter cost and find the optimal vessel fleet to install an offshore wind farm. To the authors knowledge there exist no other articles addressing the fleet size and mix problem of the installation phase of an offshore wind farm solving an optimization model with exact methods.

The proposed pattern based model can be applied as a decision support tool for wind farm owners during strategic decisions regarding the vessel fleet. Another possible application of the model is to use it for tactical decisions taken closer to the execution of the installation. For decisions taken closer to the actual installation when the vessel fleet is known, the model can be used to generate more accurate installation schedules.

This thesis is organized as follow: Chapter 2 presents relevant background information of the offshore wind industry and the installation phase, and Chapter 3 presents relevant literature within the optimization of the installation phase of an offshore wind farm and maritime fleet size and mix problems. In Chapter 4 a thorough description of the problem studied in this thesis is presented. Two mathematical models for the problem are formulated, one original model presented in Chapter 5 and one reformulated, pattern based model presented in Chapter 6. The solution method for the patterns based model is described in Chapter 7. Input data used for testing the models is presented in Chapter 8, and the computational study is found in Chapter 9. Concluding remarks and future research are presented in Chapter 10 and Chapter 11, respectively.

Chapter 2

Background

This chapter presents relevant background information on the offshore wind industry and installation of offshore wind farms. First a brief overview of the geographic location of existing wind farms is presented. Then the components of a turbine are described together with different assembly strategies. Next, the elements linked to the logistics of the installation phase are presented, i.e. the vessels and installation activities. Lastly, the weather impacts related to the maritime logistics and the installation phase of an offshore wind farm are described in Section 2.6.

2.1 Geographic Location of Offshore Wind Farms

Within the last two decades there has been a growth in the offshore wind industry motivated by political goals and improved profitability. Currently, there are several offshore wind farms located in European waters, in addition to multiple projects under construction or in the process of applying for approval. Asia and the United States has recently entered the offshore wind industry, and the first offshore wind farm in China was constructed in 2010. In the United States and at the coast outside China, Japan and South Korea several wind farms are in an early planning stage (4C Offshore ltd., 2017). Figure 2.1 gives an overview of European offshore wind farms, and the dark blue circles represent both fully commissioned offshore wind farms and projects under construction.

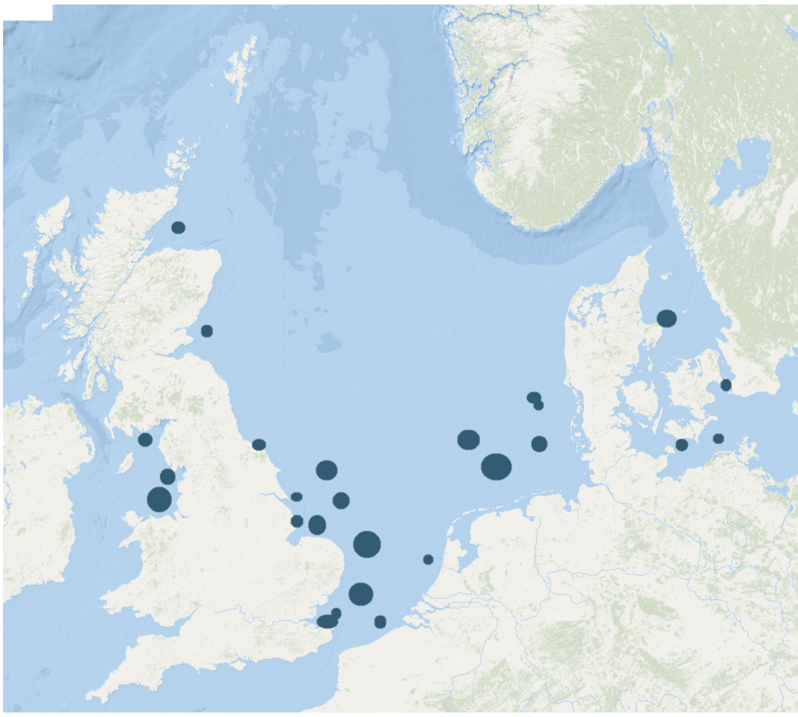


Figure 2.1: An overview of offshore wind farms in Europe

As can be seen in Figure 2.1 the majority of European wind farms are located in the North Sea outside the coast of UK, Germany, the Netherlands and Denmark. New projects are also planned at the coast of Scotland outside Dundee and Aberdeen (4C Offshore ltd., 2017).

2.2 Components of an Offshore Wind Turbine

The installation process of a wind turbine consists of assembling three main components; the sub structure, the top structure, and the cables. These components have to be mounted in a given order either onshore, at the offshore site or by a combination of offshore and onshore assembly. The assembly strategy and the turbine design are influenced by site specific characteristics, such as distance to shore and the water depth.

Sub Structure

The sub structure consists of one foundation and one transition piece. The foundation is the first component to be installed and is normally mounted to the sea bed (Livaniou et al., 2015). After the foundation is secured, the transition piece is mounted on top of it. This process is normally executed directly after the completion of the foundation (Kaiser & Snyder, 2013). One foundation type is the monopile, a cylindrical steel pile, which is hammered into the sea bed. Monopiles have been, and still is, the most popular foundation design for offshore wind turbines and accounted for 80% of installed foundations at the end of 2015 (European Wind Energy Association, 2016). Other types of foundations are tripods, jacket foundations, and gravity based foundations, see Figure 2.2.

Currently, commercial sub structures are limited to water depths of 40 m to 50 m, but with a growing trend of locating wind farms further from shore, the water depths increase. Deep-water environment starts at water depth greater than 50 m where bottom-fixed foundations are no longer an option, and it has therefor been a development within floating wind turbines (Arapogianni et al., 2013). The first pilot project of floating wind turbines, Hywind, is constructed outside the coast of Scotland and is lead by Statoil ASA (Statoil ASA, 2014). An alternative floating foundation concept is WindFloat, a concept developed by Principal Power (Principle Power, 2015). Both Hywind and WindFloat enable the turbines to be fully assembled onshore and then transported out to the offshore site, usually by a tugboat. These new technologies for deep-water turbines are still in an early stage and today's challenges related to the installation phase of an offshore wind farm are mostly related to bottom-fixed foundations such as monopiles (Principle Power, 2015). Due to this, bottom-fixed foundations will be the focus of this thesis.

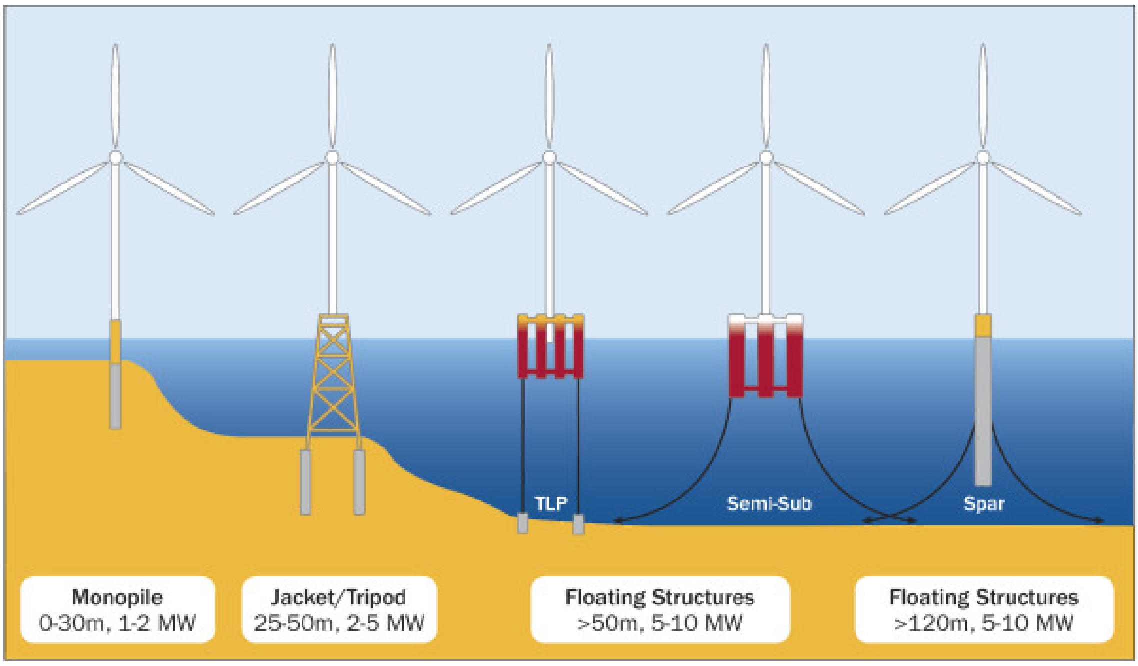


Figure 2.2: Different foundation concepts (Research Gate, n.d.)

Top Structure

The top structure of a turbine is installed after the sub structure and consists of four parts; tower, nacelle, hub and blades. The nacelle includes all the power generating systems of the turbine and is very often assembled together with the hub (Uraz, 2011). The hub together with the blades form the rotor, which is where the wind energy is converted to mechanical energy when the blades are rotating (BWE German Wind Energy Association, n.d.). A fully mounted wind turbine can be seen in Figure 2.3.

Since the beginning of the 1990s there has been a significant growth in the turbine size. The dimensions of the tower depend on the size of the turbine (MW) and the weight of the hub and nacelle. For today's projects, the turbine sizes are in the range from 6 MW up to 8 MW, and are still increasing. The height measured from sea level and up to the hub is also increasing and is normally between 100-110 m (Appendix F). The total height, from sea level to the tip of the blades, has increased in line with the increased turbine size, from around 50 m to right above 200 m for some of the most recent projects. The dimension of the blades is proportional to the generating capacity of the turbine and for recent projects the rotor diameter is about 160 m (Dong Energy et al., 2015).

Installation of these components is the most challenging part of the installation phase due to many lifts. The weather restrictions for performing lifts are strict because the wind can easily get hold of the component when it is lifted high above sea level and cause instability. As a consequence, the installation of top structures is more susceptible to delays than the other components.

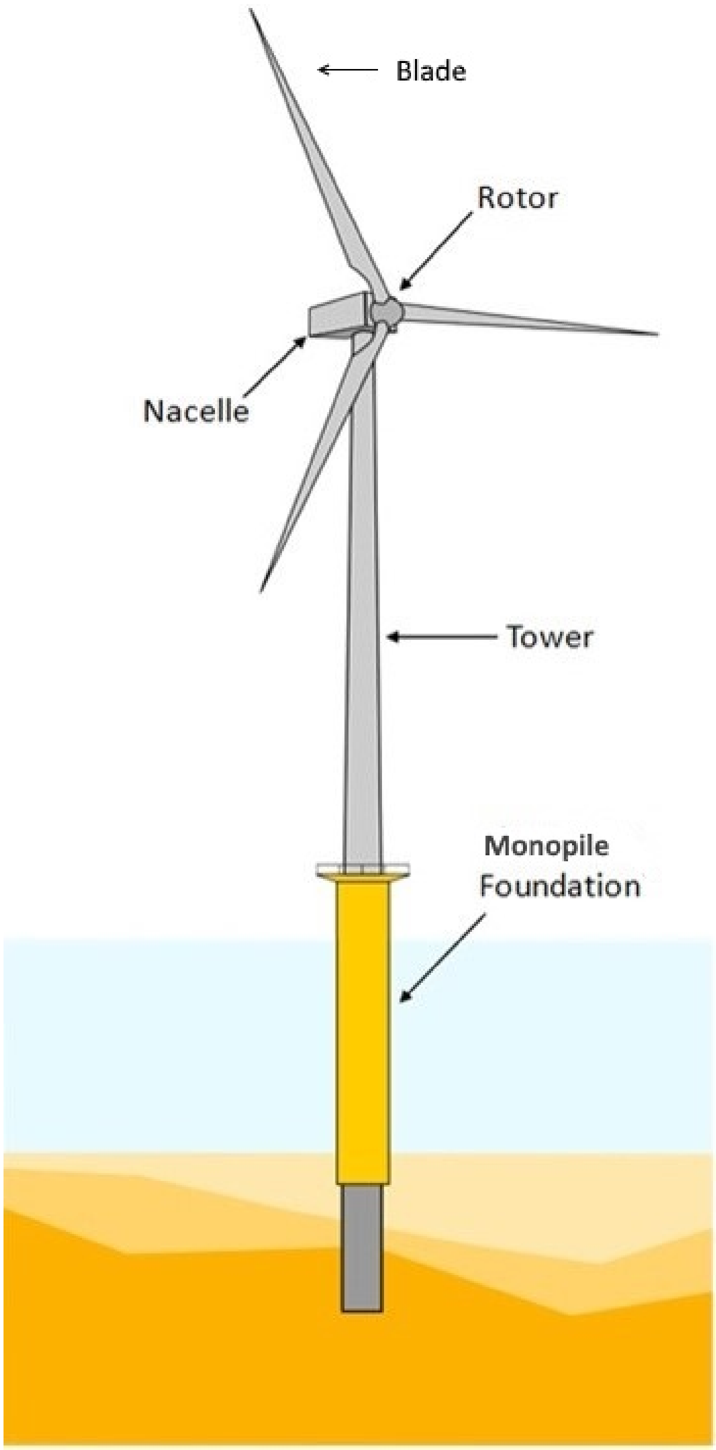


Figure 2.3: A complete offshore wind turbine
(VJ Tech, 2014)

Cables

The cables play an important part in the installation process of an offshore wind farm. Cabling at an offshore wind farm includes both the inter-array cable between the turbines and an export cable in order to transmit the generated power to shore and connect to the power grid. In order to transform the voltage of the generated energy before connecting to the power grid, one or several substations are usually connected to each wind farm, see Figure 2.4. These substations are installed in the same way as the wind turbines and make use of the same vessels (Livaniou et al., 2015). Challenges concerning installation of cables are related to geotechnical conditions of the sea bed and weather conditions, and thus this process is also vulnerable to delays (Kaiser & Snyder, 2013). Delays in cabling might affect the installation of top structure, leading to a prolonged installation time for the whole project.

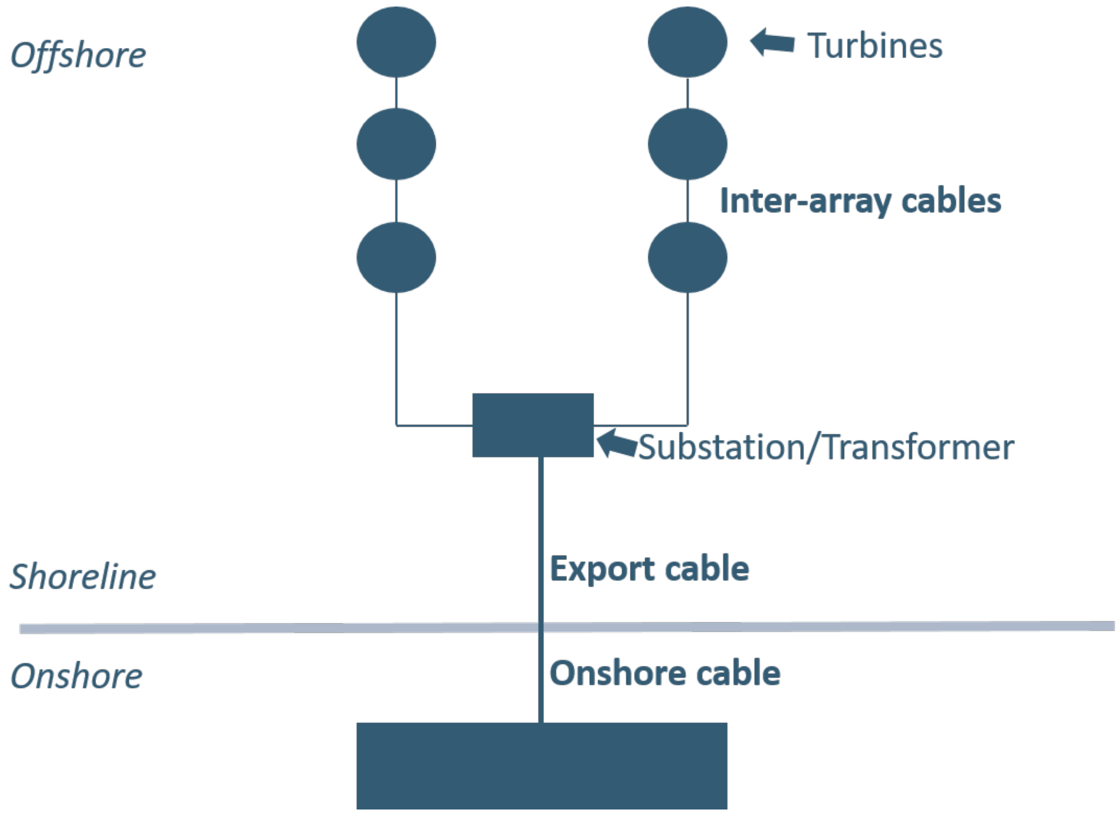


Figure 2.4: Network of cables for an offshore wind farm

The installation of cables are done by purpose built vessels, so called cable installation vessels (CIV) (Kaiser & Snyder, 2013). For some projects it is required that cables between each turbine are trenched, due to regulatory issues concerning safety, which requires additional vessel concepts. Today, the cable laying process is normally done partially in parallel with the installation of foundations. When installing cables and foundations in parallel, the CIV starts operating when approximately $^2/_3$ of all foundations are installed (Appendix F).

2.3 Assembly Strategies

There are different strategies for installing the components of an offshore wind turbine, especially for the installation of the top structure. It can either be fully done by on-site assembly or by different degrees of pre-assembly onshore. The chosen assembly strategy will influence both the suitable vessels and the requirements on weather conditions for performing the installation offshore.

Mounting components together onshore before transportation and installation reduces the total number of lifts offshore. There are, however, disagreements in the industry regarding the effect of pre-assembly. Some argue that the weather requirements are downgraded because of fewer lifts offshore, while others argue that the requirements will become stricter due to heavier and more complex lifts. A larger degree of pre-assembly requires larger vessels with higher lifting capacity because of the increased weight of each component. As of today, there exist no standardized installation strategy and the amount of pre-assembly is thus heavily dependent on project specific characteristics and previous experience (Appendix F). For installation of the hub and blades, the most commonly used assembly strategy is to install all components separately. This means that first the nacelle and the hub are installed, and then the blades are installed one at a time as pictured in Figure 2.5 (Appendix E), (Appendix D).

Figure 2.5: Installation of blades (offshoreWIND, 2014), (GAB, 2012), (Siemens UK, 2015)

The information in this section is based on several papers by Uraz (2011), Lange et al. (2012), Kaiser & Snyder (2013), Walther et al. (2013) and Barlow et al. (2015).

2.4 Installation Vessels

Several types of installation vessels exist and operate in the offshore wind industry and they all have their own specifications and limitations. The most commonly used vessel concepts for installation of offshore wind turbines today are presented below.

Cable Installation Vessel (CIV)

There are generally two vessel concepts used for installation of inter-array and export cables. A cable installation vessel is used for installing the inter-array cables and the export cable, whereas a crew transfer vessel is used to transport personnel between the turbines to complete the installation and connect the cables to the switch gear. The CIV concept is illustrated in Figure 2.6. For projects requiring cable trenching, a purpose built CIV is required (Appendix F).

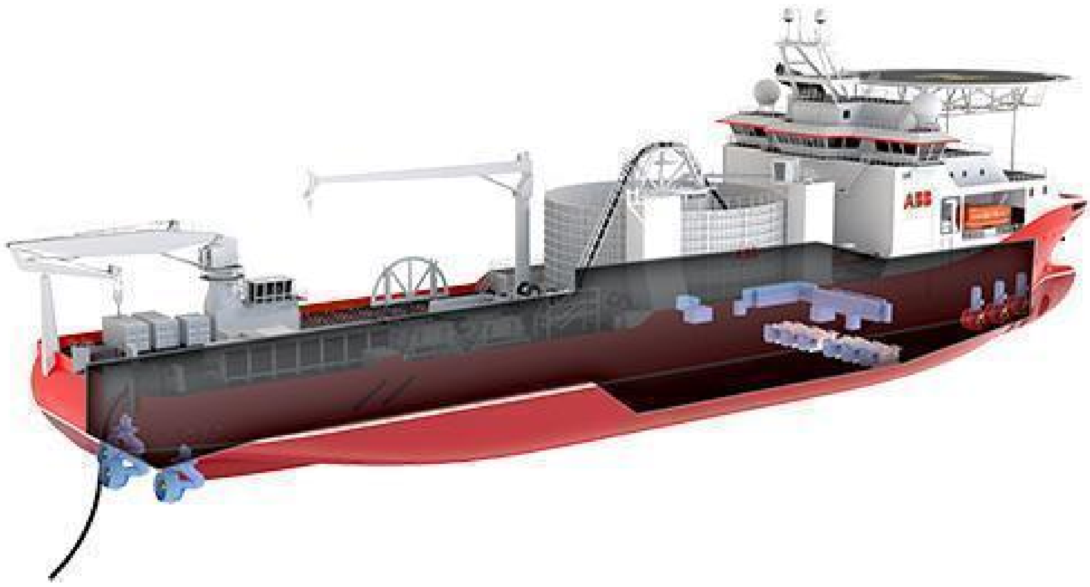


Figure 2.6: Illustration of the cable installation vessel concept (4C Offshore ltd., n.d.)

Heavy-lift Vessel (HLV)

The heavy-lift vessel concept includes vessels with high lifting capacity and are generally used to lift and install large and heavy components. Because of its high lifting capacity a HLV is mostly used for installation of the heavier components such as foundations and substations. The HLV concept does not employ a hull-elevating system, which means that jack-up is not possible and thus water depth restrictions do not apply. This type of vessel is normally self-propelled and can be either dynamically positioned or conventionally moored. There are several possible crane types that can be installed on a HLV depending on the operations it is designed for. HLVs have a lifting capacity ranging from 1 600 to 14 200 tonne and a speed range between 4 and 8 knots (Livaniou et al., 2015). Lifting capacities above 5 000 - 6 000 tonne are usually associated with purpose built vessels to fulfill the offshore wind industry's requirements. The heavy-lift vessel concept is shown in Figure 2.7.

Figure 2.7: Heavy-lift vessel (Maritime Connector, n.d.)

Jack-up Barge (JUB)

A jack-up barge is used for lifting and installation of turbines. As the name indicates this type of vessel has the possibility to jack-up the hull to create a stable platform for lifting and other installation operations. A jack-up barge can not maneuver itself and needs to be towed by a tugboat from the loading port to the offshore site. A towing tug is also needed for positioning and transportation between the various turbines at the wind farm. Due to the lack of propellers the transportation speed of a jack-up barge depends on the tugboat, but is normally between 4 and 8 knots. The size of a jack-up barge varies. A small jack-up barge has a free deck space of about 748 m^2, crane lift capacity of 272 tonne, and a deck load capacity of 10 tonne/m^2. The small jack-up barge is able to carry up to two turbines. A large jack-up barge has a free deck space of 2 500 m^2, lift capacity of 800 tonne, and a deck load capacity of 20 tonne/m^2. These large jack-up barges have the ability to carry six to eight turbines per tour (Livaniou et al., 2015). Even though it is possible to use a jack-up barge for installation of a wind turbine, this vessel concept is more commonly used in the O&M phase of an offshore wind farm. A jack-up barge can be seen in Figure 2.8.

Figure 2.8: Jack-up barge
(OffshoreWind.biz, 2013)

Self-propelled Installation Vessel (SPIV)

The self-propelled installation vessel, also called a turbine installation vessel (TIV), is a large self-elevating vessel with four to six jack-up legs. The vessel is self-propelled which distinguishes it from a jack-up barge. Due to varying size, the payload capacity varies between 1 500 and 8 000 tonne and the transit speed is between 7 and 13 knots (Livaniou et al., 2015). Due to lack of lifting capacity, lack of free deck space, and increased component size, there are several SPIV which are too small and thus not capable of performing the required installation activities. The larger SPIVs, however, can be used for both installation of the sub structure and the top structure, including tower, nacelle and blades. An example of a self-propelled installation vessel is shown in Figure 2.9.

Figure 2.9: Self-propelled installation vessel (Offshore Wind Industry, 2013)

In addition to the vessel concepts mentioned above several other vessel concepts are used both directly and indirectly during the installation phase of an offshore wind farm. This includes platform supply vessels, towing tugs, barges, crew transfer vessels, and floatels. The mentioned vessel concepts can either work separately or cooperate with other vessel concepts during the installation. The required vessel concepts varies for each project.

Trends and Future Vessel Concepts

As presented above several different vessel concepts exist, but few of them are purpose built for the installation of an offshore wind turbine. According to Walther et al. (2013), the trend of building highly specialized vessels for transportation and installation of foundations and turbines is increasing and so is the size of each vessel to handle the increasing component sizes.

Up until now, smaller jack-up vessels, barges, and pontoons have been the most popular vessel concepts in the European offshore wind industry. However, shipyards have noticed an increasing interest in specialized installation vessels. Until recently, investments in purpose built installation vessels have been limited due to poor and uncertain profitability. As the project management has gained more experience, the installation costs have been reduced and installations have become more profitable, leading to an increasing interest in investment in purpose built vessels (Appendix F). These purposed built installation vessels have features optimized for installation of offshore wind turbines, which means more free deck space, higher transit speed, and higher lifting capacities (Bard & Thaleman, 2011).

As offshore wind farms are being built further away from shore and at deeper water, new vessel concepts are necessary to provide the needed performance capacity. Especially increased deck space capacity is important in order to reduce the number of trips back and forth between the port and the offshore site. A similar development is not expected for the cable installation vessels, because the research on cables evolves around the transmission technology, which is not expected to affect the cable size significantly (Appendix F).

2.5 Ports

The increasing size of the turbines puts requirements not only on the installation vessels but also on the ports. There are several activities taking place at the port;

unloading of components from vehicles, storage of components, assembly of components, and loading of components on vessels before transportation to the offshore site (Irawan et al., 2016). For the installation phase, the most important port criteria is the physical characteristics, and includes the distance to the offshore site, the port's quay load bearing capacity, the port's water depths, and the seabed suitability, meaning the ability of the port's seabed to accommodate jack up vessels (Akbari et al., 2016). The port size will also set limitations for the possible degree of pre-assembly because components need to be mounted and stored at the port.

2.6 Weather Impacts

Weather conditions need to be considered when creating schedules for the installation vessels. Without evaluating the weather impacts, the chances of delays, and cancellations will increase, which in turn will cause higher costs. The weather conditions at sea can often be harsh with high wind speed and wave height, and the forces acting on the vessels are enormous and affect the safety of the crew and the performance of activities. Unwanted consequences can be minimized by awareness of the weather impacts on the installation process. By categorizing weather conditions and weather restrictions for each installation vessel, one can more easily evaluate available weather windows, i.e. time periods where the weather is good and allows a vessel to operate.

In this thesis the weather is categorized according to wind speed and significant wave height. The weather conditions are divided into five categories; *very good*, *good*, *medium*, *bad* and *very bad*, as shown in Table 2.1. The threshold for each weather category is based on the Beaufort wind scale which groups weather conditions according to both wind speed and wave height. The categorization is a simplification to real life situation where roll angle and other multi-parameter analysis of weather is present. Findings in the article by Sperstad et al. (2014) show that when comparing multi-parameter analysis to single-parameter analysis, which only includes significant wave height, the two approaches give relatively similar outcomes for strategic decision support models (Sperstad et al., 2014). This is thus considered a good enough approach to the real life situation.

Table 2.1: Weather categorization

Weather condition	**Category**	**Wind speed [m/s]**	**Wave height [m]**
Very bad	5	> 22	> 6.1
Bad	4	≤ 21	≤ 6.0
Medium	3	≤ 17	≤ 4.0
Good	2	≤ 11	≤ 2.9
Very good	1	≤ 6.0	≤ 0.9

Bad weather might lead to waiting-on-weather (WOW) situations where no activity can be performed (Halvorsen-Weare & Fagerholt, 2011). If the uncertainty in weather conditions is ignored when a project is planned, the costs may increase rapidly above expected costs because of sudden and unforeseen delays. One way to take into consideration unforeseen implications due to the weather is by including slack in the schedule. In this report slack is defined as a scheduled break between activities. By including extra time between activities there will be more flexibility in the schedule which, to a certain degree, will make it possible to handle bad weather without increasing the costs.

A normal strategy to reduce the chances of unforeseen delays is to take use of the summer months for the installation phase when there are more days of good weather than during winter months. The downside of this strategy is that the charter rates increase and the number of available vessels decreases in the summer time because of a market governed by supply and demand. An alternative strategy is to make use of the winter months either in addition to or instead of the summer months.

Chapter 3

Literature Review

The installation phase of offshore wind farms is a relatively new topic within operations research and existing research is thus limited. This chapter discusses relevant literature on the installation phase of an offshore wind farm and to supplement the literature and support the choices made in this thesis, the literature review also includes literature on maritime fleet size and mix problems.

3.1 Offshore Wind Farm Installation

The installation of an offshore wind farm is a complex problem to formulate and previous proposed models are often complicated and hard to solve to optimality for realistic problem instances. Several papers have therefore explored simulation as a method to solve real sized problems. The main focus in this section is on optimization papers, but some papers on simulation are also included.

Scholz-Reiter et al. (2010) present a mixed integer linear program (MILP) finding the optimal schedule for the installation phase of an offshore wind farm with the objective of minimizing total vessel operation time. Fora short planning horizon the model is able to compute the optimal schedule for exactly one vessel which can install both sub structures and top structures. The authors argue that the largest bottleneck in the value chain of an offshore wind farm installation is the global vessel fleet, and they believe that the greatest improvements regarding cost reductions lie in a more efficient use of available vessels. Due to its short planning horizon the model is rerun every time the vessel returns to port, and a new optimal schedule based on recent weather forecasts is calculated. The short planning horizon is subject for criticism and makes the model less realistic.

The MILP model by Scholz-Reiter et al. (2010) has been further developed and improved to make it able to solve larger problem instances. Scholz-Reiter et al. (2011) expand the model with a heuristic method to overcome the limitations of the previous model. The heuristic method returns an optimal schedule for a longer planning horizon and a larger fleet. The output is not optimal but rather an approximation which gives a good enough solution to support the decision maker. The results show that by applying a heuristic method the model is able to solve test instances with longer time horizon, multiple vessels, and a broader variety of weather conditions.

Irawan et al. (2015) propose a bi-objective optimization model for the installation scheduling problem of an offshore wind farm. The model minimizes both cost and time, as the author claims these objectives are conflicting. The formulated model is an integer linear program (ILP) with restrictions on both weather and available vessels. To reduce the complexity of the model, data on weather forecast and vessel availability is processed to pre-generate a set of all feasible slots where a vessel can perform a given installation activity. The problem is then to solve a combinatorial optimization problem to find the optimal configuration of feasible time slots in order to minimize total installation cost or total completion time. Even with the pre-generation of all feasible time slots the model is relatively large and hard to solve with exact methods. In order to solve larger problems two heuristic solution methods, neighborhood search (VNS) and simulated annealing (SA), are introduced. Computational studies show that these methods outperform the exact method. Walther et al. (2013) present an evaluation tool to support the decision maker when finding the vessel fleet. The solution method is based on simulation with the advantages of being easier and faster to solve than an optimization model. The tool returns an schedule for when a given installation vessel should operate and the total installation cost and time. The idea is to run the model multiple times with the same project characteristics and weather data and only change the vessel input data. Different output is then compared to determine the most economical installation vessel concept. Ait-Alla et al. (2013) present another MILP model for the aggregated installation planning problem of an offshore wind farm on a tactical level. The aim is to minimize total installation cost taking both vessel availability and weather restrictions into consideration for a medium long planning horizon (2-12 months). The model returns an optimal schedule in order to complete all installation activities.

The articles presented so far study the scheduling problem for the vessel fleet applied during the installation phase. However, to make the investigated problem more realistic and minimize the cost even further, a larger part of the value chain can be included. Lütjen & Karimi (2012) include optimization of the port inventory problem in order to coordinate stock levels at port and vessel schedules. The authors present a simulation model which determines the optimal configuration of a single-echelon inventory system including optimization of the stock level at the port. In addition, a reactive scheduling heuristic is presented. The aim of this scheduling heuristic is to coordinate the installation vessels with respect to the weather. By optimizing both schedules and inventory levels the output will be a helpful decision tool for the decision maker when planning the offshore logistics and the overall supply chain management. The scheduling heuristic is further extended with an evaluation function to also determine the optimal loading set.

3.2 Maritime Fleet Size and Mix Problems

The offshore wind industry is characterized by high costs related to the installation of the wind turbines, and currently the vessel fleet accounts for a large portion of the total installation cost. However, the most resent work within optimization of the installation phase is mostly focused on optimizing the schedules for each vessel rather than finding the optimal vessel fleet configuration. This thesis focuses on the optimal vessel fleet configuration and literature on the fleet size and mix problem within other industries is thus studied. The oil industry is an more explored industry than offshore wind, and there are many similarities in the two industries concerning the problem of finding the optimal fleet composition. Both problems usually include a depot onshore that the vessels need to visit to be loaded, and are faced with the uncertainty in weather conditions which will greatly influence the schedules.

Pantuso et al. (2013) have written a survey on the existing literature on the maritime fleet size and mix problems (MFSMP) published before 2013. In short, a MFSMP is the problem of deciding the optimal composition of vessels in a fleet in order to meet a certain demand. The objective is normally to minimize the costs of operating the fleet and often includes decision support on vessel routing and scheduling. The literature on MFSMP includes single-period problems, which is the problem of finding a fleet with long lasting characteristics, and multi-period problems, which focus on a more flexible fleet with the possibility of adding or removing vessels in order to meet changes in demand. One subgroup of papers covered in this survey address the strategic problems of which vessels to buy or charter, while the schedules and routes are uncertain because the actual demand is unknown. Another subgroup studies tactical problems dealing with the deployment of available vessels and the possibility of charter in, charter out, or lay up vessels in order to meet the realization of demand.

Fagerholt (1999) formulates a model for liner shipping application which finds the optimal fleet size. The model assumes a known demand, and seeks to find weekly routes for each vessel in the fleet assuming. A route is defined as a trip between offshore installations which originates and terminates in the depot and cannot visit the depot in between. The solution approach consists of three phases; phase one finds all single routes which are feasible for the ship with the largest capacity, phase two combines single routes to longer routes, which is a problem restricted by an upper limit on duration per route, and phase three solves a set partitioning problem.

Fagerholt & Lindstad (2000) develope an optimization model for a short-term MFSMP studying the supply service to offshore installations. The problem is to find the optimal fleet size and mix by choosing from a pool of vessels and then find optimal routes and schedules on a weekly basis. The problem contains one onshore depot and several offshore installations that need to be supplied with a weekly demand. The solution approach can be divided in two steps; first a set of all feasible schedules for every vessel in the pool is generated and then an IP is solved to decide which vessels to use and find their weekly schedules. The model does not consider uncertainty in weather and the robustness of a solution is thus evaluated by a post analysis.

Halvorsen-Weare & Fagerholt (2011) further extend the MFSMP by including uncertainty for the supply vessel planning of offshore installations. The model is solved in three steps; First all voyages for each vessel are generated a priori based on a set of conditions, e.g minimum and maximum duration and number of visits, secondly all voyages are simulated and robustness measures are assigned by considering weather data, and third combine voyages into vessel schedules in an integer program (IP). The same problem is studied and extended by Halvorsen-Weare et al. (2012). They extend the model by including a spread of departures and a maximum and minimum duration of each voyage. The model is solved using a voyage based solution method where all voyages are generated in the first step and then a voyage-based model is solved to find the optimal fleet and vessel schedules. The results show that the method is able to solve instances of realistic sizes.

3.3 Our Contribution

The literature review reveals that the number of papers on the installation phase of an offshore wind farm is limited. Among the existing research the scheduling problem is the most studied, and to the authors knowledge there exist no paper addressing the fleet size and mix problem of the installation phase of an offshore wind farm applying exact solution methods. This thesis presents two deterministic, time discrete mathematical models for solving the fleet size and mix problem for the installation phase of an offshore wind farm; one original model and one pattern based model. To solve the pattern based model we propose three pattern generation methods; one exact method which generates all feasible patterns, and two heuristic methods where only the most promising patterns are generated. The two heuristic pattern generation methods differ from existing heuristic solution methods as they are implemented in the a priori generation of patterns, rather than in the mathematical model.

In contrast to scheduling problems, where the vessel fleet is considered known, a fleet size and mix problem focuses on the vessel charter strategy, i.e. determining which vessels to charter at a given time by choosing from a vessel pool. In the reviewed articles on the installation phase schedules are constructed based on input data on available vessels, which imply that the decision on which vessels to charter is already taken. Scheduling decisions are usually taken closer to the start time of the installation project than decisions regarding the fleet composition.

The models presented in our thesis generate schedules in order to find the optimal fleet for the installation phase of an offshore wind farm. The solution methods for solving the pattern based model are based on a priori generation of feasible patterns, a solution method with similarities to the approach in Irawan et al. (2015). In contrast to the time slots generated per activity in the article by Irawan et al. (2015), a pattern is defined as a sequence of activities constructed by considering both vessel characteristics and weather conditions. In addition, more details are included in our model, i.e jacking activities and a more detailed assembly strategy, and we propose two strategies to make the solutions more robust. The pattern generation procedure also has similarities to the voyage generation in Fagerholt (1999), Fagerholt & Lindstad (2000), Halvorsen-Weare & Fagerholt (2011), and Halvorsen-Weare et al. (2012), which includes vessel characteristics when all feasible voyages are generated. A voyage is defined as the sequence of operations from depot until the vessel is back at depot, just as a pattern used in our model. In contrast to our problem, the voyage generation is solved as a travelling salesman problem to find an optimal route between the offshore installations, while routing between turbines is omitted in our model. Also, one of the advantages of our pattern generation is that the weather conditions are considered when generating feasible patterns.

Due to the increased complexity in a deterministic model some aspects of the installation problem included in simulation models, e.g. inventory levels, optimal ports, optimal assembly strategies, distance to port, and cabling, are outside the scope of this model. In comparison to a simulation model, the output returned by our optimization model is not influenced by the input given by the decision maker and hence finds optimal values of the decision variables.

Chapter 4

Problem Description

The process of installing wind turbines offshore is a challenging and complex operation and requires specialized, high performance installation vessels. In today's market, the number of such vessels is limited and the charter costs are hence high. Creating a cost efficient vessel charter strategy is thus an important factor in order to reduce the total cost of the installation phase, and make the industry more profitable and competitive to other non-fossil energy sources. The objective is to find the optimal installation vessel fleet which minimizes the total cost of the installation phase with respect to the vessel charter rates. The installation phase is in this thesis considered as the set of activities from loading of components in port, until all turbines are completely installed.

An offshore wind farm consists of a number of identical wind turbines located at an offshore site with a given distance to shore and a given water depth. The main components of a turbine are foundation, transition piece, tower, nacelle, hub, and blades, which have to be installed in a predefined sequence. This means that on a given turbine the foundation and transition piece have to be installed before the tower can be mounted. A vessel can either install several foundations before installation of towers, or it can install foundation and tower for one turbine before continuing to the next turbine. The process of installing the components include loading in port, transportation to and from the offshore site, and mounting the turbines, and is repeated until every turbine in the wind farm is completely installed. Another element of the installation process is to connect the farm to the electricity grid, which is achieved through inter-array and export cables. There is not one single vessel which is able to perform all of these installation activities, and a heterogeneous vessel fleet is thus required.

Special designed vessels perform the installation activities at an offshore wind farm. The global fleet of installation vessels consists of a number of different vessels concepts with individual characteristics designed to perform certain installation activities. These characteristics include free deck space, lifting capacity, weather restrictions, speed, charter costs, and processing times of different activities, e.g. the time to install a tower component. At the offshore site, before the installation can begin, each vessel has to position itself in order to increase stability. Some vessels are equipped with jack up legs that are placed at the sea bed and used to lift the vessel hull above sea level to further increase stability, an activity called jacking. These jack-up vessels have to jack up and jack down before and after performing installation activities on a turbine.

There are especially two factors influencing at what time an installation activity can be performed; the vessel characteristics and the weather conditions. The weather offshore can be unstable and at times very bad, which will set restrictions on when an activity can be scheduled. When scheduling activities it is normal to consider both wind speed and wave height. The total cost related to each vessel consist of two parts; a fixed cost term and a variable cost term. The variable cost includes daily charter rates and operating costs, and the fixed costs include ship expenses, insurance, depreciation and overhead costs. Of the two variable cost terms, charter rates is the dominating one and is thus the most important to consider. When the whole wind farm, or parts of it, is installed and connected to the electricity grid, the wind farm starts generating income through production of electricity. If the installation phase is prolonged unnecessary, the excess installation time can be regarded as an increased installation cost and cause loss of income due to loss of electricity production time.

In order to create a cost efficient vessel charter strategy, one can find the optimal fleet size and mix that minimizes the costs related to the installation by determining three factors: which vessel to use, the total charter period of each vessel, and what activity to perform at a given time. Activities are arranged into schedules for each vessel in order to determine the total length of the charter period for a given vessel.

Chapter 5

Mathematical Model

The problem studied in this thesis is a fleet size and mix problem of the installation phase of an offshore wind farm. A deterministic and time discrete model is formulated to find the optimal fleet which minimizes the charter costs and time span for the whole installation phase. One way to accomplish this is by designing schedules to identify when each vessel is intended to operate and by this determine the charter period for each vessel. The model presented in this chapter is a continuation and expansion of the mathematical model presented in our project thesis (Hansen & Siljan, 2016).

5.1 Assumptions

This section summarizes the underlying assumptions relevant for the mathematical model presented in Section 5.2.

Start and End Effects

A consequence of applying a time discrete model is the problem of start and end effects, and hence it is necessary to be extra cautious when using constraints with summation of time, t. For every constraint related to activities, the processing time for the activity is often added or subtracted from t in the summation. These summations will for the first and last time periods, either go below 1 or above the length of the time horizon $|T|$ causing start effect and end effect problems. Figure 5.1 illustrate the start and end effects. It is desirable to remove the summations which contains variables indexed by time periods outside the interval of $t \in T$. However, restrictions for start and end effects are not included in the formulation of the model with the intention of making the model easier to read. This is taken care of in the implementation of the model.

(a) Start effect

(b) End effect

Figure 5.1: Illustration of the start effect and end effect when applying a time discrete optimization model

Activities

Activities are defined as all operations a given vessel can perform, and includes transportation and loading, jacking, and installation of components. As described in Chapter 2, a wind turbine consists of a set of components which have to be installed in a given order. Each activity is assumed to have a pre-determined execution time given as a multiple of the defined time interval. Further, it is assumed that positioning before each installation activity is a part of the installation time of each component. Activities are given as input data in a set indexed from 1 to $|A|$, where the size of the set A depends on the chosen assembly strategy for a given installation project.

An example of the activity set is: $A = \{R,\ U,\ D,\ 4,\ 5,\ 6,\ 7,\ 8,\ \ldots,\ |A|\}$

The first three activities in the set are independent of the chosen assembly strategy and are not directly linked to the installation of a component. These activities are *loading and transportation to and from port (R)*, *jack-up (U)* and *jack-down (D)*. The remaining activities in set A are related to the installation of the components, called installation activities. The installation activities can either be installation of only one component or it can include installation of several consecutive components on the same turbine, e.g. installation of tower and top-structure. For activities including installation of more than on component an offset time, T_{vca}^{Start} and T_{vca}^{End}, is used to determine the start and finish time for each individual installation in order to control the number of completed components and components under construction. This is done to maintain the coordination of components on different turbines.

The components of a wind turbine has to be mounted in a pre-determined order which requires coordination between the installation vessels in the fleet. This is handled in the model by introducing a precedence matrix, $P_{c_1 c_2}$, which indicates the precedence relation between components. If $P_{c_1 c_2} = 1$ it means that the installation of component c_1 has to be completed before the installation of component c_2 can begin.

It is assumed that the default location of all vessels is at the offshore site, implying that before every loading the vessel has to sail to the port. Since a vessel always have to sail to port to be loaded and then sail back to the offshore site, it is convenient to include transportation in the loading activity. Also, we assume that vessel v can only be chartered once during the planning horizon.

Loading Sets

Before an installation vessel can perform the installation activities described above, it is necessary to pick up components at the onshore port. A loading set is a collection of components and can contain either one single type of components or a combination of multiple components. The loading sets are of varying sizes where the maximum number of a given component is determined by the capacity of the largest vessel. To determine which loading set a vessel can be loaded with, a matrix is used to specify which loading sets each vessel v is allowed to carry. When a vessel picks up a loading set it is assumed that every component in that set needs to be installed before the vessel can return to port for a new loading. By this, the loading set will determine which installation activities the vessel have to perform between every loading.

Weather Conditions

The weather conditions in a given time period determines whether it is possible to execute an activity or not. Vessels have different weather limitations and as a consequence the choice of vessels in the optimal fleet will be influenced by the weather data. In this deterministic model, the weather in each time period is assumed known and based on historical data. The weather in one time period is given as a number between 1 and 5, where 1 is *very good* and 5 is *very bad*. The weather category in a given time period is based on a combination of wind speed and wave height as described in Table 2.1. In the same way, each vessel has an upper limit on when it can operate given as a number based the same weather categorization. These two numbers are then compared in each time period to determine whether an activity can be scheduled or not.

5.2 Mathematical Model

The mathematical formulation of the fleet size and mix problem for the installation phase of an offshore wind farm is presented in detail in this section. A plain version of the model can be found in Appendix A.

This section first presents the definitions of sets, parameters and variables applied in the mathematical formulation followed by the model formulation with description of every constraint. Lower case letters represent decision variables and indices and capital letters represent parameters and sets.

Sets

V	Set of vessels
V^J	Subset of jack-up vessels
C	Set of components
A_v	Set of all activities vessel v can perform
A_v^I	Subset of all installation activities vessel v can perform
T	Set of time periods
L	Set of all possible loading sets

Parameters

C_v^{Fix}	Fixed cost of vessel v
C_v^V	Variable cost of vessel v
P	Penalty cost of prolonging the total installation time
N	Total number of turbines in the offshore wind farm
A_{av}	Activity matrix; 1 if vessel v can perform activity a, 0 otherwise
T_{av}	Processing time for vessel v performing activity a
W_{av}^R	Weather restrictions for vessel v performing activity a
W_t	Weather realization in time period t
L_c^{Max}	Maximum number of component c that can be loaded on any vessel
B_{cl}	Number of components c in loading set l
M_{tc}	Big M used in the loading constraints
N_{ac}^{Comp}	Number of components c in installation activity a
T_{vca}^{Start}	Shift in start time for vessel v performing installation of component c in activity a
T_{vca}^{End}	Shift of completion time for vessel v performing installation of component c in activity a
$P_{c_1c_2}$	Precedence matrix; 1 if there is a precedence between component c_1 and c_2 , 0 otherwise

Decision variables

x_{vt}	1 if vessel v is chartered in time period t, 0 otherwise
z_{vat}	1 if vessel v starts performing activity a in time period t
δ_{vlt}	1 if vessel v is loaded with loading set l in time period t, 0 otherwise
α_v	1 if vessel v is included in the optimal fleet, 0 otherwise
s_{vt}	1 if vessel v starts operating in time period t, 0 otherwise
e_{vt}	1 if vessel v finish operating in time period t, 0 otherwise
v_{ct}	Number of components c in progress at time period t
w_{ct}	Number of completed components c at the end of time period t
u_{vt}	Number of completed jack-up activities performed by vessel v in time t
d_{vt}	Number of completed jack-down activities performed by vessel v in time t
s^{Tot}	Project start time, the first time period any vessel is chartered
e^{Tot}	Project end time, the last time period any vessel is chartered

Objective Function

$$\min_{Z} \quad \underbrace{\sum_{v \in V} C_v^{Fix} \alpha_v}_{a} + \underbrace{\sum_{v \in V} \sum_{t \in T} C_v^V (t\ e_{vt} - t\ s_{vt})}_{b} + \underbrace{P(e^{Tot} - s^{Tot})}_{c} \tag{5.1}$$

The objective function of the model, (5.1), minimizes the total charter cost of the installation phase of an offshore wind farm. The first expression, a, represents the fixed cost of the vessel fleet and part b gives the total variable cost of the chartered vessels. Part c is a penalty cost implemented in order to motivate a minimization of the total project duration.

Constraints

Charter constraints

$$\sum_{a \in A_v} \sum_{t'=t-T_{av}+1}^{t} z_{vat'} \leq \sum_{t'=1}^{t} s_{vt'} \qquad v \in V,\ t \in T \quad (5.2)$$

$$\sum_{a \in A_v} z_{va(t-T_{av})} \leq \sum_{t'=t}^{|T|+1} e_{vt'} \qquad v \in V,\ t \in \{1,\ ...\ , |T|+1\} \quad (5.3)$$

$$\sum_{t \in T} (t\ e_{vt} - t\ s_{vt}) \geq 0 \qquad v \in V \quad (5.4)$$

$$\sum_{t \in T} s_{vt} = \alpha_v \qquad v \in V \quad (5.5)$$

$$\sum_{t=1}^{|T|+1} e_{vt} \leq 1 \qquad v \in V \quad (5.6)$$

$$\sum_{t \in T} t\ s_{vt} + |T|(1 - \alpha_v) \geq s^{Tot} \qquad v \in V \quad (5.7)$$

$$\sum_{t=1}^{|T|+1} t\ e_{vt} \leq e^{Tot} \qquad v \in V \quad (5.8)$$

$$e^{Tot} \geq s^{Tot} \quad (5.9)$$

$$\sum_{t'=1}^{t} s_{vt'} - \sum_{t'=1}^{t} e_{vt'} = x_{vt} \qquad v \in V,\ t \in T \quad (5.10)$$

Constraint (5.2)-(5.10) represent the charter constraints for vessel v. Constraint (5.2) and (5.3) make sure that no activity is performed by vessel v outside its charter period, and Constraint (5.4) requires a charter period to be non-negative. Constraint (5.5) and (5.6) make sure vessel v can only be chartered once during the planning horizon. The total duration of the installation project is defined by the time elapsing between the time period when the first vessel is charted and the time period when the last charter period for any vessel ends. Constraint (5.7) and (5.8) set the project start time and end time, and Constraint (5.9) requires the project duration to be non-negative. Constraint (5.10) sets the value of the auxiliary variable x_{vt} to 1 in every time period a vessel is chartered.

Installation constraints

$$\sum_{v\in V}\sum_{a\in A_v^I}\sum_{t'=1}^{t-T_{vca}^{Start}} z_{vat'}N_{ac}^{Comp} - v_{ct} = 0 \qquad c\in C,\ t\in T \quad (5.11)$$

$$\sum_{v\in V}\sum_{a\in A_v^I}\sum_{t'=1}^{t+T_{vca}^{End}-T_{av}} z_{vat'}N_{ac}^{Comp} - w_{ct} = 0 \qquad c\in C,\ t\in T \quad (5.12)$$

$$P_{c_1c_2}(v_{c_1t} - w_{c_2t}) \leq 0 \qquad c_1, c_2\in C,\ t\in T \quad (5.13)$$

$$w_{c|T|} \geq N \qquad c\in C \quad (5.14)$$

To guarantee that components are installed in the correct order the model needs to control the number of components in progress and the number of completed components at a given time. This is done by Constraint (5.11) and Constraint (5.12), respectively. To adjust for installation of components in activities where more than one component is installed, the summation over t has two offsets, T_{vca}^{Start} and T_{vca}^{End}. This is to make sure the number of components in progress and the number of completed components are updated at the correct point in time. The offset shifts time t based on the installation time of component c for vessel v.

If two components are dependent on each other, it means that for every point in time the number of ongoing installations of the dependent component cannot exceed the number of completed installations of the component of which it depends on. This is handled by Constraint (5.13). Constraint (5.14) states that the number of completed installations of each component is at least as large as the total number of turbines in the wind farm at the end of the planning horizon.

Weather constraints

$$\sum_{t'=t-T_{av}+1}^{t} z_{vat'} \leq max\{0, W_{av}^{R} - W_t + 1\} \qquad v \in V,\ a \in A_v,\ t \in T \quad (5.15)$$

Constraint (5.15) makes sure that an activity is not performed unless the weather realization in the consecutive time periods needed to complete the installation of the component is within the specified weather limits of vessel v.

Loading constraints

$$\sum_{a \in A_v^I} \sum_{t'=1}^{t-T_{av}+1} z_{vat'} N_{ac}^{Comp} - \sum_{l \in L} \sum_{t'=1}^{t-T_{Rv}+1} B_{cl} \delta_{vlt'} \leq 0 \qquad c \in C,\ v \in V,\ t \in T \quad (5.16)$$

$$\sum_{l \in L} \sum_{t'=1}^{t-1} B_{cl} \delta_{vlt'} - \sum_{a \in A_v^I} \sum_{t'=1}^{t-T_{av}+1} z_{vat'} N_{ac}^{Comp} \leq M_{tc}(1 - \sum_{l \in L} \delta_{vlt}) \qquad c \in C,\ v \in V,\ t \in T \quad (5.17)$$

$$z_{vRt} = \sum_{l \in L} \delta_{vlt} \qquad v \in V,\ t \in T \quad (5.18)$$

$$\sum_{l \in L} \delta_{vlt} - x_{vt} \leq 0 \qquad v \in V,\ t \in T \quad (5.19)$$

Constraint (5.16) makes sure vessel v cannot install more of a given component than contained in the loading set it is loaded with. When all components in a loading set are installed, the vessel has to return to port in order reload with a new loading set. Constraint (5.17) makes sure vessel v is not loaded with a new loading set in time t unless all components in the currently loaded loading set l are installed.

Constraint (5.18) ensures that a vessel performs the return and loading activity (R) whenever a new loading set is picked up and Constraint (5.19) requires vessel v to be chartered if it is loaded in a given time period t.

$$M_{tc} = min\Big\{N, \quad (t-1)L_c^{Max}\Big\} \qquad t \in T, c \in C$$

In order to make Constraint (5.17) as strict as possible, the value of big M is calculated for every time period t and component c. The value of the parameter is the minimum of the total number of turbines in the wind farm, and the maximum number of a given component in a loading set times the time elapsed up to the previous time period.

Jack-up constraints

For jack-up vessels an extra set of constraints is required to make sure that jack-up and jack-down operations are performed in the correct order. This is handled in constraint (5.20)-(5.28).

$$u_{vt} - d_{vt} \leq 1 \qquad v \in V^J,\ t \in T \tag{5.20}$$

$$u_{vt} - d_{vt} \geq 0 \qquad v \in V^J,\ t \in T \tag{5.21}$$

$$u_{v|T|} - d_{v|T|} = 0 \qquad v \in V^J \tag{5.22}$$

$$\sum_{t'=1}^{t-T_{Uv}+1} z_{vUt'} - u_{vt} = 0 \qquad v \in V^J,\ t \in T \tag{5.23}$$

$$\sum_{t'=1}^{t-T_{Dv}+1} z_{vDt'} - d_{vt} = 0 \qquad v \in V^J,\ t \in T \tag{5.24}$$

$$\sum_{a \in A_v^I} z_{vat} \leq u_{vt} - d_{vt} \qquad v \in V^J,\ t \in T \tag{5.25}$$

$$\sum_{a \in A_v^I} \sum_{t'=1}^{t} z_{vat'} \leq u_{vt} \qquad v \in V^J,\ t \in T \tag{5.26}$$

$$\sum_{a \in A_v^I} \sum_{t'=1}^{t-T_{av}+1} z_{vat'} \geq d_{vt} \qquad v \in V^J,\ t \in T \tag{5.27}$$

$$z_{vRt} \leq 1 - u_{vt} + d_{vt} \qquad v \in V^J,\ t \in T \tag{5.28}$$

Constraint (5.20) and (5.21) make sure the difference between the number of times a vessel has jacked up and jacked down is either 0 or 1 at any point in time. This is to guarantee that a jack-down operation is not performed unless the vessel has previously jacked up, and vice versa. In the last time period, $|T|$, the difference between the number of jack-up activities and jack-down activities has to be zero, which is ensured by Constraint (5.22).

Constraint (5.23) and (5.24) count the number of times vessel v is jacked up or jacked down during the planning horizon. Constraint (5.25) makes sure that an installation activity a cannot be performed by a jack-up vessel unless it is jacked up. Further more, Constraint (5.26) and Constraint (5.27) state that jack-up must be performed before an installation activity can start and that jack-down cannot start until at least one installation activity is completed by vessel v. The last constraint, Constraint (5.28), makes sure that a jack-up vessel does not return to port unless it is jacked down.

Binary constraints

$$x_{vt} \in \{0,1\} \qquad v \in V,\ t \in T \tag{5.29}$$

$$z_{vat} \in \{0,1\} \qquad v \in V,\ a \in A_v,\ t \in T \tag{5.30}$$

$$\delta_{vlt} \in \{0,1\} \qquad v \in V,\ l \in L,\ t \in T \tag{5.31}$$

$$\alpha_v \in \{0,1\} \qquad v \in V \tag{5.32}$$

$$s_{vt} \in \{0,1\} \qquad v \in V,\ t \in T \tag{5.33}$$

$$e_{vt} \in \{0,1\} \qquad v \in V,\ t = \{1,\ 2,\ 3,\ \dots,\ |T|+1\} \tag{5.34}$$

Non-negativity constraints

$$v_{ct} \geq 0\ ,\ \text{integer} \qquad c \in C,\ t \in T \tag{5.35}$$

$$w_{ct} \geq 0\ ,\ \text{integer} \qquad c \in C,\ t \in T \tag{5.36}$$

$$u_{vt} \geq 0\ ,\ \text{integer} \qquad v \in V,\ t \in T \tag{5.37}$$

$$d_{vt} \geq 0\ ,\ \text{integer} \qquad v \in V,\ t \in T \tag{5.38}$$

$$s^{Tot} \geq 0\ ,\ \text{integer} \tag{5.39}$$

$$e^{Tot} \geq 0\ ,\ \text{integer} \tag{5.40}$$

Constraint (5.29)-(5.34) handle the binary constraints for all binary variables and constraint (5.35)-(5.40) control the non-negativity and integer requirements in the model.

Chapter 6

Pattern Based Mathematical Model

The model presented in this chapter is a reformulated version of the original model presented in Chapter 5. Reformulating the model is in the literature referred to as a method for solving hard IP problems and is therefore proposed as a method to solve the FSMPIOW studied in this thesis. Throughout the rest of this thesis the model presented in Chapter 5 will be referred to as the original model, while the reformulated model presented in this chapter will be referred to as the pattern based model. The pattern based model is based on the idea of pre-processing parts of the constraints and by this add more information to each variable. The problem is divided into two parts; one part which generates all feasible patterns for each vessel a priori, i.e. before the optimization model is run, and one part which finds the optimal configuration of patterns in order to minimize the total fleet cost. A pattern is defined as the activities a vessel performs from loading of components in port until all loaded components are installed and the vessel is ready to return to port for loading of new components. Each pattern contains information about which vessel is used, the start time of the pattern, all activities performed and their start time, and the end time of the pattern.

The constraints constructing the schedules for each vessel, including the vessel capabilities and weather requirements, in the original model are moved to the pattern generation. Constraint (5.2)-(5.10) and (5.12)-(5.14) which set the charter periods and link components together are kept in the pattern based model.

Sets

V	Set of vessels
A_v^I	Set of all installation activities vessel v can perform
T	Set of time periods
P_v	Set of all feasible patterns for vessel v

Parameters

C_v^{Fix}	Fixed cost of vessel v
C_v^V	Variable cost of vessel v
P	Penalty cost of prolonging the total installation time
N	Total number of turbines in the offshore wind farm
B_{vtp}	1 if vessel v is busy in time period t performing pattern p, 0 otherwise
A_{avtp}	Number of completed installation activities of type a performed by vessel v at time t in pattern p
T_p^{Start}	Start time for pattern p
T_p^{End}	End time for pattern p

Decision variables

λ_p	1 if pattern p is performed, 0 otherwise
α_v	1 if vessel v is included in the optimal fleet, 0 otherwise
s_{vt}	1 if vessel v starts operating in time t, 0 otherwise
e_{vt}	1 if vessel v finish operating in time t, 0 otherwise
s^{Tot}	Project start time, the first time period any vessel is chartered
e^{Tot}	Project end time, the last time period any vessel is chartered

Objective Function

$$\min_{Z} \quad \underbrace{\sum_{v \in V} \sum_{t \in T} C_v^{Fix} \alpha_v}_{a} \; + \; \underbrace{\sum_{v \in V} \sum_{t \in T} C_v^{V} (t \; e_{vt} - \; t \; s_{vt})}_{b} \; + \; \underbrace{P(e^{Tot} - s^{Tot})}_{c} \tag{6.1}$$

The objective function, (6.1), is the same as in the original model and aims to minimize the total cost of the installation vessel fleet for an offshore wind farm. It includes fixed cost, variable costs and penalty cost as explained in Section 5.2.

Constraints

$$\sum_{p \in P_v} B_{vtp}\ \lambda_p \leq \sum_{t'=1}^{t} s_{vt'} \qquad v \in V,\ t \in T \quad (6.2)$$

$$\sum_{p \in P_v} B_{vtp}\ \lambda_p \leq \sum_{t'=t+1}^{|T|} e_{vt'} \qquad v \in V,\ t \in T \quad (6.3)$$

$$\sum_{t \in T} (t\ e_{vt} - t\ s_{vt}) \geq \sum_{p \in P_v} (T_p^{End} - T_p^{Start})\lambda_p \qquad v \in V \quad (6.4)$$

$$\sum_{p \in P_v} B_{vtp}\ \lambda_p \leq \alpha_v \qquad v \in V,\ t \in T \quad (6.5)$$

$$\sum_{t \in T} s_{vt} = \alpha_v \qquad v \in V \quad (6.6)$$

$$\sum_{t \in T} e_{vt} \leq 1 \qquad v \in V \quad (6.7)$$

$$\sum_{t \in T} t\ s_{vt} + |T|\ (1 - \alpha_v) \geq s^{Tot} \qquad v \in V \quad (6.8)$$

$$\sum_{t \in T} t\ e_{vt} \leq e^{Tot} \qquad v \in V \quad (6.9)$$

$$e^{Tot} - s^{Tot} \geq 0 \qquad (6.10)$$

$$\sum_{v \in V} \sum_{p \in P_v} A_{(a+1)vtp}\ \lambda_p - \sum_{v \in V} \sum_{p \in P_v} A_{av(t-1)p}\ \lambda_p \leq 0 \qquad a \in A_v^I,\ t \in T \quad (6.11)$$

$$\sum_{v \in V} \sum_{p \in P_v} A_{av|T|p}\ \lambda_p \geq N \qquad a \in A_v^I \quad (6.12)$$

Binary constraints

$$\lambda_p \in \{0, 1\} \qquad p \in P_v \quad (6.13)$$

$$\alpha_v \in \{0, 1\} \qquad v \in V \quad (6.14)$$

$$s_{vt} \in \{0, 1\} \qquad v \in V,\ t \in T \quad (6.15)$$

$$e_{vt} \in \{0, 1\} \qquad v \in V,\ t \in T \quad (6.16)$$

Non-negativity constraints

$$s^{Tot} \geq 0, \ \text{integer} \tag{6.17}$$
$$e^{Tot} \geq 0, \ \text{integer} \tag{6.18}$$

Constraint (6.2) and (6.3) set the charter period for each installation vessel in the fleet. Constraint (6.2) makes sure no pattern p is performed before the charter period of vessel v starts and Constraint (6.3) makes sure no that pattern p is performed after the charter period of vessel v ends. Constraint (6.4) requires that the length of a vessel v's charter period is greater than the difference in start and end time of all patterns performed by vessel v. In addition, each vessel can only perform one pattern at a time, which is ensured by Constraint (6.5).

The total project duration is restricted by Constraints (6.6)-(6.10) and are equal to the project duration constraints in the original model. The parameter A_{avtp} in Constraint (6.11) and (6.12) is used to control the number of completed installations of type a during the performance of pattern p. The dependency between different components is handled by Constraint (6.11) which ensures that the predefined installation sequence of components is met at every point in time. The constraint requires that the number of completed installations of one component is greater than the number of completed installation of another component if there is a precedence between the two components. Constraint (6.12) states that the number of completed installations of each installation activity a must equal the total number of turbines in the wind farm at the end of the planning horizon. Constraints (6.13)-(6.16) handle the binary requirements for all binary variables and constraints (6.17)-(6.18) control the non-negativity and integer requirements in the model.

6.1 Symmetry Breaking Inequalities

If the set of vessels, V, contains several vessels with identical characteristics, an extra amount of symmetry will be added to the problem. Symmetry will cause difficulties when solving the model, but the amount of symmetry can be reduced by introducing a set of symmetry breaking inequalities to the initial model formulation. The set V^M contains the different vessel types and the set V_m is a subset of all vessels, V, and consists of the number of vessels of type m. For each vessel in V_m and for every vessel type, the inequality presented in Constraint 6.19 is added to the pattern based model. Since all vessels in the subset V_m are identical, we utilize the inequality to require that a vessel with a lower lexicographic order, i.e. a lower ID number, has a charter period which is greater than or equal to the charter period for a vessel with a higher ID number. This will make the solutions a bit different from each other.

V^M Set of vessel types
V_m Set of vessels of type m, $V_m \subseteq V$

$$\sum_{t \in T}(te_{vt} - ts_{vt}) \geq \sum_{t \in T}(te_{v+1,t} - ts_{v+1,t}) \qquad v,\ v+1 \in V_m \quad (6.19)$$

Chapter 7

Pattern Generation

The reformulated pattern based model is based on the previous work of Hansen & Siljan (2016) and the original model presented in Chapter 5. Hansen & Siljan (2016) conclude in their project report that the proposed model only solves small test instances to optimality and hence the reformulated pattern based model is proposed in Chapter 6. The applied solution method in this thesis is to generate feasible patterns a priori, and then solve the pattern based model to find the optimal configuration of patterns. Three methods for generating feasible patterns are presented in this chapter, one exact method and two heuristic methods, presented in Section 7.1 and Section 7.2 respectively.

7.1 Exact Pattern Generation Method

In this thesis a pattern is defined as a series of activities a vessel performs from the loading of components in port until installation of all loaded components is completed. The exact method generates patterns for all possible combinations of vessels, loading sets and start times. The sequence in which each of the components loaded on the vessel is installed will affect the patterns' total duration, and is illustrated in Figure 7.1. In the example, all generated patterns start with loading in time $t = 1$. After placing the loading activity, all permutations of the loading set containing one sub structure, one tower, and one top structure are generated and placed as close to the loading as possible. As can be seen, only *Pattern 1* and *Pattern 2* are able to utilize the time periods from $t = 4$ up to $t = 10$ due to bad weather where only the sub structure activity can be safely performed and completed.

Activity	Processing time	Weather requirement
Loading	3	4
Sub-structure	2	4
Tower	1	3
Top	1	2

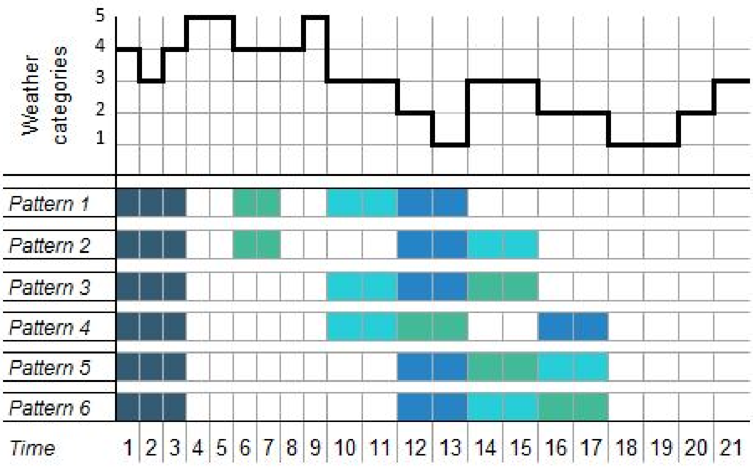


Figure 7.1: An illustration of the permutation of a loading set containing one sub structure, one tower, and one top structure.

An example of the output from the pattern based model is shown in Figure 7.2. The time from the first pattern starts to the last pattern ends defines the total project duration, and the time from the first to the last pattern performed by each vessel defines the charter period of the given vessel.

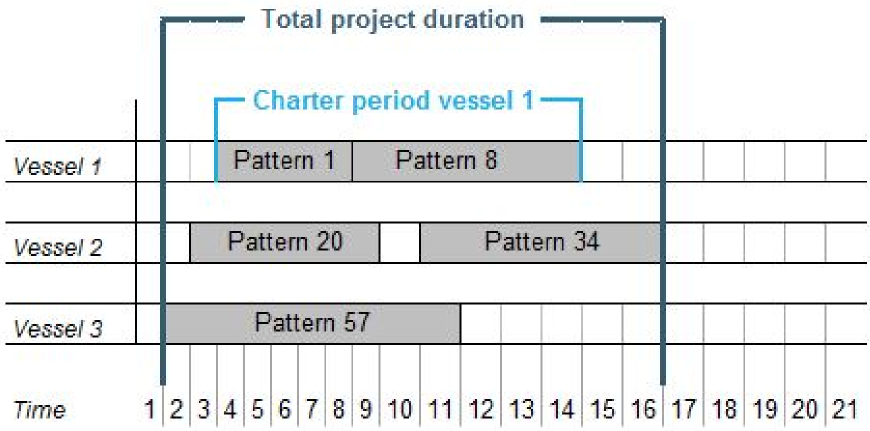


Figure 7.2: An illustration of how the patterns are combined into schedules for each vessel

When constructing patterns both vessel specific characteristics and weather conditions are considered. Christiansen et al. (2007) state that a priori generation of patterns is a preferred approach when the total number of patterns is limited. The number of patterns is highly dependent on the vessels' free deck space capacity, and today's available vessel concepts have a relatively limited free deck space capacity which limits the number of components loaded on each vessel per trip. This will limit the number of permutations of components in each loading set and hence reduce the total number of patterns. The relatively small number of feasible patterns makes a priori generation a well suited solution method for the pattern based model for the FSMPIOW.

Based on the definition of a pattern, a pattern generation program is proposed to generate all feasible patterns. The main idea of the program is shown in the flowchart in Figure 7.3. The variables v and l represent the vessel and loading set currently being evaluated and t is the start time for the pattern being generated. For a loading set l, all permutations of the components are generated and stored in the set X_l. Each permutation in X_l is represented by x.

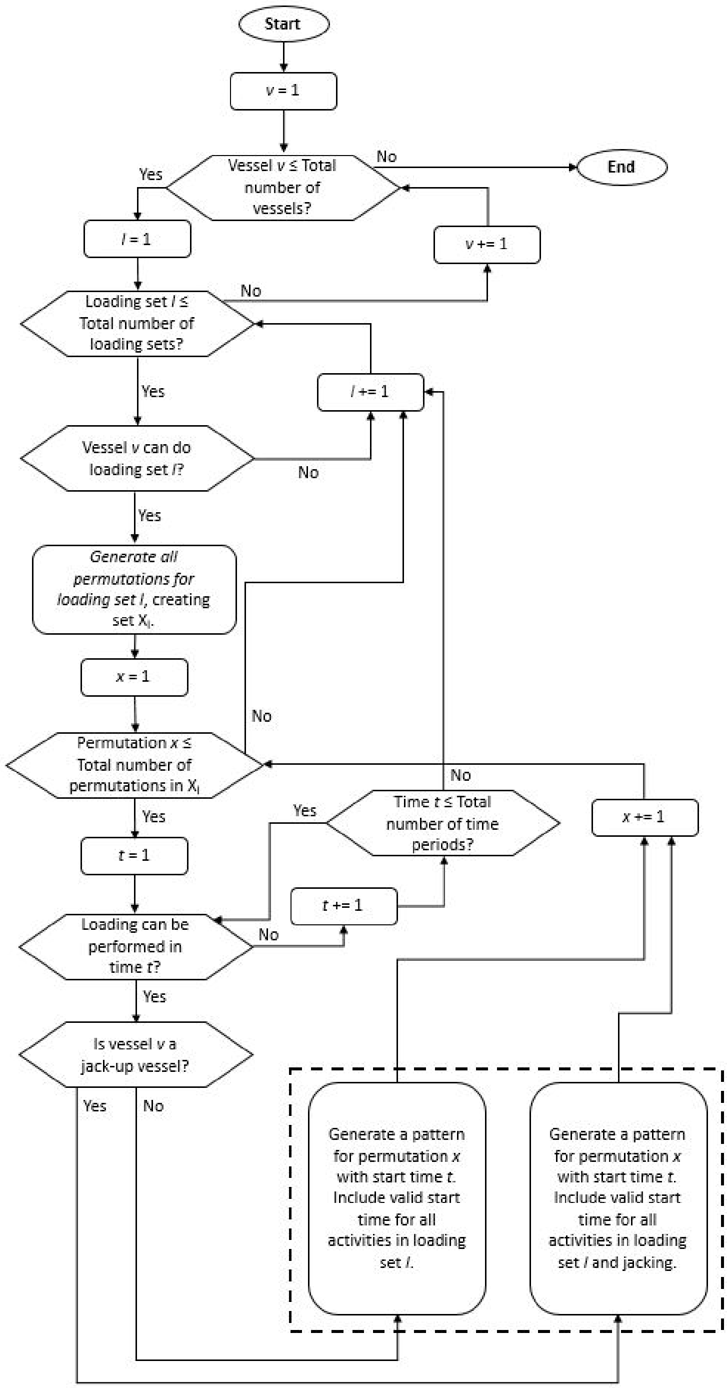


Figure 7.3: Flowchart for the pattern generation program

In order to keep the solution space as close to the original model as possible, every possible pattern is generated. By applying the idea of permutation, all possible installation sequences of the components in a loading set are created. This means that all possible permutations of the components in a loading set is generated and all possible start times for each permutation is found. The core of the program, where the patterns with start times are generated, is marked with a dashed line. This part of the program finds a valid start time for the installation of every component in a loading set based on each component's required weather condition and installation time, and is described in Algorithm 1.

Algorithm 1 Pattern Generation Program

```
Input: Vessel v, start time t, permutation x
T_p^Start = t
t = t + Loading time for vessel v
forall Activities a in loading set l with the sequence given in permutation x do
    for t ≤ length of planning horizon do
        if weather in t ≥ weather requirement for activity a and vessel v then
            Continue
        end
        Counter = 0
        for t ≤ t + Processing time of activity a by vessel v do
            if weather t ≥ weather requirement for activity a and vessel v then
                Break
            end
            Counter = Counter + 1
            if Counter = Processing time of activity a by vessel v then
                Start time for activity a is set to t
                Activity a with start time t is added to pattern
                t = t + Processing time of activity a by vessel v
            end
        end
    end
end
T_p^End = t
Result: Pattern for permutation x with start times for all activities
```

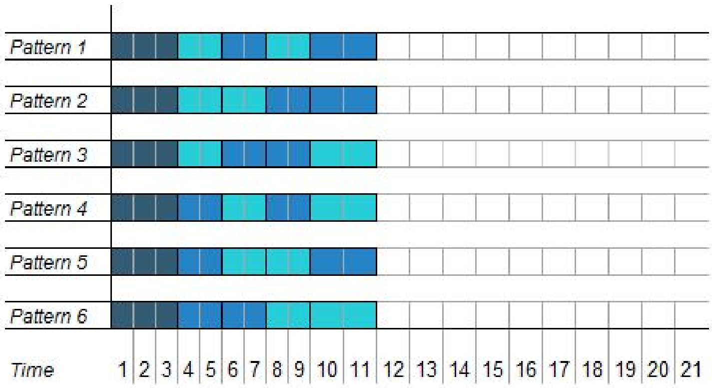
Algorithm 1 is a more thorough explanation of the logic within the dashed lines in Figure 7.3. At this point a vessel v, a loading set l, and a permutation x of the respective loading set is selected, and the start time t for loading is determined. For each activity the program loops through the time periods from the last finished activity until it finds a time period t with an acceptable weather realization. Once a time period allows operation, the idea is to check the following time periods to see if the activity can be completed without interruption of bad weather. Given that enough time periods with acceptable weather exist to complete the activity, a possible activity start time is found and added to the pattern. When all activities in permutation x is placed with a start time, a pattern is created. If the vessel is a jack-up vessel, the start time for all jacking operations are also included in the pattern. When generating patterns for a jack-up vessel it is assumed that components installed in the correct order, e.g. installation of the top structure is performed after installation of the tower without interruption of other activities in between, are performed on the same turbine and only one jack up and jack down operation is required.

7.2 Heuristic Pattern Generation Method

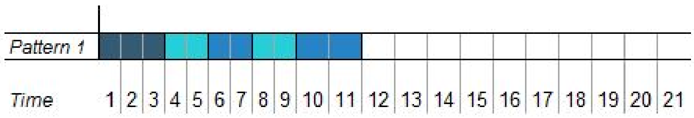
As pointed out by Christiansen et al. (2007) a priori generation of all patterns is a solution method which is only favourable as long as the number of patterns, which is determined by the number of permutations of components in a loading set, is sufficiently small. The number of generated patterns will increase linearly with an increasing number of time periods and vessels, but once the vessels' capacity increases the number of generated patterns will increase considerably. An increase in the number of patterns will cause an increase in the number of variables in the pattern based model, and hence an increased problem size. The same is true if the assembly strategy is changed and the number of components per turbine increases. This is a drawback of the proposed solution method. By using knowledge of how the installation phase is normally performed, it is possible to state some rules in order to remove patterns which are considered less realistic. This is the idea of the heuristic pattern generation program.

Two heuristic methods for generating patterns are proposed to reduce the number of feasible patterns. The first heuristic requires that if a vessel is loaded with different component types, all components for one turbine have to be mounted before the vessel can continue to the next turbine, henceforth referred to as the Complete Turbine Heuristic (CTH). CTH will eliminate all patterns where components are installed in a non-chronological sequence. The second heuristic makes sure that within a pattern the precedence between components are met, henceforth called the Precedence Heuristic (PH). The two heuristics are illustrated in Figure 7.4 with a loading set containing two towers and two top structures. The figure illustrates how the two different heuristics affect the number of patterns generated. As can be seen from Figure 7.4a, six patterns are generated with the exact method. When running the pattern generation program with CTH the number of patterns is reduced to one due to the strict requirement, Figure 7.4b. With PH the pattern generation program generates two patterns as can be seen in Figure 7.4c. As can be seen from Figure 7.4 the patterns generated with CTH are a sub set of the patterns generated with PH. Applying a heuristic pattern generation procedure is one possible solution to the mentioned drawback of the exact pattern generation program, and our two suggestions will be further analyzed in Chapter 9.

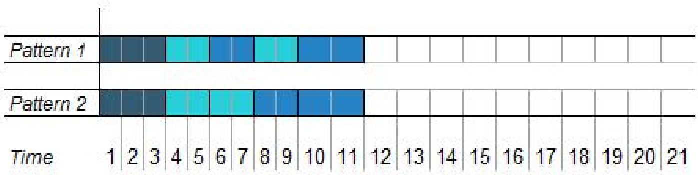
If the problem size gets too large, an alternative solution method is to apply the Branch and Price method and use a pattern generation algorithm in each node to find patterns with a negative reduced cost in order to improve the objective value in the pattern based model.



(a) All patterns generated with the exact method



(b) Complete Turbine Heuristic (CTH)



(c) Precedence Heuristic (PH)

Figure 7.4: Effect of including heuristic pattern generation

7.3 Robust Solutions

When patterns are combined into schedules and the project start time and end time are determined, the optimal solution will find the shortest possible project duration in order to minimize the objective value. This can cause an optimal solution to become infeasible with respect to the predetermined schedules, if the weather conditions change. Even a small delay when installing wind turbines, e.g. one day, will cause a significant financial loss for the wind farm operator (Irawan et al., 2015). According to actors in the offshore wind industry, one of their goals is to reduce the risk of delay in a project schedule (Appendix F). In order to implement more robustness in the solution, and hence increase the probability of a solution to be feasible in several weather scenarios, it is interesting to look at different strategies to modify the patterns and create slack which can be used in case of delay.

Slack is defined as a number of consecutive time units with a given weather restriction where a vessel is not operating. We propose two different strategies for implementing slack and improve the robustness. The first strategy is to increase the processing time of each installation activity such that the amount of added slack in a schedule varies according to the number of turbines. The second strategy is to implement slack at the end of each pattern. The strategy will add most value to the solution if the weather requirement of the slack is equal to the strictest weather restriction for any activity and any vessel. This will make it possible for all of the activities to utilize the added slack in case of delay. The two robustness strategies are illustrated in Figure 7.5 labeled *Strategy 1* and *Strategy 2* together with the original pattern that is intended to be made more robust. The table gives information on the different processing times for each activity where the first number indicates the original processing time and the second number is the added slack used in *Strategy 1*. The weather requirement for the activities are found in the third column. *Strategy 1* increases the processing times for installation activities by one time period and are illustrated by a darker color in the pattern. When increasing the processing times, the installation of top structure is moved to a later point in time than before due to bad weather. *Strategy 2* gives a more compact pattern, with the original processing times and adds three time periods of slack at the end of the pattern. The slack added requires weather category *good*, as this is the strictest weather requirement of any of the other activities.

Activity	Processing time	Weather requirement
Loading	3	4
Sub-structure	2 + 1	4
Tower	1 + 1	3
Top	1 + 1	2
Slack	3	2

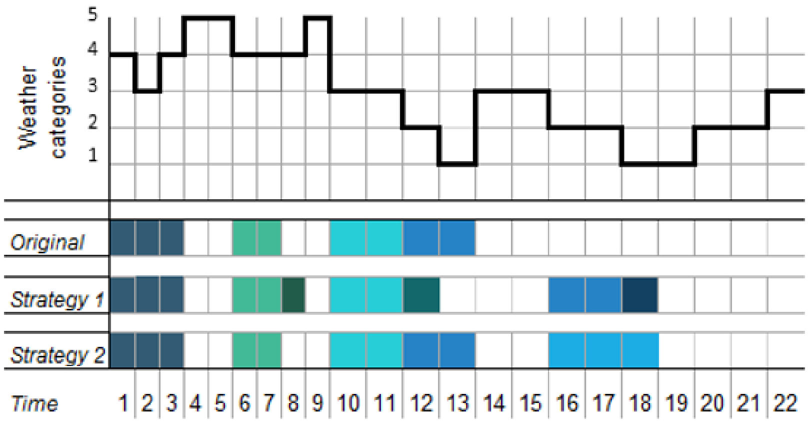


Figure 7.5: An illustration of the two proposed strategies for increasing the robustness of a solution. *Strategy 1* adds one time period to each processing time for the installation activities. *Strategy 2* adds three time periods of slack at the end of the pattern. The original solution, without the robustness measures, is labeled *Original*.

Chapter 8

Input Data

This section describes the input data used to generate test instances applied in the computational study found in Chapter 9. In order to generate realistic instances, information from the offshore wind industry is applied. However, available data is limited and reasonable estimates are used when no other data is retrievable. Various sources are used as inspiration to set the parameters; Kaiser & Snyder (2013), Maples et al. (2013), Dinwoodie et al. (2015), and information from Statoil ASA and Fred.Olsen Windcarrier AS (Appendix D - F).

Vessels

The global fleet of installation vessels consists of several different vessel concepts as presented in Chapter 2. Each vessel has individual characteristics, such as deck space capacity, lifting capacity, weather restrictions on operation, and processing times. The vessel pool used for testing the models consists of two vessel concepts, HLV and SPIV, while the number of each vessel in the pool is varied. Relevant vessel data can be found in Table 8.1 and Table 8.2.

Table 8.1: Vessel characteristics

Vessel concept	Transit speed		Free deck space capacity				Jack-up?
	Knots	km/h	Sub structure	Tower	Top	Tower + top	
SPIV	12	22	6	6	6	6	Yes
HLV	11	20	6	-	-	-	No

Table 8.2: Vessel weather requirements

Vessel concept	Weather requirements					
	Loading	Jack-up/down	Sub	Tower	Top	Tower + Top
SPIV	4	3	3	3	2	2
HLV	4	-	3	-	-	-

According to an annual report from the European Wind Energy Association (EWEA) the average distance from the offshore wind farms to shore was 44 km in 2016 (European Wind Energy Association, 2017). A SPIV sails at an average speed of 12 knots, which corresponds to approximately 22 km/h, and the average transit time from port to site can thus be set to 2 hours. Similar calculations are done for the HLV and can be found in Table 8.3. As described in Chapter 5, transit is included in the activity called loading. Jacking is a complex and time consuming activity involving several operations. First the elevating legs are placed on the seabed followed by positioning and stabilization of the vessel, before the hull is elevated above sea level. The total time needed to complete the jacking activity is set to 12 hours. For simplicity it is assumed that jack-up and jack-down requires the same amount of time. The processing times for the other installation activities are inspired by Kaiser & Snyder (2013).

Table 8.3: Vessel processing times in hours

Vessel concept	Processing time [hours]					
	Loading	**Jack-up/down**	**Sub**	**Tower**	**Top**	**Tower + Top**
SPIV	48	12	24	12	12	24
HLV	36	-	24	-	-	-

Weather

The weather input is based on historical data gathered from FINO 1, a research platform located in the North Sea. Data on wave height and wind speed is sampled on an hourly basis from 2004 to 2012 (BMU and PTJ, n.d.). Initial analysis on the available weather data, from 2004 to November 2012, show minor annual variations and it is decided to use the most resent full year, 2011, as input. Unless otherwise stated, the tests are run on weather data from either June and July 2011 or May-August 2011. In order to represent the weather in the format specified in the mathematical model, the data is first divided into intervals of the applied time discretization. Both wind speed and wave height in each time interval is then categorized according to the specifications given in Table 2.1 and the worst realization of wind speed and wave height during the interval is then chosen to represent each of them. Next, the worst value of wind speed and wave height is used to represent the weather condition in each time period.

Activities

The assembly strategy used to test the optimization model in this thesis is to install the sub structure, tower and top structure as three individual components offshore. The activities which need to be performed in order to install the wind farm can thus be divided into loading, jack-up, jack-down and installation activities. The different installation activities are divided into installation of sub structure, installation of tower, installation of top structure and installation of tower and top structure.

Each vessel's processing times for the different activities are difficult to retrieve and are, in addition, closely linked to the uncertainty in weather, since the weather condition can greatly influence the ability to operate and thus the time needed to complete an operation. However, this uncertainty will not affect the technical analysis.

As described in Chapter 2, cabling is also an important part of the installation phase. However, special designed cable installation vessels (CIV) are required when installing cables, and these CIVs are not designed to perform any other installation activities. Generally the optimal installation vessel fleet will include CIVs, but these vessels are excluded from the computational study in this thesis because cabling can be regarded as an isolated activity. Should it, however, be interesting to include cabling in the problem, the set of installation activities can be expanded with a cabling activity.

Loading Sets

According to information from the offshore wind industry the largest installation vessels have a free deck space capacity to carry up to eight turbines, i.e. eight towers and eight top structures, in one trip. The loading sets are constructed based on this maximum deck space capacity. A loading set contains between one and eight components of a given type and combinations are also possible. If a loading set contains a combination of two components there is an equal number of each component. Based on available information from the industry, it is assumed that loading sets combining substructure and top structure, or sub structure and tower is not possible.

Charter Costs

Charter rates are based on supply and demand and this market is characterized by high competition. Due to this, charter rates are concealed from the public. However, the literature gives an indication of the costs related to the chartering of vessels and also an idea of the cost ratio between different vessel concepts. The cost parameters applied in the computational study are presented in Table 8.4.

Table 8.4: Cost parameters

Vessel	Fixed [£k]	Charter [£k/day]
HLV	5 200	160
SPIV	4 300	140

Penalty Cost

In order to minimize the total installation cost and the total project duration, a penalty cost term is added to the objective function. If the optimal fleet includes more than one vessel, it is desirable to gather all vessel charter periods in order to avoid an unnecessary long project duration. If the installation is prolonged and thus completed at a later point in time, this will cause loss of electricity production and potential revenue. The value of the penalty cost is thus represented by the lost revenues of not generating electricity.

Generated energy can be found by multiplying the capacity factor of each turbine by the total number of turbines in the wind farm and the turbine rating. The capacity factor represents, on average, how much energy is actually produced by a wind turbine and is given as a percentage of the turbine rating. Looking at values from offshore wind farms in both Denmark and the UK, a capacity factor of 40% and a turbine rating of 6 MW is applied in this thesis (EnergyNumbers, 2017b), (EnergyNumbers, 2017a). The penalty cost is calculated by Equation 8.1, as the the product of generated energy, the energy price, and the number of hours per time period. The lost revenue which is represented as the last cost term in the objective value in the mathematical model is found by multiplying the penalty cost by the number of time periods in which the wind farm is under construction.

$$P = Price^{el} \times \underbrace{Capacity \times Rating \times \#Turbines}_{Generated\ electricity} \times Interval \tag{8.1}$$

Initial testing shows that a penalty cost equal to lost revenues, P, gives good results in terms of minimizing the total project duration without increasing the total costs unnecessary.

Chapter 9

Computational Study

Different tests are carried out to assess the performance of the original model presented in Chapter 5 and the pattern based model presented in Chapter 6. The results and findings are presented in this chapter. Section 9.1 presents the test instances, and the results from testing the original model and the pattern based model are presented in Section 9.2 and 9.3, respectively. Section 9.4 covers a study of the robustness of the solutions provided by the pattern based model and in Section 9.5 a seasonality study is conducted to investigate how variations in weather conditions during the year affect the solution and how this can be used to evaluate different vessel charter strategies. For more details of the results given in this chapter see Appendix C.

Both the original model and the pattern based model is implemented in the commercial optimization software FICO®Xpress 7.9, referred to as Xpress. The pattern generation program is implemented in Java Standard Edition 8 version 121 (Java SE 8.121). All tests are conducted on a computer with an Intel(R) Core(TM) i7-6700, CPU 3.40GHz processor, 32.0GB RAM, and a 64-bit operating system. The maximum run time for Xpress is set to 10 800 seconds.

9.1 Test Instances

The test instances are inspired by real cases and based on information from the industry and research articles, and designed with the intention of testing the model in the best possible way. We have used a 12 hour interval to discretize time. Unless otherwise stated, all times are given as a multiple of 12.

To test the mathematical models' performance and ability to solve real life problems, several tests have been conducted. The input data for every test is presented in Table 9.1. The name of the instance (Instance) gives information about the restriction of possible start times, the vessel pool size, and the number of turbines to install. For SxFyTw, S represents the possible start times, F represents the number of vessels in the pool and T represents the number of turbines. For example, S7F3T20 means that possible start times are restricted to every 7$^{\text{th}}$ day, the vessel pool contains three vessels, and there are 20 turbines to install. Column number two (Number of turbines) specify the number of turbines to install. Information regarding the vessel pool is given in column number three (Vessel pool). The vessel pool contains two type of vessels, HLV and SPIV, and the total number of vessels in the pool is either two, three, five, or ten. The planning horizon (Planning horizon), unless otherwise stated, is the summer months of 2011. For the planning horizon of 122 time periods June and July are applied, whereas for the planning horizon of 246 time periods the months May, June, July and August are used. The last column (Start time) specify whether or not there are restrictions on the possible start times for a vessel's charter period. If the column is blank no such restrictions are made.

Table 9.1: Complete list of test instances. Note: The table spans over two pages.

Instance	Number of turbines	Vessel pool	Planning horizon	Start Time
T3	3	HLV, SPIV	122	
T4	4	HLV, SPIV	122	
T5	5	HLV, SPIV	122	
T6	6	HLV, SPIV	122	
T7	7	HLV, SPIV	122	
T18	18	HLV, SPIV	122	
T19	19	HLV, SPIV	122	
T20	20	HLV, SPIV	246	
T30	30	HLV, SPIV	246	
T39	39	HLV, SPIV	246	
T40	40	HLV, SPIV	246	
F3T20	20	HLV, 2 SPIV	246	
F3T30	30	HLV, 2 SPIV	246	
F3T40	40	HLV, 2 SPIV	246	
F3T50	50	HLV, 2 SPIV	246	
F3T60	60	HLV, 2 SPIV	246	
F3T70	70	HLV, 2 SPIV	246	
F3T80	80	HLV, 2 SPIV	246	
F5T20	20	2 HLV, 3 SPIV	246	
F5T30	30	2 HLV, 3 SPIV	246	
F5T60	60	2 HLV, 3 SPIV	246	
F5T70	70	2 HLV, 3 SPIV	246	
F5T80	80	2 HLV, 3 SPIV	246	
F5T90	90	2 HLV, 3 SPIV	246	
F5T100	100	2 HLV, 3 SPIV	246	
F5T110	110	2 HLV, 3 SPIV	246	
F5T150	150	2 HLV, 3 SPIV	246	
F10T30	30	4 HLV, 6 SPIV	246	
S1T3	3	HLV, SPIV	122	Every day
S2T3	3	HLV, SPIV	122	Every 2nd day
S3T3	3	HLV, SPIV	122	Every 3rd day
S7T3	3	HLV, SPIV	122	Every 7th day
S14T3	3	HLV, SPIV	122	Every 14th day

Instance	**Number of turbines**	**Vessel pool**	**Planning horizon**	**Start Time**
S7T4	4	HLV, SPIV	122	Every 7th day
S7T5	5	HLV, SPIV	122	Every 7th day
S7T6	6	HLV, SPIV	122	Every 7th day
S7T7	7	HLV, SPIV	122	Every 7th day
S7F3T20	20	HLV, 2 SPIV	246	Every 7th day
S7F3T30	30	HLV, 2 SPIV	246	Every 7th day
S7F3T40	40	HLV, 2 SPIV	246	Every 7th day
S7F3T50	50	HLV, 2 SPIV	246	Every 7th day
S7F3T60	60	HLV, 2 SPIV	246	Every 7th day
S7F3T70	70	HLV, 2 SPIV	246	Every 7th day
S7F3T80	80	HLV, 2 SPIV	246	Every 7th day
S7F5T20	20	2 HLV, 3 SPIV	246	Every 7th day
S7F5T30	30	2 HLV, 3 SPIV	246	Every 7th day
S7F5T60	60	2 HLV, 3 SPIV	246	Every 7th day
S7F5T70	70	2 HLV, 3 SPIV	246	Every 7th day
S7F5T80	80	2 HLV, 3 SPIV	246	Every 7th day
S7F5T90	90	2 HLV, 3 SPIV	246	Every 7th day
S7F5T100	100	2 HLV, 3 SPIV	246	Every 7th day
S7F5T110	110	2 HLV, 3 SPIV	246	Every 7th day
S7F5T150	150	2 HLV, 3 SPIV	246	Every 7th day
S7F10T30	30	4 HLV, 6 SPIV	246	Every 7th day

9.2 Original Model

Technical analysis are carried out on the original model in order to evaluate which test instance sizes the model can handle within the given CPU time. When results are presented throughout this chapter, a (-) indicates that the instances is infeasible and a duality gap of 100% means that no integer feasible solution is found within 10 800 seconds.

The results from running the original model are found in Table 9.2 presented by the name on the test instances (Instance), their solution time (CPU time [sec]), the duality gap (Gap [%]), the primal bound (Primal bound), and the dual bound (Dual bound). As can be seen from Table 9.2 the original model only solve T3 and T4 to optimality. The duality gap for the larger test instances can be explained by examining the primal bound and dual bound. The weak bound can, as indicated by Hansen & Siljan (2016), be caused by the amount of symmetry in the problem. For example, for a given vessel v the charter period, s_{vt} and e_{vt}, can in theory be set to all possible time periods t as long as the weather condition permits operation and the total charter period is equivalent to the charter period which minimizes cost. For example, $s_{i,10}$ and $e_{i,20}$ is equivalent to $s_{i,30}$ and $e_{i,40}$ with respect to total charter cost of vessel i. Symmetry causes several sub trees in the Branch and Bound (B&B) tree to be isomorphic, meaning branches in the B&B tree have identical structures which forces a wasteful duplication of effort in the search (Margot, 2010). Symmetry will not affect the LP relaxation in the root node, but rather the potential improvements of the bounds deeper in the tree.

Table 9.2: Results of the original model for the smallest test instances with an increasing number of turbines.

Instance	CPU time [sec]	Gap [%]	Primal bound	Dual bound
T3	610	0	6 899	6 899
T4	1 905	0	7 699	7 699
T5	10 800	5	58 913	8 470
T6	10 800	27.98	13 289	9 571
T7	10 800	100		
T18	10 800	100		
T19	10 800	100		

The test instances T7 to T19 have a duality gap of 100% indicating that no integer feasible solution is found. By comparing the number of visited nodes in T7 to T4 it is observed that roughly four times as many nodes are processed in T7, see Appendix C. This indicates that the processing time of each node is not the issue but rather the amount of fractional variables in each node, which leads to a huge B&B tree to search through.

When examining the results for T5 we observe that it is a great difference between the LP relaxation and the best integer solution found. The solution space to search through is thus huge and will require a great amount of time. If the LP relaxation in the root node is weak and the B&B tree is huge, it will be harder to find feasible integer solutions, which contributes to explain the large duality gap in Table 9.2.

9.2.1 Fixing the Project Start Time

According to Klotz & Newman (2013) the upper bound can be improved by providing an obvious solution based on knowledge of the problem. One way to provide an initial solution is by fixing some of the variables (Hewitt et al., 2013). The project start date is often determined by other factors than the charter strategy and the fleet composition, and can in most cases be considered known. When starting the planning of a new project it is natural to assume that the first time period in the planning horizon is also the project start date. This argument is used to fix the variable s^{Tot} to 1. When fixing the project start time rather than finding the optimal start time, a potential drawback is that it will most likely increase the total project duration and thereby increase the total cost.

The model is tested on the same test instances as those presented in Table 9.2 and the results are found in Table 9.3. As in Table 9.2 the three first columns contains information on the name of the test instance (Instance), the solution time (CPU time [sec]), and duality gap (Gap [%]). The primal bound (Primal bound [%]) and dual bound (Dual bound [%]) are compared to the equivalent test instances in Table 9.2 and are calculated by Equation 9.1. Equation 9.1 calculates the bounds as the percentage of the reference bound.

$$\text{Bound [\%]} = \frac{\text{Current bound}}{\text{Reference bound}} \times 100 \tag{9.1}$$

Table 9.3: Results of the original model when fixing the project start to the first time period in the planning horizon. The change in the primal and dual bound are given as the percentage of the bounds from the test instances in Table 9.2.

Instance	CPU time [sec]	Gap [%]	Primal bound [%]	Dual bound [%]
T3	416	0	100.17	100.17
T4	3 113	0	105	105
T5	10 800	37.75	160.06	104.85
T6	10 800	42.09	128.55	103.37
T7	10 800	100		

The desired effect of fixing s^{Tot} is to improve the primal bound, however this is absent for every test instances. For test instance T5 and T6, the increase in the primal bound is much higher than the increase in the dual bound. This observation explains the increased duality gap compared to Table 9.2 and shows that the measure acts against its purpose. Instead of improving the upper bound, as was the intention, it is aggravated. Potential reasons for the aggravation are (1) that potentially good solutions are removed when fixing the project start to $t = 1$, (2) even if one variable is fixed there is still a huge amount of variable taking fractional values when branching through the B&B tree, (3) because the penalty cost only accounts for a small part of the objective value there are still a lot of possible solutions to investigate, and (4) by fixing one variable the search strategy performed by Xpress in the B&B tree might have changed.

9.2.2 Restricting Start Time for Charter Period

Another attempt to improve the solutions of the original model is by reducing the size of the problem, i.e. reducing the number of variables and constraints, since the B&B algorithm implicitly explores all possible solutions (Lundgren et al., 2012). By removing some of the s_{vt} variables and hence restrict possible start times for each vessel's charter period, the number of variables and the problem size is reduced. The goal is to reduce the number of feasible solutions and the computational time required to solve test instances to optimality. Applying this method will, however, in several cases also cause a worse solution in terms of the objective value. By eliminating variables, optimal solutions can be removed, causing an increase in the objective value compared to the results from running the model without this restriction. The value of this solution method depends on the trade-off between the increase in the objective value and the improvement in the model's performance.

The results are presented in Table 9.4 and Table 9.5. All columns in the tables are equivalent to those presented for Table 9.3. The two bounds are given as the percentage of the primal bound and dual bound of the equivalent test instances in

Table 9.2, and are calculated by equation 9.1.

Testing is performed on T3 to determine how many variables to remove in order to improve the solution time of the original model, see Table 9.4. Analysis show that by reducing the possible start times the number of variables is reduced between 1.8% and 3.5% depending on how strict the start time restriction is set, and the primal bound is at worst increased by 5.9%. By restricting possible start times to once a week, S7T3, the number of variables is reduced by roughly 3.4% compared to the plain version of the original model. This gives a good reduction in the problem size and improves the CPU time by 42% with only a small increase in the objective value, i.e. it gives a good trade-off between the increased objective value and the improved CPU time. Based on the results in Table 9.4 and the analysis of the problem size, it is determined to continue with a restricting start time of once a week, i.e. every 7^{th} day. It can easily be argued that it is reasonable to restrict the charter start times to every 7^{th} day, as the decision on the optimal fleet is taken years before the installation takes place and without knowing the actual weather realization. Specifying that a vessel charter period starts once a week is thus more realistic than proposing to start Wednesday 12 am.

Table 9.4: Results of the original model when varying the restriction of possible start times for a vessel's charter periods on T3. The last two columns show the primal and dual bound as a percentage of the bounds for T3 found in in Table 9.2.

Instance	CPU time [sec]	Gap [%]	Primal bound [%]	Dual bound [%]
S1T3	353	0	100	100
S2T3	293	0	101.17	101.18
S3T3	330	0	101.19	101.18
S7T3	281	0	103.54	103.54
S14T3	176	0	105.89	105.89

Table 9.5 presents the results when increasing the number of turbines and limiting the possible start times for a vessel charter period to once a week. By comparing the results in Table 9.5 to the results in Table 9.2 it is found that the good results

of initial testing on T3 is only obtained for T3 and T7. All other results are worse, either by an increased CPU time or an aggravation of the duality gap. Analysis of S7T5 show that the worse performance is mainly due to a worsening in the primal bound, implying that the model is not able to find good integer feasible solutions. The dual bound only increases by a small percentage, and the increased duality gap is believed to be caused by the aggravated primal bound. By removing possible start times, solutions which previously were feasible might have been removed, making it harder to find feasible integer solutions during the B&B search.

Table 9.5: Results of the original model when restricting the charter start times to every 7^{th} day for test instances with an increasing number of turbines. The primal bound and dual bound are given as a percentage of the results in Table 9.2. A (*) indicates that no comparison is possible due to an integer infeasible solution in the previous run.

Instance	CPU time [sec]	Gap [%]	Primal bound [%]	Dual bound [%]
S7T3	264	0	103.54	103.54
S7T4	4 230	0	102.21	102.21
S7T5	10 800	31.98	147.02	105.24
S7T6	10 800	29.08	105.47	103.86
S7T7	10 800	39.47	*	*

9.2.3 Brief Summary

Testing of the original model reviles that the model is too hard to solve to optimality for test instances of realistic size. The problem is caused by weak bounds, both primal and dual, due to symmetry and a weak LP-relaxation. Two suggestions are proposed to improve the bounds, fixing variables and removing variables, but without great improvements in the model's performance. The focus in the rest of this chapter will be on the pattern based model which is believed to solve more realistic sized test instances.

9.3 Pattern Based Model

As described in Chapter 6, a pattern based model is formulated to solve bigger and more realistic test instances. The exact solution method is based on a priori generation of all feasible patterns which are combined in the pattern based model with the goal of minimizing cost. The number of feasible patterns and the CPU time required to generate them are dependent on both the length of the planning horizon and the number vessels in the vessel pool. The pattern generation results are summarized in Table 9.6 which gives the number of time periods in the planning horizon (Horizon), the vessels in the pool (Vessel pool), the time used to generate the patterns in Java (CPU time [sec]) and the number of generated patterns (Patterns). As motivated in Section 7.1, Table 9.6 shows that there is only a small amount of generated patterns, with a maximum of 52 572 patterns for the largest instances. The number of patterns increases linearly with the number of time periods and the number of vessels in the pool. When increasing the time horizon from 122 periods to 246 there is approximately a 50% increase in the number of generated patterns. Increasing the vessel pool from one HLV and one SPIV to one HLV and two SPIVs, gives a bit less than a 50% increase in patterns.

Table 9.6: The number of patterns generated by the exact pattern generation program.

Horizon	Vessel Pool	CPU time [sec]	Patterns
122	HLV, SPIV	5	4 107
246	HLV, SPIV	9	9 093
246	HLV, 2 SPIV	17	17 193
246	2 HLV, 3 SPIV	29	26 286
246	4 HLV, 6 SPIV	66	52 572

The CPU times reported in the tables presenting results from running the pattern based model are the total CPU time of running both the pattern generation program in Java and the pattern based model in Xpress.

9.3.1 Basic Testing

A technical analysis is also conducted for the pattern based model in order to evaluate the model's performance and compare it to the original model. The model is tested in two dimensions: the turbine dimension and the vessel dimension. The turbine dimension tests the number of turbines the model can handle, and the vessel dimension studies how the number of vessels in the vessel pool affects the model's performance.

Turbine Dimension

In the same way as with the original model, the pattern based model is first tested on test instances with an increased number of turbines and the results are found in Table 9.7. The first three columns in Table 9.7 are equal to those in Table 9.2 while the last column shows the objective value of the LP relaxation given as the percentage of the LP relaxation of the results from the original model.

Table 9.7: Results of the pattern based model for test instances with an increasing number of turbines. The first block of results applies a planning horizon of 122 time periods and the last block applies a planning horizon of 246 time periods. The LP relaxation is compared to the equivalent results in Table C1.

Test instance	CPU time [sec]	Gap [%]	LP [%]
T3	22	0	351.87
T4	25	0	350.68
T5	17	0	350.22
T6	38	0	349.70
T7	37	0	349.33
T18	31	0	287.67
T19	-	-	
T20	2 071	0	538.90
T30	414	0	328.65
T39	144	0	225.31
T40	-	-	

When comparing the results in Table 9.7 to the results in Table 9.2 it is interesting to note that the CPU time is reduced for all test instances, e.g. for T3 the CPU time is reduced by approximately 96%. The LP relaxation of the pattern based model is also stronger compared to the original model. As shown Table 9.7 the LP relaxation of T3 is more than three times as good as in the original model. The problem size is reduced both in terms of the number of variables and the number of constraints, which results in a tighter LP-bound and a reduced B&B tree (Stålhane et al., n.d.). The number of variables in the pattern based model is reduced by approximately 31% for 122 time periods and 35% for 246 time period. The number of constraints is reduced by 86% for both time horizons, see Table C1 and Table C4 in Appendix C. In the pattern based model the variable z_{vat} is removed, which contributes to a reduction in symmetry. However, the variable s_{vt} and e_{vt}, as mentioned as variables causing symmetry problems in section 9.2, are still in the model and symmetry is thus not eliminated.

The results show that a planning horizon of 122 time periods is not enough time to install more than 19 turbines. In order to determine whether the number of turbines is a restricting dimension for the model, test instances with a planning horizon of 246 time periods are designed and tested. The results show that for every test instance where there exists a feasible solution, the pattern based model always finds the optimal solution.

Vessel Dimension

For solving instances with a greater number of turbines within 246 time periods, and to investigate how the model handles an increased vessel pool, a vessel pool of three, five, and ten vessels are tested. Real installation problems often include a vessel pool of 5-10 vessels and a wind farm of 50-100 turbines (Irawan et al., 2015). The pool is increased with identical vessels, which implies that the model is tested with respect to the fleet size rather than the fleet mix. The results, given by instance name (Instance), solution time (CPU time [sec]), and duality gap (Gap [%]), are presented in Table 9.8. Despite the duality gap in almost every test instance presented in the table, the performance of the pattern based model is much better than for the original model. The original model did not find one integer solution within the given CPU time for an instance of two vessels and seven turbines, while the pattern based model solves instances up to 110 turbines and ten vessels.

From Table 9.6 we can observe that by adding an additional vessel the number of feasible patterns increases, which in turn will increase the number of variables. In addition, the increased amount of symmetry when adding identical vessels to the pool causes difficulties when solving the model as discussed in Section 9.2. The duality gap in Table 9.8 is believed to be due to both the increased number of variables and the extra amount of symmetry introduced in the problem. The duality gap varies with an increasing number of turbines. For instance, for F3T30 the gap is 4.33% , for F3T40 it increases to 10.82%, and then decreases for F3T50. A more thorough discussion of this observation is found in Section 9.3.2 where a similar tendency is observed.

Table 9.8: Results of the pattern based model for test instances with an increasing vessel pool size.

Instance	CPU time [sec]	Gap [%]
F3T20	7 921	0
F3T30	11 085	4.33
F3T40	11 067	10.82
F3T50	11 080	6.41
F3T60	11 067	4.38
F3T70	11 068	0.22
F3T80	-	-
F5T20	11 556	6.06
F5T30	11 458	13.38
F5T60	11 525	14.31
F5T80	11 484	10.96
F5T90	11 444	19.66
F5T100	11 477	3.04
F5T110	11 445	1.81
F5T150	-	-
F10T30	13 370	28.95

As discussed in Section 9.2 the problem of solving the original model to optimality is due to both poor improvement of bounds and a poor LP relaxation. The results of the pattern based model show that the LP relaxation is improved and that the problem size is reduced. Hence the pattern based model solves several of the problems detected in the original model.

9.3.2 Restricting Start Time for Charter Period

To reduce the problem size further and reduce the duality gap of the more realistic problem instances, the same method of restricting the start time as described in Section 9.2.2 is applied. As in the original model, the possible start times are restricted to once a week. The results are found in Table 9.9 and reported by instance name (Instance), total CPU time (CPU time [sec]), duality gap (Gap [%]), primal bound (Primal bound [%]), and dual bound (Dual bound [%]). The primal bound and dual bound are calculated as the percentage of the results in Table 9.8, using Equation 9.1.

Table 9.9: Results of the pattern based model with start time every 7th day, a varying fleet size, and an increasing number of turbines.

Test instance	CPU time [sec]	Gap [%]	Primal bound [%]	Dual bound [%]
S7F3T20	7 921	0	102.01	102.01
S7F3T30	11 083	0	100.94	106.00
S7F3T40	11 092	0.59	102.65	114.42
S7F3T50	3 116	0	100.93	107.85
S7F3T60	1 050	0	100.38	104.98
S7F3T70	379	0	100.53	100.76
S7F3T80	-	-		
S7F5T20	2 709	0	102.01	108.59
S7F5T30	3 887	0	98.63	113.86
S7F5T60	11 453	0.45	98.48	114.42
S7F5T80	11 451	0.21	99.64	111.68
S7F5T90	2 232	0	100.32	105.06
S7F5T100	551	0	100.83	103.99
S7F5T110	9 199	0	101.62	103.49
S7F5T150	-	-		
S7F10T30	13 276	20.30	97.33	109.17

By reducing possible start times to once a week the duality gap has decreased for every test instance and for all practical purposes, the model is solved to optimality for every test instances of three and five vessels. Comparing the primal bounds from the instances in Table 9.9 to those in Table 9.8, it can be seen that they are approximately equal. The large duality gap improvements and the relatively small changes in primal bounds, indicates a good trade-off between improvements in the model's performance and increase in the objective value. The improvement is related to the increased dual bounds and the relative stable primal bound which causes a reduced solution space to search through, as discussed in Section 9.2.2.

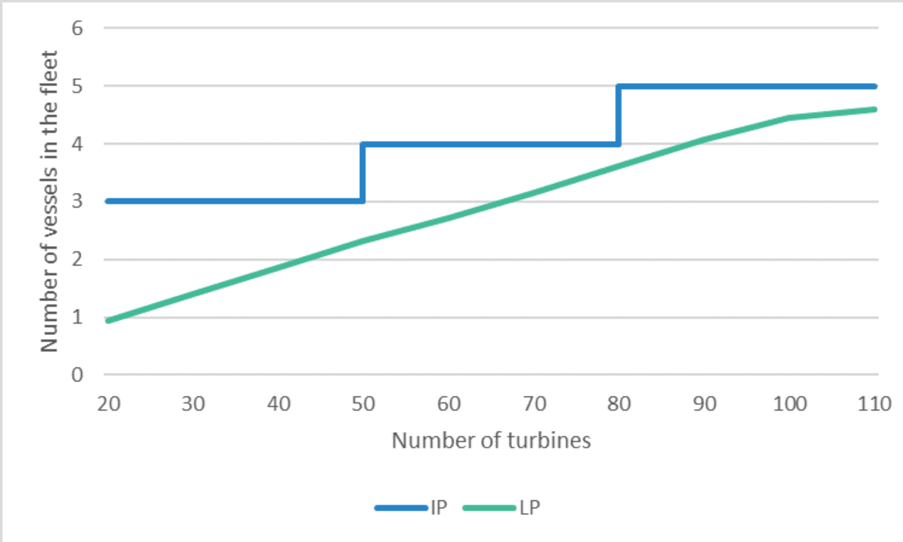


Figure 9.1: Illustration of how the number of vessels in the fleet varies with the number of turbines in both the LP relaxation and the IP solution.

As pointed out in Section 9.3.1 the duality gap varies with an increased number of turbines. For instance, S7F4T30 is solved to optimality, S7F3T40 has a duality gap, and S7F3T50 is solved to optimality. Analyzing the LP relaxation and the IP solution of the test instances with an increasing number of turbines, gives an idea of the potential reason for this variation in the duality gap. As illustrated in Figure 9.1 an increasing number of turbines results in a step wise function of the number of vessels in the optimal fleet in the IP solution. The LP relaxation yields a continuous increase in the number of vessels. Looking at the IP function in Figure 9.1 a threshold is observed every time there is a jump in the function where an increase in the number of turbines requires an additional vessel in the optimal fleet. Comparing the two graphs shows that the distance between the IP and LP solution decreases up to the threshold where the jump in the IP function causes a new increase in the distance before it decreases again until the next threshold.

The conclusion of the analysis of the LP relaxation is that there exist a threshold where an increase in the number of turbines will require one extra vessel in the optimal fleet in order to complete the installation and minimize cost. For some amount of turbines there exist solutions where all turbines can be installed with a vessel fleet of x vessels, but the optimal solution in order to minimize charter cost is a vessel fleet of $x + 1$ vessels. For such cases the LP solution in the root node will be weak, and it is thus harder to solve these test instances. Once the number of turbines increases further, the fractional value in the LP solution will increase and the distance between the LP solution and the IP solution will decrease.

9.3.3 Symmetry Breaking Inequalities

As has been described in Section 9.3.1 and Section 9.3.2 adding several identical vessels to the vessel pool increases the amount of symmetry in the problem and the model struggles to solve these test instances to optimality. A set of symmetry breaking inequalities is formulated in Section 6.1 to reduce this symmetry. The inequalities are implemented and tested on test instances with 30 turbines and a vessel pool of varying size. The results are presented in Table 9.10 and show that the symmetry breaking inequalities improve the performance of the model when solving test instances with a vessel pool of five and ten vessels. Analysis of the bounds of F5T30 and F10T30 show that both the primal and dual bound improves compared to the initial test results in Table 9.8, which results in a better duality gap. For F3T30, there is no improvement in the duality gap due to a small deterioration in the dual bound and almost no change in the primal bound. A more thorough analysis of the test results of F3T30 shows that the number of processed nodes when including the symmetry breaking inequalities is roughly halved compared to the original F3T30 test instance. It is believed that the increased processing time of each node is the reason of the (small) deterioration in the dual bound. The results in Table 9.10 suggests that the symmetry breaking inequalities proposed are more powerful when the amount of symmetry in the problem increases.

Table 9.10: Results of the pattern based model when adding symmetry breaking inequalities. The primal bound and dual bound is compared to the equivalent test results without symmetry breaking inequalities presented in Table C5.

Instance	CPU time [sec]	Gap [%]	Primal bound [%]	Dual bound [%]
F3T30	11 066	5.91	100.27	99.07
F5T30	11 438	2.90	97.70	109.52
F10T30	13 288	12.90	99.93	122.46

9.3.4 Guided Search

Another method for improving the solutions of the pattern based model is to implement a guided search strategy. It is determined to test the effect of the search strategy on a small portion of the previous test instances. Instances with an increasing number of turbines previously solved to optimality and instances with an increasing number of vessels not solved to optimality are used to observe the different effects of a guided search.

A guided search strategy exploits the user's knowledge about the problem in order to determine the most important variables and then uses this information to branch on these variables first. By giving a higher priority to decision variables affecting the objective value the most, the upper bound is updated in a more efficient way, which makes it easier to prune a branch in the B&B tree at an earlier stage. The three most important variables in this problem are λ_v, s_{vt} and e_{vt}. In Xpress the guided search is implemented by the function: `setmipdir(x:mpvar,t:integer,r:real)`. The last parameter in the function is used to indicate the priority of the variable. The priority is set to 1 for all λ_v, 2 for all s_{vt} and 3 for all e_{vt}. When determining the value of these three variables several other variables are implicitly determined, e.g. if $\lambda_v = 0$ all variables for vessel v is set to zero since vessel v is not chartered. The same is true for the start and end time of each vessel's charter period. As soon as the charter period of vessel v is determined all patterns starting earlier than specified by s_{vt} and ending later than specified by e_{vt} are set to zero since these are not feasible. Decisions on the charter period will also cause the model to search for patterns with a start time as close to the value of s_{vt} as possible. Determining these variables early in the B&B search will hence reduce the problem size and make the model run faster.

Implementation of the guided search strategy yields the results shown in Table 9.11. The table contains information about the CPU time required to solve the problem (CPU time [sec]), the change in the CPU time compared to previous results of the respective test instances (Chang in CPU time [sec]), the duality gap (Gap [%]), the change in duality gap (Change gap [%]), the primal bound (Primal bound [%]), and the dual bound (Dual bound [%]). The change in CPU time is given as a reduction (-) or increase (+) in seconds compared to previous tests. The change in the duality gap is given as a percentage increase (+) or decrease (-) compared to previous tests.

Table 9.11: Results of the pattern based model when implementing a guided search strategy. The first block is test instances previously solved to optimality while the second block is the same instances as used for testing the symmetry breaking inequalities.

Instance	CPU time [sec]	Change CPU time [sec]	Gap [%]	Change gap [%]	Primal bound[%]	Dual bound[%]
T20	669	-1 402	0	0	100	100
T30	292	-122	0	0	100	100
T39	149	+5	0	0	100	100
F3T30	11 066	-19	3.27	-24.5	99.04	101.58
F5T30	11 442	-16	12.32	-7.9	98.15	99.35
F10T30	13 528	+158	18.43	-36.3	98.25	112.79

For all test instances the solutions are improved, either by a faster CPU time or an improved duality gap, when applying a guided search strategy. For the three first results the improvement in CPU time is the most interesting, since these are already solved to optimality. The CPU time is either decreased or roughly equal to the previous results presented in Table 9.7.

For the test instances with an increasing vessel pool size there has been a reduction in the duality gap when implementing the guided search strategy. Analysis of the bounds show that the primal bound is improved for all three test instances, indicating that a better solution is found compared to test results without guiding. The dual bound is slightly improved for F3T30, and greatly improved for F10T3 and both duality gaps are highly improved when implementing the guided search. We can conclude that implementing a guided search contributes to finding good integer feasible solutions earlier in the B&B search because of the reduced CPU times for the test instances solved to optimality and the improvements in the duality gap for the other test instances.

By comparing the three last test instances in Table 9.11 to the results in Table 9.10 we can conclude that for the test instances with a larger vessel pool, symmetry breaking inequalities have a greater positive effect on the solution than a guided search strategy. Symmetry breaking inequalities are specifically designed to reduce the amount of symmetry in a problem, while the improvements caused by implementing a guided search strategy in the B&B tree will only suggest smart choices when traversing the tree.

9.3.5 Heuristic Pattern Generation

The heuristic rules introduced in Section 7.2 are implemented in the pattern generation program and the results from running the heuristic pattern generation program are presented in Table 9.12. Table 9.12 contains the same information as presented in Table 9.6, and in addition the percentage amount of patterns generated with the heuristic pattern generation program compared to the exact pattern generation program (Patterns [%]). The percentage amount of patterns is calculated by Equation 9.2. As can be seen from the last column, the number of patterns is noticeably reduced to roughly 1/3 and 1/2 of the original numbers for CTH and PH, respectively.

$$\text{Pattern [\%]} = \frac{\text{Current \# of patterns}}{\text{Reference \# of patterns}} \tag{9.2}$$

Table 9.12: Heuristic pattern generation

	Horizon	Vessel Pool	CPU time [sec]	Number of patterns	Patterns [%]
CTH	246	HLV, 2 SPIV	1	6 165	35.86
	246	2 HLV, 3 SPIV	1	9 744	37.07
PH	246	HLV, 2 SPIV	21	8 345	48.54
	246	2 HLV, 3 SPIV	32	13 014	49.51

The results from running the pattern based model with the heuristic generated patterns are shown in Table 9.13, Table 9.14, Table 9.15, and Table 9.16. The tables present the test instance (Instance), the CPU time (CPU time [sec]), including the heuristic pattern generation program's CPU time, the duality gap (Gap [%]), and the primal bound (Primal bound [%]) and dual bound (Dual bound [%]) as a percentage of the reference results presented in Table C5. These percentages are calculated by Equation 9.1.

Table 9.13: Results of applying CTH and PH on test instances with a vessel pool of three vessels, a planning horizon of 246 time periods, and an increasing number of turbines.

	Instance	CPU time [sec]	Gap [%]	Primal bound [%]	Dual bound [%]
CTH	F3T20	1 125.38	0	100.24	98.26
	F3T30	1 263.52	0	100.88	105.93
	F3T40	6 407.65	0	101.75	114.15
	F3T50	10 889.80	2.65	69.86	105.77
	F3T60	10 890.04	1.5	103.31	106.42
	F3T70	799.38	0	102.64	102.87
	F3T80	92.37	-		
PH	F3T20	4 587.79	0	100	100
	F3T30	7 309.54	0	100.27	105.29
	F3T40	10 938.26	0.95	99.47	110.48
	F3T50	10 939.7	4.12	100.65	103.11
	F3T60	1 857.71	0	99.43	103.98
	F3T70	1 813.27	0	102.46	102.69
	F3T80	125.97	-		

The results of implementing a heuristic pattern generation program and running the model on test instance with a vessel pool of three vessels and an increasing number of turbines are shown in Table 9.13. For all test instances both CTH and PH improves the solution, and most test instances are solved to optimality. Those not solved to optimality have a great improvement in the duality gap compared to the equivalent previous test instances. The same can be observed in Table 9.14 for test instances of five vessels. For F5T100 with PH the duality gap increases with approximately 1% compared to the results of F5T100 in Table 9.8. The slightly increased duality gap is most likely caused by a change in the B&B search, causing good solutions to be found at a later point in the search.

The intention with the implemented heuristics is to reduce the number of patterns and thus the number of variables in the pattern based model. As mentioned, the number of patterns are more than halved compared to the number of patterns generated by the exact pattern generation program and by comparing the number of variables for the test instances in Table 9.13 and Table 9.14 to the previous solutions we can conclude that the heuristics work as intended. The number of variables for F3Tw and F5Tw for CTH and PH are 40.9%, 42.5%, 52.6% and 53.8% of the original number of variables, respectively. In the same way as when restricting possible start times, a heuristic solution might cause a higher objective value than the optimal solution found with exact pattern generation due to feasible solutions being removed.

Table 9.14: Results of applying CTH and PH on test instances with a vessel pool of five vessels, a planning horizon of 246 time periods, and an increasing number of turbines.

	Instance	CPU time [sec]	Gap [%]	Primal bound [%]	Dual bound [%]
CTH	F5T20	9 724	0	100.24	106.70
	F5T30	11 039	0.95	98.56	112.71
	F5T60	11 030	13.10	102.19	103.63
	F5T80	11 040	2.27	100.69	110.52
	F5T90	11 030	2.11	104.56	107.19
	F5T100	11 038	2.16	103.94	104.88
	F5T110	2 337	0	102.07	103.94
	F5T150	235	-		
PH	F5T20	11 134	2.63	100	103.65
	F5T30	11 154	6.49	97.97	105.77
	F5T60	11 143	12.72	99.32	101.16
	F5T80	11 157	7.95	99.88	103.26
	F5T90	11 136	4.85	102.66	102.30
	F5T100	11 158	4.72	103.95	102.15
	F5T110	2 960	0	101.52	103.39
	F5T150	355	-		

Previous tests show good effect of restricting the start time to once a week, and the heuristic pattern generation is thus combined with a restricting start time to see if the solutions can be further improved. The results are shown in Table 9.15 and Table 9.16 in the same way as the results above. As discussed previously, restricting the start time to once a week improves the model's performance by reducing the dual bound, and by comparing Table 9.15 to Table 9.13 it can be seen that all results either improve or are approximately equivalent compared to previous results in terms of duality gap or CPU time. When restricting the start time to once a week for the test instances with five vessels, all results are improved compared to previous test results in Table 9.14 and all feasible test instances are solved to optimality.

Table 9.15: Results of applying CTH and PH on test instances with a vessel pool of three vessels, a planning horizon of 246 time periods, an increasing number of turbines, and restricting the start time to every 7^{th} day.

	Instance	CPU time [sec]	Gap [%]	Primal bound [%]	Dual bound [%]
CTH	S7F3T20	226	0	102.60	102.59
	S7F3T30	261	0	101.54	106.63
	S7F3T40	437	0	104.90	117.62
	S7F3T50	230	0	102.59	109.62
	S7F3T60	147	0	104.44	109.22
	S7F3T70	115	0	104.40	104.64
	S7F3T80	-	-		
PH	S7F3T20	4 634	0	100	100
	S7F3T30	7 370	0	100.27	105.29
	S7F3T40	10 945	0.83	99.47	110.61
	S7F3T50	10 944	4.20	100.65	103.02
	S7F3T60	1 863	0	99.43	103.98
	S7F3T70	1 775	0	102.46	102.69
	S7F3T80	-	-		

Table 9.16: Results of applying CTH and PH on test instances with a vessel pool of five vessels, a planning horizon of 246 time periods, an increasing number of turbines, and restricting the start time to every 7$^{\text{th}}$ day.

	Instance	CPU time [sec]	Gap [%]	Primal bound [%]	Dual bound [%]
CTH	S7F5T20	929	0	102.60	109.22
	S7F5T30	921	0	99.21	114.54
	S7F5T60	5 556	0	100.12	116.84
	S7F5T80	2 833	0	102.33	114.93
	S7F5T90	844	0	104.76	109.71
	S7F5T100	703	0	104.53	107.80
	S7F5T110	-	-		
	S7F5T150	-	-		
PH	S7F5T20	1 879	0	102.01	108.59
	S7F5T30	3 274	0	98.62	113.86
	S7F5T60	1 636	0	98.48	114.93
	S7F5T80	823	0	100	112.30
	S7F5T90	824	0	102.81	107.67
	S7F5T100	759	0	103.62	106.87
	S7F5T110	-	-		
	S7F5T150	-	-		

9.3.6 Brief Summary

The results from testing the pattern based model show great improvements in performance compared to the original model. By reformulating the model and solving it with a priori pattern generation we were able to solve test instances with up to ten vessels and between 30 and 110 turbines.

The four proposed improvement measures all contribute to make further improvements to the solutions. Restricting possible start times for the charter periods to once a week is argued to be a more realistic and reasonable choice than allowing start every time period, and gives satisfactory results in terms of improved duality gap for all test instances. The symmetry breaking inequalities contribute to solve some of the issues related to adding identical vessels to the pool and both primal bound and dual bound are strengthen for the largest vessel pools. Another way of finding better solutions without increasing the problem size is done by guiding the search in the B&B algorithm, which proved to find better solutions at an earlier stage in the search and thereby reduce the duality gap or CPU time. The last tested strategy is to generate patterns by using heuristic methods to reduce the number of feasible patterns. Both PH and CTH give a significant reduction in the number of patterns and the number of variables in the problem which resulted in good solutions. Combining the heuristic pattern generation and a charter start of once a week improve the solutions even further and we are able to solve all test instances of five vessels and up to 100 turbines to optimality.

9.4 Robustness Testing

As pointed out in the brief summary of Section 9.3 all proposed improvement measures improve the solutions from the pattern based model. Based on the previous results it is determined to perform robustness testing with all four measures; restricting start time, symmetry breaking inequalities, guided search, and heuristic pattern generation. A restriction on the start time to once a week is applied as this is considered more realistic for a strategic decision tool which is run several years in advance of the actual installation. The PH is applied since it gives a significant reduction in the number of variables without removing too many good solutions.

In order to evaluate the chance of delay in the optimal schedules, a robustness study is carried out. When performing the robustness testing we look at the out of sample stability. This is a method usually applied in stochastic programming to evaluate the quality of the scenario trees. However, it can also be applied to test the stability of a solution. In the problem presented in this thesis each scenario is a realization of the weather conditions. Using the terminology of stochastic programming and uncertainty, each scenario tree in our model has only one realization of the random variable; the weather for a given year. According to Kaut & Wallace (2003) the purpose of performing an out of sample stability test is that "if we generate several scenario trees for a given random vector, and solve the stochastic programming problem with each tree, we should get (approximately) the same value of the true objective function". Transferred to our problem this means that by fixating the charter start time found in the optimal solution in one scenario and solving the model for other scenarios, we should get approximately the same objective value.

In order to evaluate the robustness of an optimal solution the model is first run on weather from May-August 2011, which is used as reference. The test instance used for all tests presented in this section consists of a vessel pool of five vessels and 60 turbines (S7F5T60). In contrast to the technical tests previously presented, the robustness testing applies a 6 hour time interval to create greater flexibility when implementing different robustness measures. The optimal solution from the 2011 planning horizon is evaluated by running the S7F5T60 test instance on weather data from 2004 - 2012. From the optimal solution of 2011 we get the value of s_{vt} and α_v, which are fixed when the model is run on the other years. The initial results where no robustness measures are implemented are found in Table 9.17. The table presents the objective value (Objective value) of the year 2004-2012 as a percentage of the results of the reference year 2011, and the project duration both as the number of time periods (Project duration) and the number of days (Project duration in days). The results in Table 9.18, Table 9.19, Table 9.20, and Table 9.21 are presented in the same way. Infeasible solutions are market in italic.

Table 9.17: The robustness results when without any improvement measures. The tests are run on the the test instance S7F5T60, and a time interval of 6 hours is applied. The result from 2011 is marked in bold and the scenarios where the optimal solution is infeasible are marked in italic.

Instance	Objective Value	Project duration [time periods]	Project duration in days
2011	**87 136**	**233**	**58.25**
2004	85 284	230	57.5
2005	85 789	229	57.25
2006	84 466	223	55.75
2007	-		
2008	*92 609*	*258*	*64.5*
2009	84 439	230	57.5
2010	81 155	211	52.75
2012	86 546	229	57.25

The results in Table 9.17 show that when no actions to improve the robustness is taken, the optimal solution of 2011 is feasible for 75% of the other scenarios. By fixing the charter start time for each vessel to the optimal solution from 2011, the project duration increases or the solution becomes infeasible in two of the scenarios (2007 and 2008). This suggests that the robustness of the optimal solution from the pattern based model is insufficient. As described in Section 7.3, two different strategies are proposed to improve the robustness of the solution; increasing the processing times and adding slack at the end of each pattern. These measures are implemented in the 2011 scenario to find new values for s_{vt} and α_v which are then fixed and the original S7F5T60 is run for the other years. Firstly, the strategy of increasing the processing time for every installation activity of every vessel is implemented and tested.

Table 9.18: The robustness results when increasing the processing time by 12 hours. The tests are run on the the test instance S7F5T60, and a time interval of 6 hours is applied. The result from 2011 is marked in bold.

Instance	Objective Value	Project duration[time periods]	Project duration in days
2011	**116 178**	**344**	**86**
2004	87 789	241	60.25
2005	87 383	245	61.25
2006	85 735	235	58.75
2007	92 694	269	67.25
2008	95 028	273	68.25
2009	87 554	241	60.25
2010	82 201	216	54
2012	92 063	264	66

Table 9.18 shows the results of increasing the processing times by two time periods, i.e. 12 hours. The amount of added slack in the schedules increases the objective value of the optimal solution by 33.33% compared to the solution found in Table 9.17. The new solution is feasible in 100% of the scenarios. In order to say something about the trade-off between the increase in the objective value and the robustness of the solution, increasing the processing times by one time period, i.e. 6 hours is also tested. Results can be found in Table 9.19.

Table 9.19: The robustness results when increasing the processing time by 6 hours. The tests are run on the the test instance S7F5T60, and a time interval of 6 hours is applied. The result from 2011 is marked in bold.

Instance	Objective Value	Project duration[time periods]	Project duration in days
2011	**101 436**	**330**	**82.5**
2004	89 067	292	73
2005	88 821	298	74.5
2006	84 822	268	67
2007	94 065	304	76
2008	94 565	304	76
2009	84 984	267	66.75
2010	81 529	254	63.5
2012	91 166	289	72.25

Increasing the processing times of the installation activities with one time period results in a 16.41% increase in the objective value and the solution is still valid in 100% of the scenarios. Testing of the robustness strategy of adding slack through increased processing times shows that this strategy improves the robustness of the solution but the cost is relatively high. One reason for the significant increase in the objective value when increasing processing times for each turbine is that the number of time periods of slack increases with the number of turbines in the wind farm. The result is considered to be too conservative and the second proposed strategy is implemented in order to investigate whether it can give a better trade-off between the cost of adding slack and the added robustness in the solutions. The second strategy adds an amount of slack at the end of every pattern and the total amount of slack in each solution will therefor depend on the number of patterns in optimal solution. Two tests are conducted with this strategy, one adding three time periods of slack in each pattern and one adding two time periods of slack. The results are presented in Table 9.20 and Table 9.21, respectively. The added slack requires weather of category *good*.

Table 9.20: The robustness results when adding a slack of 18 hours at the end of each pattern. The tests are run on the the test instance S7F5T60, and a time interval of 6 hours is applied. The result from 2011 is marked in bold and the scenarios where the optimal solution is infeasible are marked in italic.

Instance	Objective Value	Project duration[time periods]	Project duration in days
2011	**96 216**	**270**	**67.5**
2004	87 789	241	60.25
2005	87 383	245	61.25
2006	85 735	235	58.75
2007	92 694	269	67.25
2008	*95 028*	*273*	*68.25*
2009	87 554	241	60.25
2010	82 201	216	54
2012	92 063	264	66

Table 9.21: The robustness results when adding a slack of 12 hours at the end of each pattern. The tests are run on the the test instance S7F5T60, and a time interval of 6 hours is applied. The result from 2011 is marked in bold and the scenarios where the optimal solution is infeasible are marked in italic.

Instance	Objective Value	Project duration[time periods]	Project duration in days
2011	**94 313**	**264**	**66**
2004	87 789	241	60.25
2005	87 383	245	61.25
2006	85 735	235	58.75
2007	*92 694*	*269*	*67.25*
2008	*95 028*	*273*	*68.25*
2009	87 554	241	60.25
2010	82 201	216	54
2012	92 063	264	66

Adding three time periods, i.e. 18 hours of slack in each pattern gives a 10.42% increase in the optimal objective value and the solution is valid in 88% of the scenarios. When adding two time periods of slack the cost increase by 8.24% and the optimal solution from 2011 holds in 75% of the scenarios. Compared to the first strategy, adding slack in each pattern results in a less costly solution but at the same time decreases the robustness of the solution. However, it can be argued that adding a slack of three time units to each pattern gives a good enough trade-off since the solution holds in all but one scenario and the objective value is only increased by roughly 10%. Since only nine years of weather data are available, the data might not be of statistical significance. The added robustness in the solution causes an increase in the objective value, but this is considered acceptable since the total cost of delay easily can become much higher than the cost of the added robustness. If a project is delayed it might be necessary to charter additional vessels in order to complete the installation. The spot charter rates will most likely be higher and will contribute to increasing the total costs of the vessel fleet considerable.

9.5 Seasonal Variations

As pointed out in Chapter 8 the summer months from May to August are used during the techinical analysis of the two proposed models. It is, however, interesting to investigate how the seasonal variations during a year influence the solution. This is a more economical analysis and can be used to consider alternative chartering strategies. Today most installation activities of an offshore wind farm take place in the summer months because of generally better weather. However, as the charter rates for vessels depend heavily on supply and demand, the total cost for the optimal fleet will be higher during summer when demand is higher (Dalgic et al., 2013). By running the model on weather data from other seasons, we can investigate whether it will be of interest to charter vessels and perform the installation in seasons with lower demand. Also, we can perform calculations to find the break even charter rates in order to make it profitable to perform installation outside the summer months.

As pictured in Figure 9.2 there is a great amount of seasonal variations during a year. The diagram shows the distribution of the different weather categories for four different case. Four combinations of months are made for testing the seasonal variations, and can be seen in Figure 9.2. The goal is to look at all four seasons of the year; spring, summer, autumn and winter. March-June represent spring, May-August represent summer, August-November represent autumn and November-February represent winter. Not surprisingly, May, June, July and August have the best weather with the greatest number of weather categories *very good-medium*. The winter months November, December, January, and February, have a higher percentage of weather category *bad* and *very bad*, which makes it harder to find enough usable time periods to complete the installation.

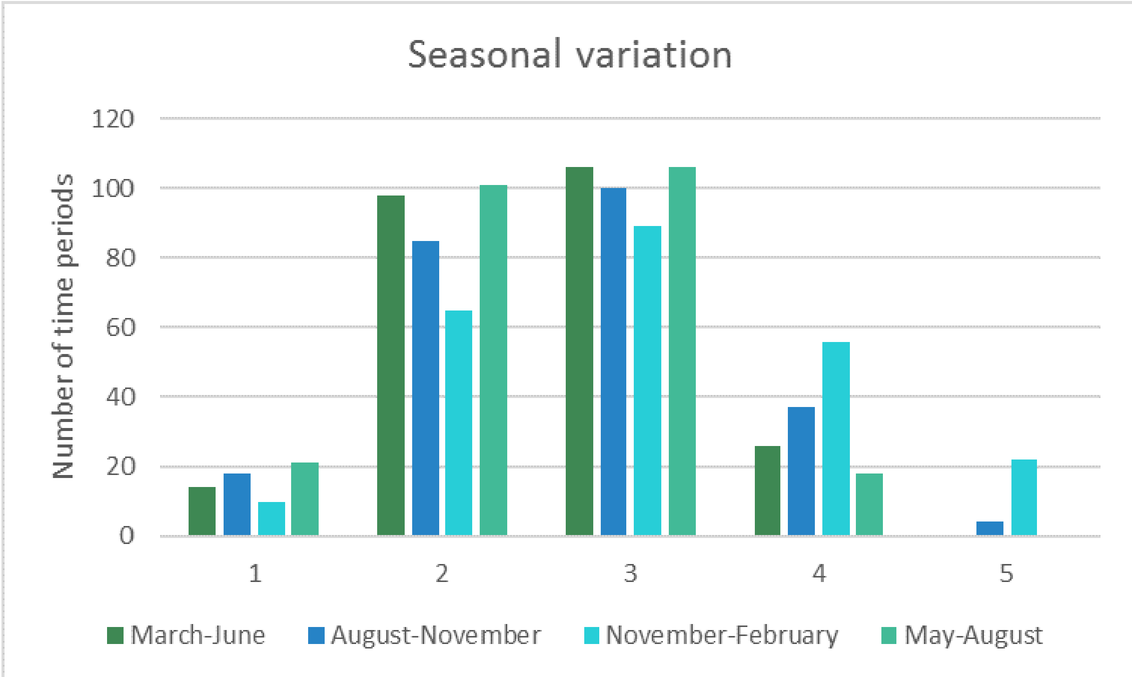


Figure 9.2: Distribution of weather categories in different seasons.

Table 9.22: Results of the seasonality study. The interval of months written in bold is the reference. For the other seasons, the increase in cost is given as the percentage increase compared to the reference

Instance	Season	Objective value	Project duration [day]	Increased cost
F2T35	**May-August**	**59 801**	**212**	
	March-June	64 223	234	7.40 %
	August-November	65 750	240	9.95 %
	November-February	-	-	-
S7F3T50	**May-August**	**74 574**	**152**	
	March-June	82 333	174	10.40 %
	August-November	83 154	177	11.51 %
	November-February	-	-	-
S7F5T70	**May-August**	**102 223**	**136**	
	March-June	111 688	153	9.26 %
	August-November	116 486	181	13.95 %
	November-February	-	-	-

The seasonality study is performed on three different test instances which are all run on the four different combinations of weather data. The results are presented in Table 9.22. The first column indicates which test instance is used (Instance), then the respective season is shown in column two (Season), before the absolute value of the objective function (Objective value), the project duration in days (project duration [day]), and the increased cost (Increased cost [%]) is presented in column three, four, and five, respectively. The increased cost is calculated as the percentage increase of the current test instance with respect to the reference test of May-August for the respective test instance, see Equation 9.3.

$$\text{Increased cost [\%]} = \frac{\text{Reference obj.val - Current obj.val}}{\text{Reference obj.val}} \tag{9.3}$$

For every test instance the results of spring (March-June) is consequently better than the results of autumn (August-November). None of the tests are feasible when run on winter months. Compared to the reference case, May-August, the increase in cost is calculated and shows an average increase of about 9% for March-June and roughly 12% for August-November. These results can be used to calculate the break even charter rate for these months, i.e. the required charter rate in order to make it desirable and profitable to schedule installation outside the summer months. For example, the results in Table 9.22 suggest an 9% decrease of charter rates during spring, based on an average of the three cases. If charter rates are reduced to this level a wind farm owner can accept more delay in the schedules and thus a longer total project duration without increasing the total charter costs. Another possible charter strategy, which was mentioned in Chapter 2, is to schedule only parts of the installation to spring or autumn. One applied strategy is to install sub structures during the winter months, i.e. October-March, and tower and top structure during the summer. This strategy can reduce the required length of a charter period during summer when charter rates are at the highest and could thus result in a more profitable solution. This can be studied with a similar approach as just presented by solving separate problems for installation of sub structure and the tower and top structure.

Chapter 10

Concluding Remarks

The problem studied in this thesis is a fleet size and mix problem for the installation phase of an offshore wind farm. Specialized vessels with high charter rates are required to perform the installation of offshore wind turbines which makes the costs related to the vessel fleet the second largest part of the total installation cost. Optimizing the vessel fleet will contribute to a reduction in installation costs, a problem which consists of creating schedules for each vessel in order to decide on the type and number of vessels needed to complete the installation of every turbine in the wind farm. Normally these decisions are taken several months or years in advance of the installation process and can be regarded as strategic decisions.

Two time discrete deterministic mathematical models are formulated to solve the problem, one original model and one reformulated pattern based model which generates patterns a priori and then finds the best combination of patterns. Three methods are developed to generate patterns, one exact method to find all feasible patterns and two heuristic methods where only a subset of the most promising patterns are generated. The models minimize the charter costs, find the optimal vessel fleet, and return a schedule for each vessel. Schedules include information on when and which activities the vessels have to perform.

The computational study reveals that the original model performs poorly and only solves small test instances with four turbines to optimality. The pattern based model performs much better and is able to solve test instances of realistic size, e.g. wind farms of up to 110 turbines and a vessel pool of up to ten vessels. To solve the largest test instances a strategy which restricts the possible start times for the charter periods to once a week is implemented. Only allowing charter periods to start every 7^{th} day is considered more realistic for a strategic decision tool and improves the solutions in terms of both duality gap and CPU time with less than 3% increase in the objective value. Implementing a guided search strategy also improves the solution with up to 1 400 seconds reduction in CPU time and up to a 10% reduction in the duality gap. Symmetry breaking inequalities are added to the model formulation in order to reduce the additional amount of symmetry introduced to the problem when increasing the vessel pool with identical vessels. The results show that the effect of adding these inequalities increase with the number of identical vessels, e.g. for a vessel pool with five vessels the duality gap improves by more than 50%.

The heuristic pattern generation methods reduce the number of generated patterns by roughly 1/3 for the Complete Turbine Heuristic (CTH) and 1/2 for the Precedence Heuristic (PH). The results with PH and CTH show a good trade-off between the improved duality gap and the increased objective value. By combining the heuristic pattern generation with restrictions on the charter start time to once a week, the solutions are further improved and returns the optimal solution for more than 90% of the test instances. All proposed improvement strategies are combined in the robustness study. The robustness test concludes that measures need to be taken in order to create robust schedules with reduced chance of delay. Two different robustness strategies are proposed, one which increases the processing time of all installation activities and one which adds slack to the end of each pattern. Both strategies improve the robustness of the solutions, however, based on the results presented in this thesis the strategy of adding slack to each pattern seems to be the preferred option. The added slack improves the robustness in the schedules by 17% with only a 10% increase in the objective value.

Chapter 11

Future Research

Research within the installation phase of offshore wind farms is relatively limited and the fleet size and mix problem of the optimal installation fleet is no exception. This thesis explores some of the issues and challenges related to the installation phase and the installation fleet, but it also arises some questions which need to be further researched. These questions can be grouped in two groups; those related to how realistic the problem is modeled and those related to the optimization aspects and how to improve the model in this thesis.

To formulate a mathematical model several assumptions have been made in order to make the problem more manageable and some details in the real life problem are therefor omitted. However, to make the model even more realistic and to create a more detailed picture of the problem, some of these simplifications can be reconsidered. The treatment of weather is one such simplification of the real world problem. In the formulated models the weather is handled as a deterministic parameter, but is in reality an uncertain parameter. A stochastic expansion of the model could thus be studied. Another simplification is done in the representation of weather data. In real life, different activities have different requirements for wind speed and wave height, and some activities are more sensitive to wind speed while other are more sensitive to wave height. A more realistic version of the model can incorporate more detailed weather data. Other details about the problem which can be studied in the future includes varying loading times which more realistically reflects the number of components that are loaded, include a larger part of the value chain, for example the choice of onshore port(s), and fluctuating charter rates throughout the planning horizon. Finally it would be interesting to implement the possibility of using ships that cooperate, i.e. one vessel is stationed at the offshore site while another vessel travels back and forth between the offshore site and the onshore port to pick up components and feed the stationed vessel.

As pointed out in Chapter 7, the number of patterns will increase rapidly if the vessel deck space capacity increases. This will increase the problem size and create difficulties when solving the pattern based model. In addition, it will cause an exponential increase in the CPU time for the pattern generation program. To overcome this limitation different solution methods should be evaluated, and could include both heuristic solution methods and solution methods based on dynamic column generation.

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Appendix A

Mathematical Model

Sets:

V	Set of vessels
V^J	Subset of jack-up vessels
C	Set of components
A_v	Set of all activities vessel v can perform
A_v^I	Subset of all installation activities vessel v can perform
T	Set of time periods
L	Set of all possible loading sets

Parameters:

C_v^{Fix}	Fixed cost of vessel v
C_v^V	Variable cost of vessel v
P	Penalty cost of prolonging the total installation time
N	Total number of turbines in the offshore wind farm
A_{av}	Activity matrix; 1 if vessel v can perform activity a, 0 otherwise
T_{av}	Processing time for vessel v performing activity a
W_{av}^R	Weather restrictions for vessel v performing activity a
W_t	Weather realization in time period t
L_c^{Max}	Maximum number of component c that can be loaded on any vessel
B_{cl}	Number of components c in loading set l
M_{tc}	Big M used in the loading constraints
N_{ac}^{Comp}	Number of components c in installation activity a
T_{vca}^{Start}	Shift in start time for vessel v performing installation of component c in activity a
T_{vca}^{End}	Shift of completion time for vessel v performing installation of component c in activity a
$P_{c_1c_2}$	Precedence matrix; 1 if there is a precedence between component c_1 and c_2 , 0 otherwise

Decision variables:

x_{vt}	1 if vessel v is chartered in time period t, 0 otherwise
z_{vat}	1 if vessel v starts performing activity a in time period t
δ_{vlt}	1 if vessel v is loaded with loading set l in time period t, 0 otherwise
α_v	1 if vessel v is included in the optimal fleet, 0 otherwise
s_{vt}	1 if vessel v starts operating in time period t, 0 otherwise
e_{vt}	1 if vessel v finish operating in time period t, 0 otherwise
v_{ct}	Number of components c in progress at time period t
w_{ct}	Number of completed components c at the end of time period t
u_{vt}	Number of completed jack-up activities performed by vessel v in time t
d_{vt}	Number of completed jack-down activities performed by vessel v in time t
s^{Tot}	Project start time, the first time period any vessel is chartered
e^{Tot}	Project end time, the last time period any vessel is chartered

$$\min_{Z} \quad \underbrace{\sum_{v\in V} C_v^{Fix}\alpha_v}_{a} \;+\; \underbrace{\sum_{v\in V}\sum_{t\in T} C_v^{V}(t\ e_{vt} - t\ s_{vt})}_{b} \;+\; \underbrace{P(e^{Tot} - s^{Tot})}_{c} \tag{A.1}$$

$$\sum_{a\in A_v}\sum_{t'=t-T_{av}+1}^{t} z_{vat'} \le \sum_{t'=1}^{t} s_{vt'} \qquad v\in V,\ t\in T \tag{A.2}$$

$$\sum_{a\in A_v} z_{va(t-T_{av})} \le \sum_{t'=t}^{|T|+1} e_{vt'} \qquad v\in V,\ t\in\{1,\ \dots\ ,|T|+1\} \tag{A.3}$$

$$\sum_{t\in T}(t\ e_{vt} - t\ s_{vt}) \ge 0 \qquad v\in V \tag{A.4}$$

$$\sum_{t\in T} s_{vt} = \alpha_v \qquad v\in V \tag{A.5}$$

$$\sum_{t=1}^{|T|+1} e_{vt} \le 1 \qquad v\in V \tag{A.6}$$

$$\sum_{t\in T} t\ s_{vt} + |T|(1-\alpha_v) \ge s^{Tot} \qquad v\in V \tag{A.7}$$

$$\sum_{t=1}^{|T|+1} t\ e_{vt} \le e^{Tot} \qquad v\in V \tag{A.8}$$

$$e^{Tot} \ge s^{Tot} \tag{A.9}$$

$$\sum_{t'=1}^{t} s_{vt'} - \sum_{t'=1}^{t} e_{vt'} = x_{vt} \qquad v\in V,\ t\in T \tag{A.10}$$

$$\sum_{v\in V}\sum_{a\in A_v^I}\sum_{t'=1}^{t-T_{vca}^{Start}} z_{vat'}N_{ac}^{Comp} \ - \ v_{ct} = 0 \qquad c\in C,\ t\in T \tag{A.11}$$

$$\sum_{v\in V}\sum_{a\in A_v^I}\sum_{t'=1}^{t+T_{vca}^{End}-T_{av}} z_{vat'}N_{ac}^{Comp} \ - \ w_{ct} = 0 \qquad c\in C,\ t\in T \tag{A.12}$$

$$P_{c_1c_2}(v_{c_1t} \ - \ w_{c_2t}) \le 0 \qquad c_1,c_2\in C,\ t\in T \tag{A.13}$$

$$w_{c|T|} \geq N \qquad c \in C \quad \text{(A.14)}$$

$$\sum_{t'=t-T_{av}+1}^{t} z_{vat'} \leq max\{0, W_{av}^R - W_t + 1\} \qquad v \in V,\ a \in A_v,\ t \in T \quad \text{(A.15)}$$

$$\sum_{a \in A_v^I} \sum_{t'=1}^{t-T_{av}+1} z_{vat'} N_{ac}^{Comp} - \sum_{l \in L} \sum_{t'=1}^{t-T_{Rv}+1} B_{cl} \delta_{vlt'} \leq 0 \qquad c \in C,\ v \in V,\ t \in T \quad \text{(A.16)}$$

$$\sum_{l \in L} \sum_{t'=1}^{t-1} B_{cl} \delta_{vlt'} - \sum_{a \in A_v^I} \sum_{t'=1}^{t-T_{av}+1} z_{vat'} N_{ac}^{Comp} \leq M_{tc}(1 - \sum_{l \in L} \delta_{vlt}) \qquad c \in C,\ v \in V,\ t \in T \quad \text{(A.17)}$$

$$z_{vRt} = \sum_{l \in L} \delta_{vlt} \qquad v \in V,\ t \in T \quad \text{(A.18)}$$

$$\sum_{l \in L} \delta_{vlt} - x_{vt} \leq 0 \qquad v \in V,\ t \in T \quad \text{(A.19)}$$

$$u_{vt} - d_{vt} \leq 1 \qquad v \in V^J,\ t \in T \quad \text{(A.20)}$$

$$u_{vt} - d_{vt} \geq 0 \qquad v \in V^J,\ t \in T \quad \text{(A.21)}$$

$$u_{v|T|} - d_{v|T|} = 0 \qquad v \in V^J \quad \text{(A.22)}$$

$$\sum_{t'=1}^{t-T_{Uv}+1} z_{vUt'} - u_{vt} = 0 \qquad v \in V^J,\ t \in T \quad \text{(A.23)}$$

$$\sum_{t'=1}^{t-T_{Dv}+1} z_{vDt'} - d_{vt} = 0 \qquad v \in V^J,\ t \in T \quad \text{(A.24)}$$

$$\sum_{a \in A_v^I} z_{vat} \leq u_{vt} - d_{vt} \qquad v \in V^J,\ t \in T \quad \text{(A.25)}$$

$$\sum_{a \in A_v^I} \sum_{t'=1}^{t} z_{vat'} \leq u_{vt} \qquad v \in V^J,\ t \in T \quad \text{(A.26)}$$

$$\sum_{a \in A_v^I} \sum_{t'=1}^{t-T_{av}+1} z_{vat'} \geq d_{vt} \qquad v \in V^J,\ t \in T \quad \text{(A.27)}$$

$$z_{vRt} \leq 1 - u_{vt} + d_{vt} \qquad v \in V^J,\ t \in T \quad \text{(A.28)}$$

$$x_{vt} \in \{0,1\} \qquad v \in V,\ t \in T \tag{A.29}$$
$$z_{vat} \in \{0,1\} \qquad v \in V,\ a \in A_v,\ t \in T \tag{A.30}$$
$$\delta_{vlt} \in \{0,1\} \qquad v \in V,\ l \in L,\ t \in T \tag{A.31}$$
$$\alpha_v \in \{0,1\} \qquad v \in V \tag{A.32}$$
$$s_{vt} \in \{0,1\} \qquad v \in V,\ t \in T \tag{A.33}$$
$$e_{vt} \in \{0,1\} \qquad v \in V,\ t = \{1,\ 2,\ 3,\ \dots,\ |T|+1\} \tag{A.34}$$
$$v_{ct} \geq 0\ ,\ \text{integer} \qquad c \in C,\ t \in T \tag{A.35}$$
$$w_{ct} \geq 0\ ,\ \text{integer} \qquad c \in C,\ t \in T \tag{A.36}$$
$$u_{vt} \geq 0\ ,\ \text{integer} \qquad v \in V,\ t \in T \tag{A.37}$$
$$d_{vt} \geq 0\ ,\ \text{integer} \qquad v \in V,\ t \in T \tag{A.38}$$
$$s^{Tot} \geq 0\ ,\ \text{integer} \tag{A.39}$$
$$e^{Tot} \geq 0\ ,\ \text{integer} \tag{A.40}$$

Appendix B

Decomposed Mathematical Model

Sets:

V	Set of vessels
A_v^I	Set of all installation activities vessel v can perform
T	Set of time periods
P_v	Set of all feasible patterns for vessel v

Parameters:

C_v^{Fix}	Fixed cost of vessel v
C_v^V	Variable cost of vessel v
P	Penalty cost of prolonging the total installation time
N	Total number of turbines in the offshore wind farm
B_{vtp}	1 if vessel v is busy in time period t performing pattern p, 0 otherwise
A_{avtp}	Number of completed installation activities of type a performed by vessel v at time t in pattern p
T_p^{Start}	Start time for pattern p
T_p^{End}	End time for pattern p

Decision variables:

λ_p	1 if pattern p is performed, 0 otherwise
α_v	1 if vessel v is included in the optimal fleet, 0 otherwise
s_{vt}	1 if vessel v starts operating in time t, 0 otherwise
e_{vt}	1 if vessel v finish operating in time t, 0 otherwise
s^{Tot}	Project start time, the first time period any vessel is chartered
e^{Tot}	Project end time, the last time period any vessel is chartered

$$\min_{Z} \quad \underbrace{\sum_{v\in V}\sum_{t\in T} C_v^{Fix}\alpha_v}_{a} \; + \; \underbrace{\sum_{v\in V}\sum_{t\in T} C_v^{V}(t\ e_{vt} - \ t\ s_{vt})}_{b} \; + \; \underbrace{P(e^{Tot} - s^{Tot})}_{c} \tag{B.1}$$

$$\sum_{p\in P_v} B_{vtp}\ \lambda_p \le \sum_{t'=1}^{t} s_{vt'} \qquad v\in V,\ t\in T \tag{B.2}$$

$$\sum_{p\in P_v} B_{vtp}\ \lambda_p \le \sum_{t'=t+1}^{|T|} e_{vt'} \qquad v\in V,\ t\in T \tag{B.3}$$

$$\sum_{t\in T}(t\ e_{vt} - t\ s_{vt}) \ge \sum_{p\in P_v}(T_p^{End} - T_p^{Start})\lambda_p \qquad v\in V \tag{B.4}$$

$$\sum_{p\in P_v} B_{vtp}\ \lambda_p \le \alpha_v \qquad v\in V,\ t\in T \tag{B.5}$$

$$\sum_{t\in T} s_{vt} = \alpha_v \qquad v\in V \tag{B.6}$$

$$\sum_{t\in T} e_{vt} \le 1 \qquad v\in V \tag{B.7}$$

$$\sum_{t\in T} t\ s_{vt} + |T|\ (1-\alpha_v) \ge s^{Tot} \qquad v\in V \tag{B.8}$$

$$\sum_{t\in T} t\ e_{vt} \le e^{Tot} \qquad v\in V \tag{B.9}$$

$$e^{Tot} - s^{Tot} \ge 0 \tag{B.10}$$

$$\sum_{v\in V}\sum_{p\in P_v} A_{(a+1)vtp}\ \lambda_p - \sum_{v\in V}\sum_{p\in P_v} A_{av(t-1)p}\ \lambda_p \le 0 \qquad a\in A_v^I,\ t\in T \tag{B.11}$$

$$\sum_{v\in V}\sum_{p\in P_v} A_{av|T|p}\ \lambda_p \ge N \qquad a\in A_v^I \tag{B.12}$$

$$\lambda_p \in \{0,1\} \qquad p\in P_v \tag{B.13}$$

$$\alpha_v \in \{0,1\} \qquad v\in V \tag{B.14}$$

$$s_{vt} \in \{0,1\} \qquad v\in V,\ t\in T \tag{B.15}$$

$$e_{vt} \in \{0,1\} \qquad v\in V,\ t\in T \tag{B.16}$$

$$s^{Tot} \ge 0\ ,\ \text{integer} \tag{B.17}$$

$$e^{Tot} \ge 0\ ,\ \text{integer} \tag{B.18}$$

Appendix C

Test Results

Table C1: Original Model - Increasing number of turbines. The test instances T20-T40 are only solved with the LP relaxation of the model in order to compare the pattern based model to these results

Instance	LP relaxation	Original variables	Original constraints	Nodes
T3	829	6 716	7 701	99 184
T4	1 109	6 716	7 701	182 777
T5	1 388	6 716	7 701	434 712
T6	1 668	6 716	7 701	427 402
T7	1 948	6 716	7 701	419 182
T18	9 855	6 716	7 701	394 399
T19	11 193	6 716	7 701	376 195
T20	2 807	13 536	15 513	
T30	11 122	13 536	15 513	
T39	29 013	13 536	15 513	
T40	31 481	13 536	15 513	

Table C2: Original model - Varying start times

Instance	Primal bound	Dual bound	LP relaxation	Original columns
S1T3	6 899	6 899	837	6 594
S2T3	6 980	6 981	852	6 532
S3T3	6 981	6 981	869	6 512
S7T3	7 143	7 143	941	6 488
S14T3	7 306	7 306	1 108	6 480

Table C3: Original model - Start times every 7$^{\text{th}}$ day

Instance	Primal bound	Dual bound	LP relaxation	Original variables
S7T3	7 143	7 143	941	6 488
S7T4	7 869	7 869	1 254	6 488
S7T5	13 104	8 913	1 571	6 488
S7T6	14 016	9 940	1 887	6 488
S7T7	18 170	10 936	2 207	6 488

Table C4: Patter based model - Increasing number of turbines

Instance	Primal bound	Primal bound	LP relaxation	Original variables	Original constraints
T3	6 899	6 899	2 917	4 599	1 112
T4	7 699	7 699	3 889	4 599	1 112
T5	85 559	8 559	4 861	4 599	1 112
T6	10 033	10 033	5 833	4 599	1 112
T7	11 323	11 323	6 805	4 599	1 112
T18	28 351	28 351	24 544	4 599	1 112
T19	-	-	-	4 599	1 112
T20	30 511	30 511	15 124	10 081	2 228
T30	47 361	47 361	36 552	10 081	2 228
T39	68 744	68 744	65 368	10 081	2 228
T40	-	-	77 557	10 081	2 228

Table C5: Pattern based model - Increasing vessel pool size

Instance	Primal bound	Dual bound	LP relaxation	Original variables
F3T20	29 653	29 653	14 949	18 674
F3T30	41 874	39 878	22 424	18 674
F3T40	56 471	50 361	30 248	18 674
F3T50	73 887	69 148	49 371	18 674
F3T60	91 645	87 635	73 108	18 674
F3T70	114 281	114 024	101 789	18 674
F3T80	-	-		18 674
F5T20	29 653	27 855	14 949	28 753
F5T30	42 858	37 123	22 424	28 753
F5T60	88 779	76 075	45 372	28 753
F5T80	120 723	107 488	85 160	28 753
F5T90	136 484	130 322	109 656	28 753
F5T100	160 946	156 058	137 231	28 753
F5T110	184 168	180 838	170 203	28 753
F5T150	-	-		28 753
F10T30	43 958	31 235	22 424	57 504

Table C6: Pattern based model - Start times every 7$^{\text{th}}$ day

Instance	Primal bound	Dual bound	LP relaxation	Original variables
S7F3T20	30 248	30 248	15 222	17 987
S7F3T30	42 269	42 269	22 833	17 987
S7F3T40	57 970	57 625	42 425	17 987
S7F3T50	74 574	74 574	56 776	17 987
S7F3T60	91 995	91 995	77 502	17 987
S7F3T70	114 887	114 887	109 062	17 987
S7F3T80	-	-		17 987
S7F5T20	30 248	30 248	15 222	27 608
S7F5T30	42 269	42 267	22 833	27 608
S7F5T60	87 433	87 043	48 599	27 608
S7F5T80	120 294	120 042	90 491	27 608
S7F5T90	136 914	136 914	116 254	27 608
S7F5T100	162 284	162 284	146 159	27 608
S7F5T110	187 156	187 156	181 804	27 608
S7F5T150	-	-	-	27 608
S7F10T30	42 783	34 098	22 833	55 214

Table C7: Pattern based bodel - Symmetry breaking inequalities

Instance	Primal bound	Dual bound	LP relaxation	Nodes
F3T30	41 989	39 508	22 424	49 428
F5T30	41 874	40 658	22 424	44 564
F10T30	43 928	38 250	22 424	12 890

Table C8: Pattern based model - Guided search

Instance	Primal bound	Dual bound	LP relaxation	Nodes
T20	30 511	30 511	15 124	16 353
T30	47 361	47 361	36 552	1 013
T39	68 744	68 744	65 368	7
F3T30	41 474	40 507	22 424	82 546
F5T30	42 067	36 883	22 424	59 589
F10T30	43 190	35 229	22 424	24 781

Table C9: Heuristic pattern generation - F3Tw

		Primal bound	Dual bound	LP relaxation	Original variables
CTH	F3T20	29 723	29 723	15 080	7 646
	F3T30	42 241	42 241	22 620	7 646
	F3T40	57 461	57 455	31 778	7 646
	F3T50	75 130	73 141	51 615	7 646
	F3T60	94 683	93 260	76 200	7 646
	F3T70	117 300	117 292	107 035	7 646
	F3T80	-	-		7 646
PH	F3T20	29 653	29 653	14 978	9 826
	F3T30	41 989	41 989	22 467	9 826
	F3T40	56 172	55 637	31 450	9 826
	F3T50	74 364	71 300	51 190	9 826
	F3T60	91 126	91 126	75 649	9 826
	F3T70	117 098	117 091	106 497	9 826
	F3T80	-	-		9 826

Table C10: Heuristic pattern generation - F5Tw

	Instance	Primal bound	Dual bound	LP relaxation	Original variables
CTH	F5T20	29 723	29 721	15 080	12 211
	F5T30	42 241	41 441	22 620	12 211
	F5T60	90 720	78 838	47 665	12 211
	F5T80	121 562	118 797	88 910	12 211
	F5T90	142 701	139 692	114 280	12 211
	F5T100	167 284	167 674	143 014	12 211
	F5T110	187 981	187 965	178 615	12 211
	F5T150	-	-		12 211
PH	F5T20	29 653	28 873	14 978	15 481
	F5T30	41 989	39 265	22 467	15 481
	F5T60	88 174	76 955	47 175	15 481
	F5T80	120 573	110 991	88 221	15 481
	F5T90	140 113	133 317	113 463	15 481
	F5T100	167 307	159 412	142 275	15 481
	F5T110	186 960	186 960	177 752	15 481
	F5T150	-	-		15 481

Table C11: Heuristic pattern generation - S7F3Tw

		Primal bound	Dual bound	LP relaxation	Original variables
CTH	S7F3T20	30 423	30 421	15 395	6 959
	S7F3T30	42 521	42 521	23 097	6 959
	S7F3T40	59 240	59 235	34 256	6 959
	S7F3T50	75 803	75 803	55 286	6 959
	S7F3T60	95 712	95 712	81 302	6 959
	S7F3T70	119 310	119 310	115 855	6 959
	S7F3T80	-	-		6 959
PH	S7F3T20	29 653	29 653	14 978	9 826
	S7F3T30	41 989	41 989	22 467	9 826
	S7F3T40	56 172	55 705	31 450	9 826
	S7F3T50	74 364	71 239	51 190	9 826
	S7F3T60	91 126	91 126	75 648	9 826
	S7F3T70	117 098	117 091	106 497	9 826
	S7F3T80	-	-	-	9 826

Table C12: Heuristic pattern generation - S7F5Tw

	Instance	Primal bound	Dual bound	LP relaxation	Original variables
CTH	S7F5T20	30 423	30 423	15 398	11 066
	S7F5T30	42 521	42 521	23 097	11 066
	S7F5T60	88 884	88 884	51 384	11 066
	S7F5T80	123 541	123 539	95 106	11 066
	S7F5T90	142 981	142 970	121 954	11 066
	S7F5T100	168 233	168 233	155 140	11 066
	S7F5T110	-	-		11 066
	S7F5T150	-	-		11 066
PH	S7F5T20	30 248	30 248	15 284	14 336
	S7F5T30	42 269	42 269	22 926	14 336
	S7F5T60	87 433	87 433	50 778	14 336
	S7F5T80	120 714	120 712	94 273	14 336
	S7F5T90	140 323	140 317	121 000	14 336
	S7F5T100	166 775	166 775	154 313	14 336
	S7F5T110	-	-		14 336
	S7F5T150	-	-		14 336

Appendix D

Minutes Fred.Olsen Renewables and Windcarrier

Minutes Fred. Olsen Windcarrier - September 20th 2016

What are your biggest challenges?
One of the biggest challenges in the industry is the cost related to installation and operation of offshore wind farms. There are also some political challenges, i.e allocation of subsidies. A land based wind farm (800MW) have succeeded in driving down costs to approximately one billion for 25-30 turbines. This means that the cost level is approaching a level which is able to compete with regular electricity prices (30-40 øre).

As an economical support and political initiative, green certificate are given to “green-energy” projects. However, this arrangement is considered being ended by 2020.

Offshore operation:
The installation costs of offshore wind farms are generally very high, approximately three times higher than a land based wind farm. This makes higher demands on the revenue of generating electricity in order to cover the expenses. However, offshore wind has some advantages. Because of more stable winds, the capacity factors increase with up to 50%.

Situations called Waiting-on-weather(WoW), when the weather conditions are so bad that no operations can be performed, increases the cost considerably. As a way of reducing the risk of unexpected days with WoW situations, Fred.Olsen is including a certain number of days in their schedules that can be used in case of delays.

The installation time for an offshore wind farm is much longer than for a land based wind farm due to harder operating conditions offshore. A normal assembly strategy is to assemble as many of the components in port before transportation out to the offshore site. Such a strategy will reduce the required number of lifts and trips back and forth the port, which might save money.

Appendix E

Minutes Statoil ASA I

Skype meeting with Statoil AS - September 19th 2016

Foundation:

The most commonly used foundation concept today consist of a monopile and a transition piece. Monopiles have a diameter of 7-8 m and a weight of approximately 800 kg. The large dimensions require large vessels for transporting the piles from port to the offshore site. Statoil uses vessels that can transport between 3 and 4 turbines per trip and mounts one foundation each day. Before the tower can be mounted, a transition piece is installed on top of the monopile. This phase of the installation takes about 4-5 months. At the end of the installation of foundations, when approximately 3/2 of the foundations are installed, the cable installation can begin. Special designed vessels are used for cabling both between each turbine and from the park to shore.

For floating wind turbines, the whole turbines is mounted in a port and then special vessels transport the whole turbine out to the offshore site where it is anchored.

In Statoil's projects, they usually finish the installation of foundations and cabling before they start installing towers and top-structures. Normally, these two phases are scheduled in different seasons of the year. Performing both phases in parallel might cause complexity because the activities become more dependent on each other and delays in one process might cause delays in other processes. Having vessels waiting in port without performing any installation activity will increase the cost rapidly due to high charter rates.

Another installation strategy is having vessels working together, one transporting components from port to the offshore site where another vessel is anchored and installs the components. One challenge for this strategy is to have two vessels cooperating when the movement patterns are unbalanced.

Challenges:

In general, one wishes to to assemble as much of the turbine onshore as possible, because it is cheaper to assemble components in port. The installation processes offshore are restricted by strict wheather requirements, especially the lifts because strict wind speed requirements are imposed. Cabling is the installation activity with less weather requirements.

The larger the vessels, the less weather restrictions are imposed. This leads to a trade off between time and cost because the large vessels are more expensive, but use less time on the installation.

All in all, the complexity in the installation phase is the biggest challenge. Many activities are to be coordinated and are dependent on each other. The most difficult part to install is the turbine because of all the lifts.

Time:

Normally, one wishes to avoid installing during winter months because of harsh weather. However, there are some benefits. Charter rates are lower during winter due to a lower demand. With lower charter rates, the project can tolerate more days with bad weather and still be profitable.

Decisions on the fleet size and mix are usually taken 1,5 - 1 year in advance of a project. If the market is bad, the decisions are taken even earlier (2-3 years in advance).

Appendix F

Minutes Statoil ASA II

Skype meeting Statoil ASA - February 2nd 2017

Offshore Wind Farm Installations:

Today, normal installation time is roughly 2 years. However, Dong Energy, which is a leader within offshore wind, have managed to install wind farms in one year by applying the just-in-time strategy. Assembly of the top structure is conducted by first mounting the hub and then install the blades one at a time. Installation of blades can, with today's technology, be conducted in wind speeds up to 12 m/s.

Trends:

The offshore wind industry is in constant development. Turbine design is changing rapidly and the size of these are constantly increasing. To be able to transport larger components the vessels needs to increase too. The offshore wind industry has been uncertain and thus development of specialized designed vessels has been slow. However, the industry is becoming more stable which makes investments in specialized vessels safer. Sites close to shore are mostly developed and new sites are often further out with longer distance to shore. To cope with the increasing distance to shore, the deck space capacity is essential and larger vessels will be required. Increased size is required in order to reduce the number of trips back and forth between the offshore site and the onshore port.

Vessels:

The costs related to the installation of offshore wind farms consist of several cost terms, including vessel charter costs. Since the costs related to vessels are relatively high, efficient use and resource planning is important. The use of SPIVs is limited when it comes to foundation installation due to the foundation size and weight. Several of today's SPIVs lack deck space and lifting capacity to install foundations. It is normal to use HLVs to install foundations, but the it is important to minimize the charter period for HLVs as much as possible due to the high charter rates. Specialized designed HLVs for the offshore wind industry with extra large deck capacities. Jacking vessel legs are in the range 60-80 m and the hull can stop at any height. It is not necessary to lift the hull all the way to the top of the jacking legs. However, there are limitations in how far above the sea level the hull can be jacked due to balancing and gravity. Jacking requires knowledge about the geotechnical conditions at the site and the water depth at the site. Cost of installation vessels and cable vessels are roughly the same.

Vessel Charter Strategies:

Charter strategies for vessels depends in characteristics of the wind farm being installed, i.e. distance to shore and water depth. If the farm is located far from shore, one commonly used strategy is to have one or several vessels stationed at the offshore site and use feeder vessels to transport components from the onshore port to the offshore site. If the farm is located close to shore it might be more profitable to apply smaller installation vessels with lower charter rates, which travels back and forth between the offshore site and onshore port by themselves to pick up components and install them.

Challenges related to installation projects:

A main challenges related to the installation phase is scheduling of activities and planning the amount of time needed for each activity. The industry focuses on float between activity a and activity b, meaning the time between the two activities. They aim for a just-in-time strategy in order to reduce storage costs in port, however the just-in-time strategy can rapidly become very expensive if one or several installation processes are delayed. In general: It is important to schedule enough float between all activities, but at the same time minimize the float as much as possible in order to limit unnecessary high costs.The overall goal for operators within the offshore wind installation industry is to reduce the risk of delay.