Kristoffer Strand Bergem

Multi-Product, Multi-Period Supply Chain Network Optimization for Offshore Wind Projects under Uncertainty

Master's thesis in Industrial Economics and Technology Management
Supervisor: Magnus Stålhane
June 2023

Master's thesis

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Preface

This masters thesis was written within the field of Applied economy and optimization (TIØ 4905) at NTNU during the spring of 2023. The participant of this thesis is Kristoffer Strand Bergem. This thesis is a continuation of the project report written by Olav Loennechen and myself in the fall of 2022.

I would like to thank my supervisor, Associate Professor in Operations Research Magnus Stålhane at NTNU. Your guidance throughout the semester has been highly valuable and appreciated. Additionally, I would like to thank Lars Magne Nonås and Elin Espeland Halvorsen-Weare representing my collaborator SINTEF Ocean for giving important insights about the problem. As well as Chandra Irawan Associate Professor in Operations Management at University of Nottingham Ningbo China for insightful data files.

Summary

In this thesis, the supply chain for an offshore wind project is studied. The problem studied is to plan and coordinate the supply in order to minimize total costs. The problem is under uncertainty and this thesis aims to study a trade-off. A trade-off between having substantial buffers of parts and components that leads to greater inventory costs, as opposed to lowering the buffers, but being more exposed not meeting the demand of the installation schedule.

The problem is a Multi-Product, Multi-Period supply chain optimization problem under uncertainty and a model is formulated as a two-stage stochastic model. In addition, a matheuristic has been developed to aid the solution of the problem. The results do indicate a higher service level and robustness when facing uncertainty.

Due to a lack of research regarding supply chain optimization in the offshore wind industry, this thesis aims to contribute to fill a void in the literature. Especially because the model takes uncertainty into account which proves to be a pain-point in the industry.

Sammendrag

I denne oppgaven studeres forsyningskjeden til et offshore vindprosjekt. Problemet som studeres er planlegging og koordinasjon forsyningskjeden med hensikt å minimere total kostnad. Problemet tar hensyn til usikkerhet og denne oppgaven ønsker å studere en trade-off (avveining). En trade-off mellom å ha betydelige buffere av deler og komponenter som fører til større lagerkostnader, i motsetning til å ha lavere buffere, men være mer utsatt for å ikke møte etterspørselen som er satt av installasjonsplanen.

Problemet er et fler-produkt-, fler-periode-forsyningskjede-optimaliseringsproblem med usikkerhet og en to-stegs stokastisk modell har blitt formulert. I tillegg har det blitt utviklet en matheristikk for å gjøre løsningsprosessen av problemet enklere. Resultatene viser et høyere leveransenivå og robusthet i møte med usikkerhet.

Som følge av mangel på forskning på forsyningskjedeoptimering i offshore-vind industrien, forsøker denne oppgaven å bidra til å tette et vakuum i litteraturen. Spesielt siden modellen tar hensyn til usikkerhet som viser seg å være en verkebyll for industrien.

Table of contents

List of figures

List of tables

List of Algorithms

Terminology

OWF - Offshore wind farm

OWT - Offshore wind turbine

MPMP - Multi-product, multi-period

OEM - Original equipment manufacturer

1. Introduction

The European Commission has set a goal for the EU to reduce greenhouse gas emissions by at least 55% by 2030 (European Commission, 2022). According to (NorthWind, 2021, p.7) offshore wind will play a major role in the journey of reaching the climate targets, due to its high availability and ability to respect nature. The EU has set a specific target of 300 GW of installed offshore wind capacity by 2050, and it is therefore of great importance to research and innovate to improve the technology and reduce costs (NorthWind, 2021, p.18). Poulsen & Lema (2017, p.9) state that the European offshore wind supply chain is ready for growth but that the technology needs to become more competitive with respect to costs.

Catapult Offshore Renewable Energy (2022) states that the accumulated costs related to the construction of all parts necessary for the offshore wind farm amount to 50-60% of the total wind farm development costs. The development is highly dependent on a complex logistic and shipping process, especially due to the enormous proportions of the turbine components (Irawan et al., 2017). Therefore there might be a big potential to reduce costs by optimizing the supply chain of the offshore wind farms projects. In an interview, Fred. Olsen Windcarrier (20.oktober, 2022), who deals with the installation process, expressed frustration with episodes when certain components weren't ready at the installation port. This brought the installation process to a halt as all components must be available for the installation process to proceed.

In light of the significant demand of offshore wind power, combined with the complex logistics that evidently suffer from delays and uncertainty, this thesis aims to study the supply chain, taking uncertainty into account. To do so a two-stage stochastic model has been formulated to tackle the Multi-Product, Multi-Period supply chain optimization problem. In addition a matheuristic has been developed to aid the solving of the problem in more complex cases. This model takes uncertainty into account in the form of production disruption and delay in transportation. The thesis' purpose is to study the model's robustness in the face of uncertainty. This entails studying the trade-off between generating large buffers to cope with uncertainty, as opposed to smaller buffers that are under higher risk of not meeting the demand of the installation schedule.

This thesis is structured as follows: Chapter 2 provides an overview of the offshore wind farm, including the anatomy of the offshore wind turbines and an introduction to the offshore wind supply chain elements. Next, Chapter 3 presents a thorough description of the problem discussed in this report, while Chapter 4 gives an overview of the existing literature relevant to the problem of supply chain optimization. The described problem is formulated as a mathematical model in Chapter 5. Chapter 6 presents the developed matheuristic. Further, computational results are presented and analyzed in Chapter 7. Concluding remarks about the report's discoveries and approach are given in Chapter 8. Finally, we present suggestions for possible future research in Chapter 9.

2. Background

This chapter aims to give introduction of a general offshore wind farm supply chain, including specific aspects and conditions that provides the necessary insight to understand the problem at hand. Section 2.1 gives an overview of the offshore wind farm and turbine anatomy, with focus on bottom-fixed turbines. Next, Section 2.2 presents the elements of the offshore wind supply chain. Finally, Section 2.3 and 2.4 give insight to how contracts and delay affects the supply chain, respectively. This chapter is based on the project report of Bergem, K. S. and Loennechen, O. (2022).

2.1 Offshore Wind Farms and Turbines

To fully understand the supply chain of offshore wind farms, it is necessary to have a grasp of the complexity of the grand constructions that are shipped out to sea. For perspective, the number of sub-components required can aggregate to 8000 for a single onshore wind turbine (Todd, F., 2019). According to WindEurope (2021), Europe added 2.9 GW of offshore wind capacity, yielding a total offshore wind capacity of 25 GW through the 5402 turbines that were installed in 112 offshore wind farms in 12 European countries. The report states that the average size of an offshore wind farm (OWF) installed in Europe in 2020 was 788 MW.

Dividing the total number of offshore wind turbines (OWT) over the number of OWF, the average number of turbines per wind farm in 2020 is approximately 48 turbines. The average turbine size was calculated to be 8.2 MW. Figure 2.1 shows the realistic scale of a commercial offshore wind farm by displaying the offshore wind farm “Dudgeon”, located in the United Kingdom.

Figure 2.1: The Dudgeon wind farm (Letcher, 2020, p.339)

2.1.1 An overview of the offshore wind farm

An offshore wind farm mainly consists of offshore wind turbines that transform the energy from the wind into electricity through a generator (Letcher, 2020, p.339). Through an arrangement of array cables, the OWTs connect to an offshore substation whose main purpose is to stabilize the electricity before further transportation to an onshore substation that connects to the main electricity grid. To transport the power, the offshore substation is connected to an export cable which transports the power to the onshore substation. See figure 2.2 for a simple overview of all the components of an OWF.

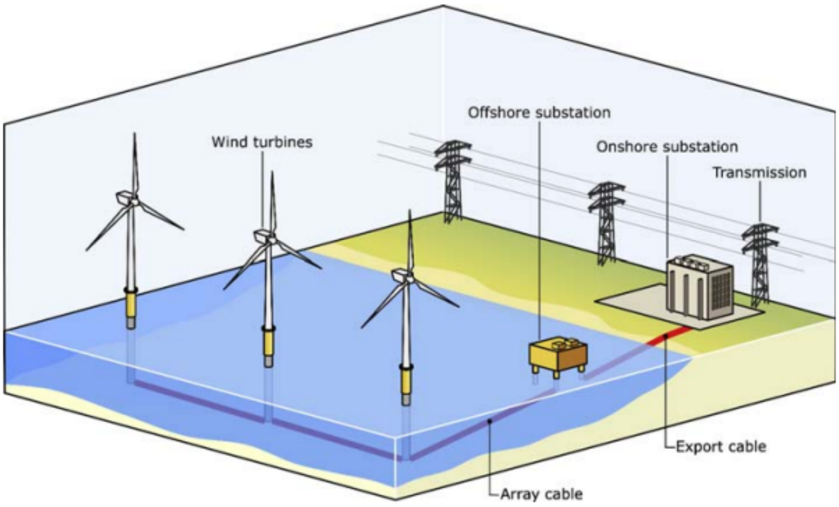

Figure 2.2: A common layout for an offshore wind farm (Letcher, 2020, p.340).

2.1.2 An overview of the offshore wind turbine

As stated in the previous section, the offshore wind turbine (OWT) is the most important component of the OWF. Offshore wind turbines consist of a sub- and top-structure. The sub-structure is the foundation upon which the rest of the turbine is installed (Letcher, 2020, p.340). These structures can either be fixed to the bottom of the ocean or be floating foundations. Whether the turbine should be based on a floating or a bottom-fixed structure depends on the water depth at the site of the wind farm. If the water depth is less than 60 meters, bottom fixed sub-structures are used due to the lower costs of producing and installing these substructures. The bottom-fixed substructures come in a variety of different types, such as monopiles, jackets, tripods and gravity based sub-structures. An illustration of these substructures is provided in Figure 2.3.

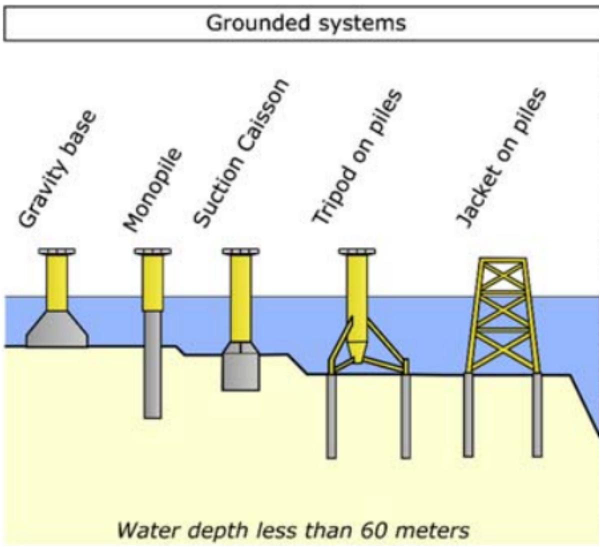

Figure 2.3: Common substructures for offshore wind turbines (Letcher, 2020, p.342).

The most common one is the monopile substructure, due to its low cost of production and installation (Letcher, 2020, p.340). One disadvantage with the monopile, however, is that it is limited to a water depth of 30m. The jacket-substructure is the second most common one, due to its ability to be used at greater water depths up to 60m. Figure 2.4 shows the share of each type of substructure in 2018.

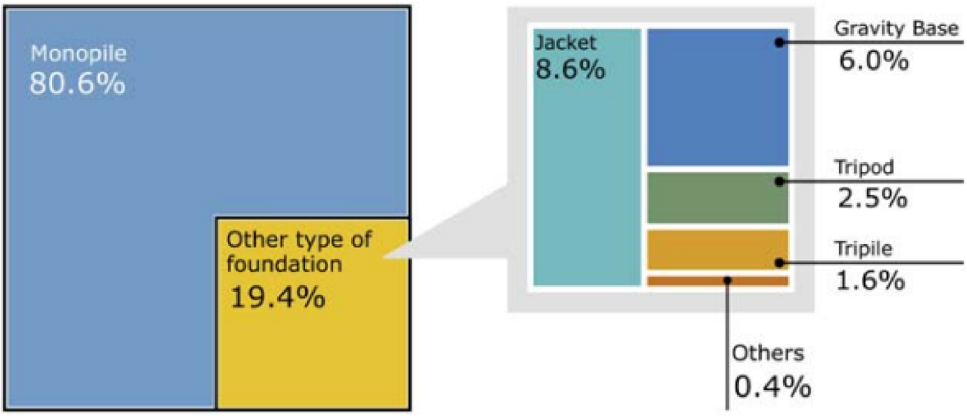

Figure 2.4: Share of Foundation Types in Europe for 2018 (Letcher, 2020, p.342).

The top structure of an OWT is generally made up of a tower, nacelle and rotor (Letcher, 2020, p.340). The tower is a simple steel structure that contains all necessary electrical and control components, and also serves as support for the nacelle. A 10 MW turbine has a tower that is about 100m high and a mass of 600 tonnes, with the steel plating accounting for 90% of the tower's mass (BVGAssociates, 2019, s.52). The nacelle contains the generator and the gearbox, as well as sensors that can be used to register which way the rotor and the blades should turn to maximize generated power (BVGAssociates, 2019, s.34). For a 10MW OWT, the nacelle is 20-25m long, 9-12m high and 7-9m wide and has a mass of 400-500 tonnes. Finally the rotor component is what converts kinetic energy from the wind into the rotational energy that is converted into electric energy inside the nacelle (BVGAssociates, 2019, s.44). Some of the important parts of the rotor are blades, hub casting and blade bearings. The blades connect to the hub, and are allowed to rotate independently by the use of blade bearings. The rotor for a typical 10MW OWT has a diameter of 170 - 200m and a mass of 150 tonnes. The blades are 90 m long and weigh 30-40 tonnes.

A transition piece connects the top and sub-structure, and also gives operating personnel access to the turbine via its platform. How all the components are put together is illustrated in Figure 2.5 that shows examples of three different bottom-fixed OWTs and their components. All the components must be manufactured at suppliers before they are transported to the installation port, where they are stored until the installation process begins.

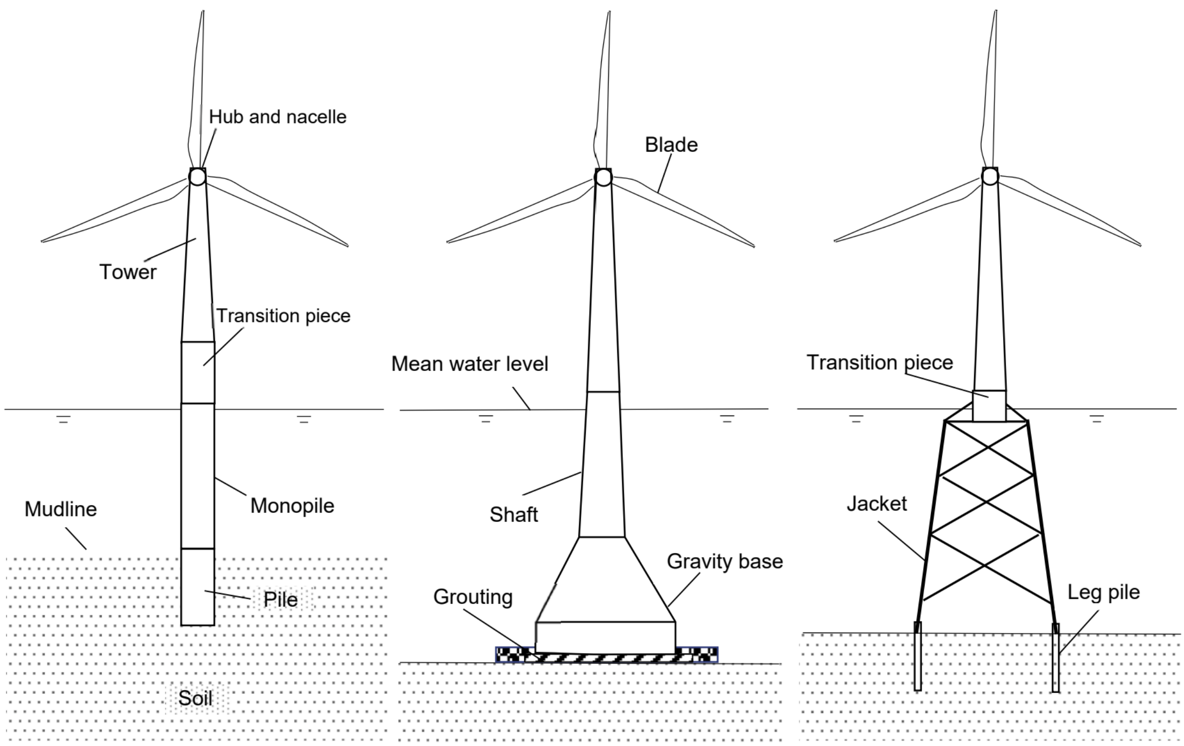

Figure 2.5: Illustration of monopile, gravity based and jacket foundations (Jiang, 2021a, p.2)

2.2 The Offshore Wind Farm Supply Chain

The European offshore wind turbine market is dominated by three original equipment manufacturers (OEMs): Siemens Gamesa Renewable Energy (SGRE), GE Renewables Energy and Vestas. SGRE has the by far greatest market share, with approximately 52% of the offshore wind energy installations in Europe in 2020 (Shields et al., 2022, p.112). Vestas holds a market share of about 19.5% in 2019, and GE about 10.8%. The main components of the OWT are commonly manufactured at different suppliers, due to the specific fabrication and storage constraints of each component type (Shields et al., 2022, p.113).

2.2.1 Suppliers of Parts and Components

As described, an offshore wind turbine consists of a sub- and top-structure that connect via a transition piece. The sub-structure, also called foundation, and the transition piece are produced and delivered by different suppliers than those of the turbine-components. There are few suppliers in the market as it is difficult for new actors to compete with the established suppliers due to the high investment costs, big projects and low sales volumes associated with offshore wind farms (BVGAssociates, 2019, p.33). For the European market, it is typical for a project to operate one or two facilities for manufacturing of nacelles and blades, as this number of suppliers suits the project sizes well.

2.2.2 Turbine Components - Costs and Producers

The top structure of the OWT is composed of a tower, nacelle and rotor. The cost of the top structure for a 10 MW OWT is approximately £10 million, including all the component, installation and design costs (BVGAssociates, 2019, p.33). Due to the huge dimensions of the main components, logistical challenges in terms of fabrication, storage and transportation may occur (Shields et al., 2022, p.59). The tower manufacturers are normally based at coastal locations, and often the tower itself is supplied by the wind turbine suppliers, while the parts of the tower are bought from external specialist suppliers (BVGAssociates, 2019, p.52). Once the tower structure has been manufactured, it is fitted with the necessary internal components and stored at the producer site until transportation. The typical cost for a 10MW OWT tower is £700 000, with the steel structure contributing to £600 000 of the cost. Some of the main tower producers are CS Wind, Gestamp Renewable Industries and GSG Towers. The steel can be supplied by a range of suppliers, while some of the internal tower parts are bought-in by the tower manufacturer.

As described in section 2.1.2, the nacelle is the component that converts the rotational energy that the rotor generates into electrical energy. The cost for a typical 10 MW OWT nacelle is £4 million (BVGAssociates, 2019, p.34). The nacelles are often assembled by the wind turbine suppliers, using parts that are sourced from a range of external suppliers. The manufacturing of nacelles needs to happen at large assembly facilities with big storage space and coastal access to support component delivery (Shields et al., 2022, p.59). The rotor mainly consists of the blades, the hub casting and the blade bearings. The cost for a typical 10 MW OWT rotor is £1.7 million, with the blades accounting for £1.3 million of the rotor cost (BVGAssociates, 2019, p.44). The rotor components are often assembled by the wind turbine suppliers, based on parts that are sourced from a wide range of external suppliers.

According to (Shields et al., 2022, p.114), the biggest OEM SGRE has manufacturing facilities in Spain, Portugal, Morocco and Denmark. Vestas and GE on the other hand, out-source some of their blade manufacturing. Furthermore, the component costs make up about 65% of the total OWT cost. Factors such as design, transportation, consulting, etc. make up the rest of the costs.

2.2.3 Foundation and Transition Piece - Costs and Suppliers

As described in section 2.1.2, the foundation provides support for the top-structure. Choice of foundation for OWTs depends on several factors, including water depth, wave heights, wind speeds, and seabed structure. The foundation is also where the electrical array cable enters the OWT. The foundation type that is most commonly used is the monopile, accounting for more than 80% of offshore wind capacity installed in 2019 (BVGAssociates, 2019, p.63). The monopile requires more steel mass than the second most used foundation, the jacket foundation, but the production, storage and installation is easier with the monopiles. For a 10MW OWT, a monopile used in 30m water depth has an indicative mass of 1650 tonnes, while a jacket foundation used in 40m water depths has an indicative mass of 1450 tonnes (BVGAssociates, 2019, p.63). For a 1GW wind farm that uses monopiles at 30m water depth, the cost of foundations is about £280 million. Normally, about two thirds of the cost is steel. As water depths go beyond 35m, the jacket foundation becomes more cost effective than the monopile foundation. Some other conditions that make the jacket foundation more suitable than the monopile is when the ground is too hard or too soft for the monopile or when noise regulations restrict the noisy operation of installing the big monopiles. The biggest foundation suppliers to the offshore wind energy market are the EEW Group and Sif, who are also the largest monopile manufacturers (BVGAssociates, 2019, p.64).

To connect the sub- and top-structure, a transition piece is needed. It also acts as a platform where personnel can enter the OWT, and supports both cables and the corrosion protection system. For a 1GW wind farm using monopiles, the transition piece cost amounts to about £100 million (BVGAssociates, 2019, p.66). The transition piece is often supplied through a joint venture with the supplier of the monopiles. For a jacket foundation, the transition piece will not be a separate piece that is bolted onto the foundation, but rather an integrated part of the jacket structure. There is also often a davit crane installed on the transition piece to allow for lifts from the support vessel to the platform.

2.2.4 Transportation

After the manufacturing of the main components is done, the components are transported to the installation harbor. According to Ulstein (2022), heavy transport vessels and feeder vessels transport turbine components and foundations from the manufacturer ports to the installation port and the OWF. Figure 2.6 illustrates the most common concept for transportation and installation of OWFs, where each component is transported by heavy-lift vessels from manufacturer to installation port (Rippel et al., 2019, p.2). The foundations are typically transported directly to the offshore wind farm site from the foundation manufacturer, not entering the installation port (Asgarpour, 2016, p.2).

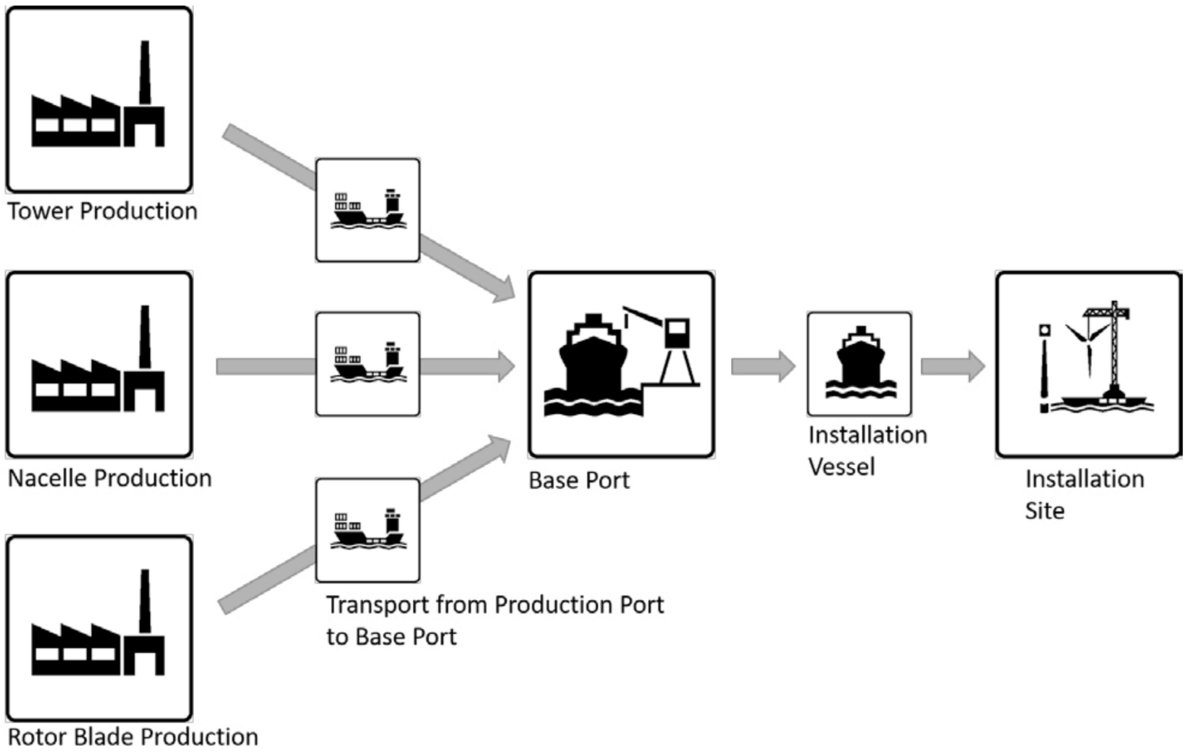

Figure 2.6: Conventional Installation Concept (Rippel et al., 2019, p.2)

Due to the large size of the components, as well as the limited storage space on both transportation vessels and in the installation harbor, all components are not transported at the same time. Thus, based on the planned installation strategy, a set of certain components should be delivered to the installation port once the previous set of components at the port has been loaded onto an installation vessel (Asgarpour, 2016, p.2). Consequently, the manufacturers of the components should start the production process at a time such that the components are manufactured close to the scheduled loading onto the transportation vessel. This strategy would be beneficial for the supply chain and the project delivery company as it reduces the inventory holding costs in relevant parts of the chain.

As described, heavy-lift vessels are usually used to transport components from the manufacturers to the installation port. Since the installation port has the necessary equipment to perform loading operations, there is no need for such equipment on board of the heavy-lift vessels. Such vessels are expensive, and are often chartered at rates of €10 000 to €20 000 a day (Rippel et al., 2019, p.2).

After delivery from the manufacturer, the main components are stored at the installation port. The tower component is often delivered in several pieces that need to be assembled in the installation port. Additionally, the rotor is often assembled to some degree. The two common methods are to either assemble the nacelle, the hub and two blades in a “bunny ear”-formation, or to assemble the nacelle, the hub and three blades in a “rotor-star”-formation before the structure is loaded onto the installation vessel (Asgarpour, 2016, p.3).

2.2.5 Installation

When all the necessary components are at the installation port, the installation process can begin. The main installations included are installation of foundations, turbines, and cables.
The first component that is installed is the foundation. The type of foundation used for the wind turbine varies depending on water depth on the wind farm site. If the water is too deep, bottom-fixed foundations are no longer appropriate. Then it is necessary to utilize a floating foundation.

After the foundation is in place, the turbine is to be installed. As described in 2.2.1 the turbine consists of the tower, nacelle and rotor. There are different techniques to mount these parts, some of which are depicted in Figure 2.7.

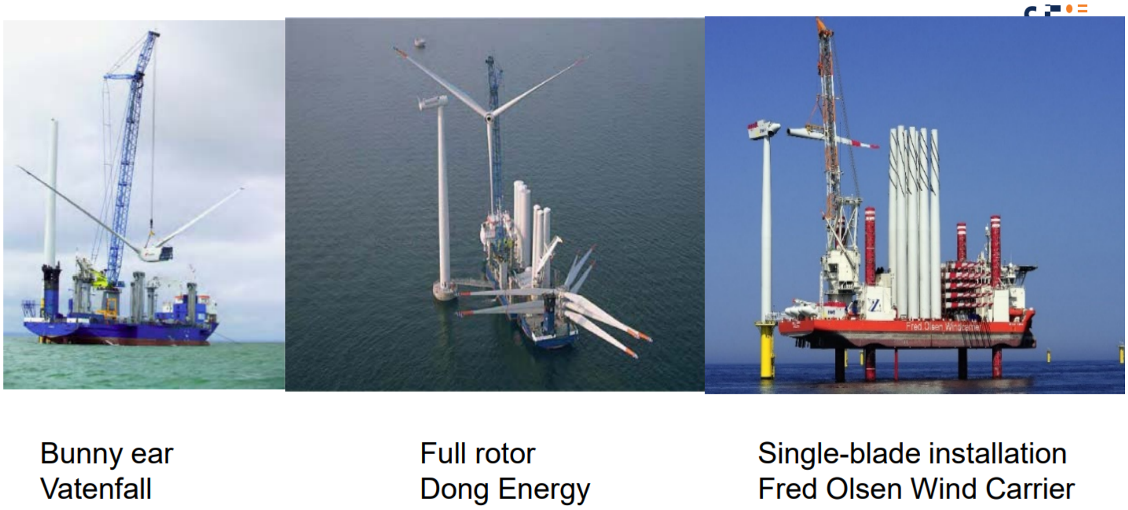

Figure 2.7: Different Techniques to Mount Turbine Components (Jiang, 2021b, slide 7).

To transfer the power from the wind farm to shore cables are installed. These are layed and buried from the turbines, through substation and then to the electrical grid on shore.
The different installation activities require different ships to be executed.

2.3 Contracts

Throughout the supply chain there are several contracted transactions between the actors. Manufacturers of parts (subcomponents in Figure 2.8) are contracted to and typically acts as vendors for subassembly suppliers. Subassembly manufacturers are, similarly, contracted to suppliers of finished components and provide them with subassemblies that serve a specific purpose in the finished components. Moving up the supply chain, manufacturers of the finished components are contracted directly to the project developer (Shields et al., 2022, p.5). For projects scheduled for 2024 and later, most wind turbine supply chain contracts are yet to be awarded. The construction of additional production capacity in Europe will be determined on the basis of these pending contracts.

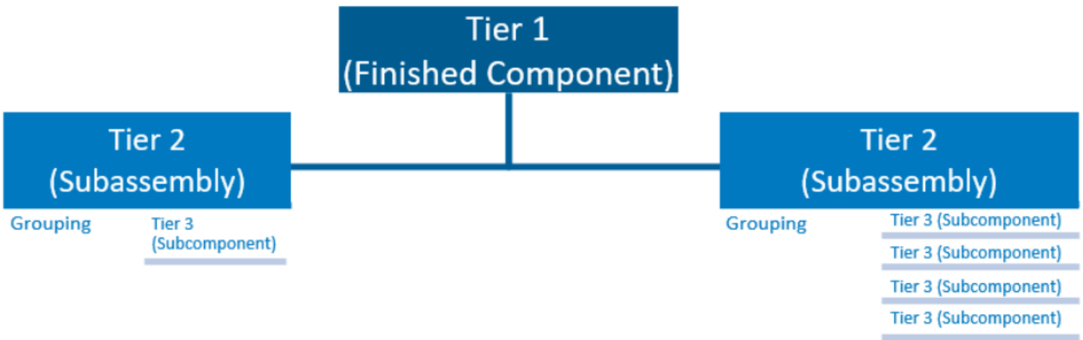

Figure 2.8: Hierarchy Map of the Three Tiers (Shields et al., 2022, p.55).

As the installation process depends on a variety of specialized ships, how these vessels are contracted to the project is essential. The vessels are often on a time charter, which, as mentioned, is set in advance. Any delays that shifts the schedule will make it difficult to execute installation activities. To mitigate the risk attached to the vessels not being able to operate in the chartered time, these contracts can contain extension of time clauses. Such clauses will allow some leeway for unexpected delays to execute installation activities with the necessary vessels available. Time extensions may entail prolonging costs for the project developer (Hill, R. and Robertsen, D., 2020). However, if delays cause the installation to exceed the extended date it may lead to significant setbacks. This is a consequence of the vessels already being chartered to new projects and a general scarcity of vessels with specific attributes needed in installation.

If a contractor is to blame causing delay in the installation process and fails to deliver on their promises, they are usually contractually obliged to pay liquidated damages. This mechanism is supposed to ensure employers that are provided with the agreed upon services, by giving incentive to minimize delay and avoid unexpected costs and loss of revenue (Norsk Industri, 2020). This is especially appropriate for projects with many actors involved, as is the case for offshore wind farms, to avoid any knock-on effects.

2.4 Delays

As any other supply chain there is often a risk of delay in OWT projects. Bagchi et. al. points out four interrelated flows as vital factors that affect the course of the whole supply chain (Bagchi and Paik, 2007). Namely, the flow of material, information, ownership and payment. The coordination of these four aspects are essential to avoid delays throughout the supply chain. The main issue of this thesis will be the flow of material and how it shapes the supply chain. Which is reflected in the focus on parts and components previously in this chapter and throughout the thesis.

With focus on the material flow, sources of delay can be associated with shortages in material production and delays in delivery of materials (Rahman et. al., 2017). In an OWT project material shortages can happen in all stages. Together with machinery failure, shortage of materials can cause delays in production. These uncertainties can materialize in both production of parts at the suppliers and production of components at the producers. Delay in delivery of materials can occur in transportation between stages. This impact can be caused by vessel failure as well as unfavorable weather conditions.

As all the stages in the supply chain are connected any delays in any stage may affect the following stages in the chain and potentially cause a ripple effect through the stages of the chain (Dolgui et. al., 2017). For instance, if production of parts were to shut down due to shortage of materials or machinery failure and cause a delay at a supplier. That could manifest further to the producers that wouldn't get the necessary parts for the production of components and could ultimately affect the ability to meet the demand of the installation schedule at the installation port.

3. Problem Description

The problem studied in this thesis is to plan and coordinate the supply chain of an offshore wind project in order to minimize total costs. The problem consists of determining the selection of suppliers of parts, producers of components, when production starts and stops at each supplier, as well as when to ship the parts and components between the links in the supply chain. As any other supply chain is prone to uncertainty, which has to be taken into account.

The project involved in the problem has one predetermined installation port, where all installations and assemblies of offshore wind turbines take place. An installation schedule determines the timing and quantity of components needed from producers in each period to fulfill the demand necessary for installation. To satisfy the installation schedule while minimizing costs which suppliers, producers and transport vessels utilized in the supply chain is decisive.

The suppliers, at the start of the supply chain, provide all the necessary parts needed to construct the components that the fully assembled offshore wind turbine consists of. The parts are all produced at the supplier and then stored at the site until the chosen transportation vessel is ready for loading and departure. For each part, this entails a unit production cost and outbound unit inventory holding cost per period. Both production and inventory costs may vary depending on the choice of supplier. The capacity of the suppliers may also vary, as all suppliers are subject to a maximum production capacity, as well as a maximum outbound inventory capacity.

When the parts arrive at the producer plant they are used to produce components. Consequently, the production of components has a defined number of each part required to produce each component. These parts must be on site before the production process can begin. Having the required parts at the producer plant the production process has a production period associated with each component. The duration of this period may vary depending on the producer that is chosen. Similar to the suppliers, the producer has a unit production cost for each component. They also have an inbound unit inventory holding cost for parts received from suppliers, as well as an outbound unit inventory holding cost for produced components that are yet to be transported to the installation port. Both production and inventory costs may vary depending on the choice of producer. The capacity of the producers may also vary, as producers also are subject to a maximum production capacity, as well as a maximum inbound and outbound inventory capacity.

Both parts from suppliers and components from producers are transported by maritime transportation vessels to the next stage in the supply chain. These vessels have a maximum loading capacity for parts and components that can be transported per voyage. Each vessel is also associated with a transportation time from departure to arrival at either producer or port. All transportation vessels that are used need to be booked beforehand and these bookings entail booking cost for each transportation vessel.

Upon arrival at the installation port, the components need to be unloaded and stored until the installation process begins and the components get loaded onto installation vessels. Therefore, the installation port is associated with defined inbound unit inventory holding costs per day for each component stored. Additionally, the port has a maximum storage capacity for the inbound inventory.

The decisions that have to be made to solve the problem and set up the supply chain regard the flow of materials and the selection of suppliers, producers and transport vessels.

In greater detail, to initiate the supply chain flow, what suppliers to use and when to start and stop production has to be determined. As well as, what producers to use and the booking of transportation vessels. Furthermore, how many parts that are transported from suppliers to producers in each period must be decided, as well as which vessels that are utilized to transport the desired number of parts. The same goes for how many components that are transported from producer to port and which vessels they are assigned to. Finally, which components from the port inventory that are taken for installation purposes to fulfill the installation schedule must be decided.

All parts and components are stored at each stage before they can be transported to the next. Therefore, one must keep track of all the inventory levels throughout the supply chain in each period. These being outbound inventory levels for parts at suppliers, inbound inventory levels for parts and outbound inventory levels for components at the producers and the inbound inventory level for components at port before they are used in installation.

The supply chain may be subject to risk of delay. Since offshore wind projects are of a finite nature and thus have strict contractual time limits to adhere to, delays may be very costly. Therefore, there is a penalty cost associated with failing to meet the requirements of the installation schedule. Assuming that delays can occur in either production or transportation and that each stage in a supply chain depends on the one before, a ripple effect can arise, as explained in the previous chapter. In the planning problem this creates a trade-off issue between having substantial buffers of parts and components that entails greater inventory costs, as opposed to lowering the buffers, but being more exposed not meeting the demand of the installation schedule.

In summary, the problem in this thesis is deciding among sets of suppliers, producers, and transportation vessels to minimize the total cost of the supply chain. In greater detail, what suppliers and producers to utilize and when to start and stop production. As well as booking transport vessels to enable the flow of parts and components between them and the installation port. While keeping track of production, inventory holding and transportation booking costs and weighing the safety and cost of inventory buffers up against the risk of being penalized for not fulfilling the installation schedule.

4. Literature Review

This chapter provides an overview of the existing literature that is relevant to the problem studied in this thesis. The process of obtaining this overview aims to illuminate similarities and differences between the problem presented in this thesis and the existing literature. The problem in this thesis is solved using a two-stage stochastic supply chain optimization model for an offshore wind farm project. Literature that directly deals with supply chains in the offshore industry has been proven rather scarce in the literature review. To strengthen the foundations of this claim, Irawan et al. (2017) points out “there is a dearth of papers in the literature that address supply chain optimisation in an offshore wind farm”. This still seems to be the case in 2023. Therefore, it is appropriate to extend the literature search to also review literature regarding supply chains using optimization methods in other industries. The aim of this extended review is to find similar characteristics that can provide further insight of how a similar supply chain has been handled and which methods that have been applied. Parts of this chapter is based on the project report of Bergem, K. S. and Loennechen, O. (2022).

Due to the mentioned limited research on offshore wind farm supply chain optimization, it is relevant to identify the most important characteristics of the problem and study supply chain optimization models with similar characteristics to gain valuable insight into the optimization problem. The following sections reflect the different characteristics. Section 4.1 presents the research strategy. Section 4.2 looks at MPMP network supply chain problems. Uncertainty is covered in section 4.3 and section 4.4 covers solution methods. Finally, section 4.5 presents our contribution.

4.1 Literature search strategy

The model presented in this thesis was originally inspired by the paper presented by Irawan et al. (2017). The paper gives an overview of existing research on problems related to the offshore wind supply chain optimization problem. The main literature is on the MPMP supply chain network problem, which has several similar characteristics to the problem in this thesis. This literature laid a natural basis for parts of the literature review. In addition, Google Scholar was used as the main search engine, to supplement the literature provided by Irawan et al. (2017). The purpose of these searches was to get a wider overview of the relevant literature. This was necessary to ensure that potential later research didn't go overlooked, as well as finding more research regarding the characteristics of the model where this thesis strays from the literature from Irawan et al. (2017). Google Scholar is efficient because it allows users to limit their search results by providing filtering options such as authors, publication date, sorting by relevance etc. The search words used in this review are presented in Table 4.1.

Table 4.1: Summary of search words used in the literature search.

Offshore Wind Supply Chain	**MPMP**
Planning Installation	Distribution Network Product Allocation Production disruption

4.2 Multi-Product, Multi-Period Supply Chain Network Optimization Problem

In a paper proposed by Al-Ashhab (2017), a Mixed Integer Linear Programming (MILP) model is formulated to solve a multi-product, multi-period supply chain network design problem. It finds the best combination of locations of the suppliers, facilities, distributors and customers and sets up the transportation between them to maximize total profit by considering relevant capacities and costs. Some of the assumptions the model makes are that customer locations are fixed and known, and that their respective demands are known for all products in all periods. The model also assumes that product weights are different, and that an integer number of batches must be transported. Further, all capacities are known for each period. A verbal formulation of the model is presented below:

Maximize:

Total profit = Total income - Total cost = Total income - (fixed costs + material costs + manufacturing costs + non-utilized capacity costs + shortage costs + transportation costs + inventory holding costs).

Subject to:

Balance constraints

Capacity constraints

Linking (contracts)-Shipping constraints

Shipping-Linking constraints

Maximum number of activated locations constraints

It is assumed that all cost parameters are known for each location and product in each period. The shortage cost depends on the shortage quantity for each product and time, and the holding costs depend on the weight of product and residual inventory at the end of each period for each product. Further, the transportation costs depend on transported quantities, the weight of products transported and the linear distance between locations. Finally, the manufacturing costs depend on the manufacturing hours for each product and their respective hourly cost, and the material cost differs for each product depending on its weight.

The "*balance*"- constraints ensure that the flow into each facility and each distributor is equal to the flow out of them. They also ensure that the flow entering into each customer does not exceed the customer demand and the accumulated shortages for each product. The "*capacity*"-constraints ensure that all flows in the network respect the related capacities, i.e. that the flow exiting each supplier does not exceed the supplier capacity, that the flow entering facilities from suppliers does not exceed the respective facility capacities etc. Further, the "*linking (contracts)-shipping*"-constraints ensure that no link between locations can exist without any shipment in any period, and the "*shipping-linking*"-constraints ensure that there is no transportation between any non-linked locations. Finally, the "*maximum number of activated locations*"-constraints are responsible for limiting the number of selected locations.

Al-Ashhab's (2017) model has several similarities to the problem formulation of our report; our problem includes multiple products that must be manufactured and transported from multiple manufacturers over multiple periods. The model proposed by Irawan et al. (2017) is based on the concept of multi-product multi-period supply chain optimization. While Al-Ashhab's (2017) model considers transportation to only be dependent on product weights and quantities and transportation distance, Irawan et al. (2017) includes the choice of a transportation mode. It allows the model to choose between inland and sea transportation modes, which will incur different transportation costs, capacities and times.

4.2.1 Objective Function

Literature suggests that the most common objective of multi-product, multi-period supply chain network optimization problems is to minimize the total network costs. The total costs commonly consist of at least some variable unit production, transportation and inventory holding costs. The objective of minimization is applied in papers by Bilgen and Ozkarahan (2007), Eksogliu et al. (2006), Akbari and Karimi (2015) and Irawan et al. (2017). The minimization function can be extended further. In the minimizing objective function in the model of Ardakani et al. (2020) it is included to minimize costs related to the establishment of additional warehouses, as well as the cost of potential shortage on customers' demand. Other cost minimization extensions, such as the ones described in Akbari and Karimi (2015), include the minimization of fixed costs related to the assignment of customers to distribution centers.

Other models, like McDonald and Karimi (1997) and Ardakani et al. (2020), suggest bi-objective functions that in addition to minimizing the total network cost also aim to maximize some measure. For instance, in the paper of Ardakani et al. (2020), a bi-objective MILP model is presented where the objective is to minimize the total network cost in addition to maximizing social responsibility. As described in the model of Pasandideh et al. (2015), another possible measure to maximize is the number of products sent to customers, but this implies that the model is considering some uncertainty in the reliability of the supply chain. Other bi-objective models are presented to also minimize some measurement of gas emissions. The paper by Jinawat et al. (2021) presents a bi-objective model that minimizes total cost and minimizes carbon dioxide emissions, while Wang and Wan (2021) provide a bi-objective model that maximizes profit and minimizes overall carbon emissions. Finally, some models, like Al-Ashhab (2017), aim to maximize total profit in a single objective optimization problem.

4.2.2 Capacities

For MPMP supply chain problems it is common to include some sort of capacity restrictions at the nodes in the network. According to a survey presented by Mula et al. (2010) the most usual capacity to include in the model is some sort of production capacity, as approximately 84% of the papers included in the survey include some production capacity. Further, about 48% of the papers include capacities on the inventory holding of products in the supply chain, and about 32% include transportation capacities. The intention of defining capacities is to constrain the quantities produced, transported and stored in the model, as this often is the case in real life situations. As described in the next paragraph, models may contain one, several or none of these types of capacities.

Irawan et al. (2017) take production capacities, as well as inbound and outbound storage capacities into account at each plant. Additionally, storage capacities are used for ports, and also capacities related to transportation of products is included. Bilken and Ozkarahan (2007) present a model in which various capacities are accounted for, including blending, loading, draft and vessel capacities. Wang and Wan (2021) include production and storage capacities, but no transportation capacities. In the paper of Park (2005) there is a production capacity associated with each plant, but only the retailers are restricted by storage capacities. Some papers present models without including any capacities, such as the model proposed in Eksogliu et al. (2006). Such uncapacitated models are, however, rarely used in supply chain optimization models, as no capacity-constraints is not close to real problem descriptions.

4.3 Uncertainty

The majority of the papers dealing with uncertainty in supply chains deal with demand under uncertainty. For instance, Al-Ashhab (2017) considers stochastic customer demand. In the case of an OWF-project the demand of components is set by an installation schedule. The source of uncertainty is therefore not related to the demand, but is rather related to the flow of parts and components through the supply chain. More accurate, the uncertainty is rooted in potential production disruption and delay in transportation.

According to Malik & Sarkar (2020) literature describes production disruption as any form of disturbance during a production process, including power cut, tool failure, machine breakdown and more. A disruption that causes production to halt may lead to financial or reputational losses, as the shortage of products and unfulfilled customer demand become clear to the market. Therefore, it could be wise to include some sort of disruption element in the planning models of companies' supply chains. Ardakani et al. (2020) propose a model that evaluates the possibility of disruption in both manufacturing plants and transportation. Pasandideh et al. (2015) present a model in which uncertainty related to the distribution center reliability is assumed to exist due to the distribution centers being subject to a possibility of random failures that may occur. Wang and Wan (2021) also considers network uncertainty as well as uncertain customer demand.

4.3.1 Reliability constraints

Pasandideh et al. (2015) present a model in which uncertainty related to the distribution center reliability is assumed to exist due to the distribution centers being subject to a possibility of random failures that may occur. This is expressed as reliability constraints. It is assumed that all distribution centers are initially functional, and that they can not return to functional state after a disruption has occurred. The reliability of a distribution center in dispatching products to customers is modeled with the exponential distribution. This is used to maximize the total number of products sent to customers. Ardakani et al. (2020) considers, as mentioned, the possibility of disruption for both manufacturing plants and transportation modes. This model also considers the exponential distribution to be suitable for the time required for failure. When a distribution center faces disruption, all inventory is lost. Likewise, when a transportation vehicle is disrupted, all transported products are considered lost. The exponential distribution is assumed because it allows the failure rate not to change through a period, while it allows failure to happen at any time.

4.3.1 Scenarios and multi-stage stochastic model

Ardakani et al. (2020) uses scenarios to express a stochastic customer demand. These scenarios are implemented in a two-stage stochastic model. The stochastic demand of the customers is distributed with mean μ and standard deviation σ. Wang and Wan (2021) similarly utilized a scenario-based method to manage network uncertainty. The scenarios were implemented in a multi-stage stochastic model.

4.3.3 Penalty cost

Pasandideh et al. (2015), Wang and Wan (2021), Ardakani et al. (2020) and Al-Ashhab (2017) all deal with shortage costs. These shortage costs represent lack of inventory and subsequently the loss of business. An OWF-project differs from this representation since the projects have a more determined and finite project period. To say that a lack of inventory results in lack of business would be a simplification. An OWF-project needs to meet the demand of the installation schedule and any contractual extensions prove to be very costly. The penalty cost, subsequently, punishes the objective function in higher order of magnitude.

4.4 Solution Methods

The MILP models presented by Irawan et al. (2017) and Bilken and Ozkarahan (2007) all provide solutions found by running the model in a commercial solver, like XpressMP or IBM ILOG CPLEX, with exact solution methods. A feature that is common for the models is that none of them are considering uncertainty in the supply chain. Also, the models are presented as single objective optimization problems (SOP), with the model either minimizing the total costs or maximizing the total profit.

The MPMP problem is also solved as a multi-objective optimization problem (MOP) in some cases. Papers presented by Pasandideh et al. (2015) and Ardakani et al. (2020) include MPMP problems that are modeled as MOPs, and solved by the use of the commercial software GAMS. The use of several objectives in the model may further increase the complexity, which is reflected in the solution methods of the two papers. Pasandideh et al. (2015) present a set of different solution methods for MOPs, including the maximin, goal-attainment, lexicographic and goal programming methods, and a few others. Which solution method to apply depended on the objective to optimize. Ardakani et al. (2020) present the use of the MOP solution method “Epsilon-constraint”-method. One main difference in the solution methods applied by Pasandideh et al. (2015) and Ardakani et al. (2020) is that none of the former’s presented solution methods yield a Pareto frontier, while the latter’s use of the “Epsilon-constraint”-method does yield a Pareto-frontier.

4.5 Our Contribution

As mentioned, Irawan et al. (2017) pointed out a dearth of papers in the literature that address supply chain optimization in an offshore wind farm. To our knowledge, that is still the case in 2022. Thus, this thesis is based on a range of papers not directed to the offshore wind industry, multi-product, multi-period (MPMP) supply chain optimization problems. A summary of important characteristics of those papers’ modeling approaches is presented in Table 4.2.

As the literature on offshore wind supply chain optimization, this thesis contributes to the research by solving a model for an MPMP supply chain optimization problem in the offshore wind industry under uncertainty. Solving the problem under uncertainty sets this thesis apart from Irawan et al. (2017), through a scenario-based two-stage stochastic model. Modeling the uncertainty in the form of both production disruption and transportation delay is also unlike a lot of the literature concerning MPMP supply chain optimization.

Much of the literature performed on MPMP supply chain optimization problems rarely considers capacities in terms of production, storage and transportation, and so this report further complements the existing research by considering the combination of all the capacities. This choice is made to make the model more applicable to real cases, where the supply chains are, indeed, subject to such capacities. Because the model is separated from the dataset, and thus is a general model, it is applicable not only in the offshore wind industry. Therefore, it may also contribute to the research on MPMP supply chain optimization in other cases where maritime transportation of products is applied.

Table 4.2: Comparison of our problem and relevant studies

Paper	Objective Function	Capacities	Penalty cost for unmet demand	Uncertainty	Means of managing uncertainty	Industry
This thesis	Minimize total cost	-Production -Inventory -Transportation	Yes	- Production disruption - Transportation delay	Scenario-based two-stage stochastic model	Offshore Wind
Irawan et al. (2017)	Minimize total cost	-Production -Inventory -Transportation	No	Deterministic	-	Offshore Wind
Bilgen and Ozkarahan (2007)	Minimize total cost	-Production -Inventory -Transportation	No	Deterministic	-	Bulk grain shipping
Eksioglu et al. (2006)	Minimize total cost	No	No	Deterministic	-	General research
Al-Ashhab (2017)	Bi-objective	-Production -Inventory	Shortage cost	- Uncertain demand	Scenario-based two-stage stochastic model	General research
Ardakani et al. (2020)	Bi-objective	-Inventory -Transportation	Shortage cost	- Network uncertainty	Reliability constraints	General research
Pasandideh et al. (2015)	Bi-objective	-Inventory -Transportation	Shortage cost	- Uncertain demand - Network uncertainty	Reliability constraints	General research
Wang and Wan (2021)	Bi-objective	-Production -Inventory	Shortage cost	- Uncertain demand - Network uncertainty	Scenario-based multi-stage stochastic model	General research

5. Mathematical Model

This chapter presents a mathematical formulation of the problem described in Chapter 3. The mathematical formulation is based on the deterministic model from the project report by Bergem, K. S. and Loennechen, O. (2022), which has been developed to a stochastic model that takes uncertainty into account. Section 5.1 presents the assumptions that have been made when developing the model. Section 5.2 presents all sets, parameters and decision variables. Finally, section 5.3 presents the mathematical formulation, including objective function and constraints.

5.1 Assumptions

In this section the assumptions that lay the basis of the model are presented.

5.1.2 Problem structure

The structure of the model is a MPMP-model using two-stage stochastic optimization. The objective function is to minimize total costs, including production, inventory holding, booking of transportation vessels and penalty costs. The first stage of the model deals with the timing of the start of production and when to stop producing parts at the suppliers. In which periods transportation vessels are booked is also decided in the first stage. These decisions are assumed to have to have been done before the first period of the project's supply chain planning horizon.

The second stage is influenced by weighted scenarios and deals with how the parts and components flow through the supply chain. These decisions include the number of parts transported from supplier to producer, number of components produced at the producers and number of components transported from producers to the installation port. The second stage also deals with the inventory level associated with suppliers, producers and installation port.

5.1.2 Flow of parts and components

The model deals with how the parts and components can flow through the supply chain. There are assumptions made to emphasize the most important aspects, while keeping a holistic picture of reality. For instance, an OWT consists of thousands of parts that make the necessary components. To simplify the data needed to solve the model, many of these parts are aggregated to be expressed by a single part in the model. The purpose behind this simplification is to maintain a manageable level of complexity so that other dimensions of the problem can be investigated, without the distraction and noise from thousands and thousands of additional variables.

Another assumption that the model makes regarding flow of parts and components in an effort to simulate reality, is that the parts and components are not placed on available routed vessels, where a portion of the capacity can be booked. Instead, entire transportation vessels are booked. This is due to the size of the parts and components that go into the construction of an OWT. The transportation cost is therefore different from what Irawan et. al (2017) and many other supply chains express it as. While they assert a transportation variable and cost to each unit, the transportation cost and decision variable in this model is expressed as the booking of each transportation vessel.

5.1.3 Demand

As mentioned, in a typical OWF-project the planning horizon is often of a rather strict and finite nature. This separates the OWF supply chain from other chains that often have a running, indefinite demand and operational planning horizon. The delimitation is materialized through a predetermined installation schedule. The demand in the supply chain is therefore assumed to be fixed.

5.1.4 Uncertainty

Given the assumption that demand is fixed, the uncertainty in this model is instead assumed to occur in production or transportation. Potential disruption or delays in the operational processes are realized through several weighted scenarios. In these scenarios any disruption leading to delays are expressed in the input data in the form of reduced production quantities at the supplier-level or longer transportation times. The named sources of uncertainty can make it more difficult to meet the demand of the installation schedule. The model assumes that recourse during the project's supply chain planning horizon is difficult and therefore seeks to take pre-emptive action to avoid delays. In practice, these actions will be setting the timing of production start and stop and when to book transportation vessels in order to have the opportunity to build up a material buffer to cope with disruptions occuring during the planning horizon. Such buffers will inherently yield increased inventory holding costs. To encourage the model to take the risk of delay into account there is a penalty cost associated with not adhering to the demand of the installation schedule. This penalty cost also aims to simulate the costly extension clauses the contracts described in Chapter 2.4 can be. The mechanisms of buffer creation and penalty cost induces a trade-off between taking caution, but consequently aggregating more inventory holding costs, and exposing the supply chain for the risk of being penalized for not being robust enough to deal with potential disruption and shortage of components at the installation port.

5.2 Definitions of sets, indices, parameters and variables

5.2.1 Definition of Sets

S - Set of suppliers S, indexed by s

P - Set of producers P, indexed by p

V - Set of vessels V, indexed by v

D - Set of parts D, indexed by d

K - Set of components K, indexed by k

T - Set of time periods T, indexed by t

U - Set of scenarios U, indexed by u

5.2.2 Definition of Parameters

Suppliers:

C_{su} - Total costs at supplier s in scenario u

C_{ds} - Production unit cost for part d at supplier s

H^{O}_{ds} - Outbound inventory holding cost at supplier s for part d per period

M^{O}_{s} - Inventory capacity for supplier s

G_{dstu} - Number of parts d produced at supplier s in period t in scenario u

Producers:

C_{pu} - Total costs at producer p in scenario u

C_{kp} - Production unit cost component k from producer p

H^{I}_{p} - Inbound inventory holding cost at producer p for part d per period

H^{O}_{p} - Outbound inventory holding cost at producer p for component k per period

M^{prod}_{p} - Production capacity at producer p

M^{I}_{p} - Inbound inventory capacity at producer p for parts

M^{O}_{p} - Outbound inventory capacity at producer p for components

T_{kpu} - Production time for component k at producer p in scenario u

Port:

C^{port}_{u} - Total costs at port in scenario u

H_k^{port} - Inventory holding cost for component k in port per period

M^{port} - Inventory capacity in port

D_{kt} - Demand for component k in port in period t

$C_{ktu}^{penalty}$ - Penalty cost for component k in port in period t in scenario u

β_u - Probability of scenario u

Transportation:

$C^{transport}$ - Total transportation costs

C_{spvt}^{book} - The cost of booking a vessel v from supplier s to producer p in period t

C_{pvt}^{book} - The cost of booking a vessel v from producer p in period t

U_{spv} - Maximum capacity at vessel v transported from supplier s to producer p

U_{pv} - Maximum capacity at vessel v transported from producer p to port

T_{spvtu} - Transportation time from supplier s to producer p using vessel v

T_{pvtu} - Transportation time from producer p to port using vessel v

Components & Parts:

A_d - Inventory space needed for part d

A_k - Inventory space needed for component k

A_{dk} - Parts d needed to produce component k

5.2.3 Decision Variables

g_{st}^{start} - Production start at supplier s

g_{st}^{stop} - Production stop at supplier s

g_{dstu}^{last} - Number of parts d produced at supplier s in the last period before stop of production in scenario u

x_{dspvtu} - Transferred parts d from supplier s to producer p with vessel v in period t

x_{kpvtu} - Transferred component k from producer p to port with vessel v in period t

f_{dptu} - Number of part d received at producer p in period t

f_{ktu}^{port} - Number of component k received at port in period t

l_{dstu} - Inventory level of part d at supplier s in period t

l_{dptu} - Inbound inventory level of part d at producer p in period t

l_{kptu} - Outbound inventory level of component k at producer p in period t

l_{ktu}^{port} - Inventory level of component k at port in period t

q_{kptu} - Production quantity of component k at producer p in period t

i_{ktu}^{port} - Number of components k delivered to installation in period k in scenario u

y_{spvt} - Binary variable, 1 if executed transport from supplier s to producer p with vessel v in period t, 0 otherwise

y_{pvt} - Binary variable, 1 if executed transport from producer p to port with vessel v in period t, 0 otherwise

5.3 Mathematical Formulation

5.3.1 Objective value

$$min\, Z = C^{transport} + \sum_{u\in U} \beta_u \left(\sum_{s\in S} C_{su} + \sum_{p\in P} C_{pu} + C_u^{port} + \sum_{k\in K}\sum_{t\in T} C_{ktu}^{penalty}\left(\sum_{t=1}^{t} D_{kt} - \sum_{t=1}^{t} i_{ktu}^{port}\right)\right)$$

, (5.1)

The objective function (5.1) minimizes the total cost, consisting of all costs related to supply chain. C_{su} is the total cost associated with suppliers, C_{pu} is the total cost associated with producers, C_u^{port} is the total cost related to port operations, and $C^{transport}$ covers all relevant costs for transportation. $C_{ktu}^{penalty}$ represents the penalty cost for the demand of the installation schedule that isn't met. All scenario dependent costs are multiplied by the respective scenario weight, β_u. The different terms of the objective function is further elaborated in the coming sections.

5.3.2 Supplier subset of the model

$$C_{su} = \sum_{d\in D}\sum_{t\in T}(H^{O}_{ds} l_{dstu} + C_{ds}\sum_{p\in P}\sum_{v\in V} x_{dspvtu}), \qquad s \in S,\ u \in U, \qquad (5.2)$$

$$l_{dstu} = l_{ds(t-1)u} - \sum_{p\in P}\sum_{v\in V} x_{dspvtu} + G_{dstu}(\sum_{\tau=1}^{t} g^{start}_{s\tau} - \sum_{\tau=1}^{t+1} g^{stop}_{s\tau}) + g^{last}_{dt},$$

$$d \in D,\ s \in S,\ t \in T, u \in U, \qquad (5.3)$$

$$\sum_{\tau=1}^{t} g^{start}_{s\tau} \geq \sum_{\tau=1}^{t} g^{stop}_{s\tau}, \qquad s \in S,\ t \in T, \qquad (5.4)$$

$$G_{dstu}\, g^{stop}_{s(t+1)} \geq g^{last}_{dstu}, \qquad d \in D, s \in S,\ t \in T, u \in U, \qquad (5.5)$$

$$\sum_{\tau=1}^{t} g^{start}_{s\tau} \leq 1, \qquad s \in S,\ t \in T, \qquad (5.6)$$

$$\sum_{d\in D} A_{d} l_{dstu} \leq M^{O}_{s}, \qquad s \in S,\ t \in T, u \in U, \qquad (5.7)$$

$$l_{dstu},\ g^{last}_{dstu} \geq 0, \qquad d \in D, s \in S,\ t \in T, u \in U, \qquad (5.8)$$

$$g^{start}_{st},\ g^{stop}_{st} \in \{0, 1\}, \qquad s \in S, t \in T, \qquad (5.9)$$

The total supplier costs are related to outbound unit inventory holding costs per part $d \in D$ that is stored at each supplier $s \in S$, as well as the unit production costs for each part $d \in D$ at each supplier $s \in S$ (5.2). Constraint (5.3) ensure outbound inventory balancing of parts, setting the variables $l_{ds(t-1)}$ to zero when (t-1) < 0. Together with constraint (5.4) it also ensures that suppliers only can produce in the interval between start and stop of production. Further, constraint (5.5) ensures that in the last period of production, g^{last}_{dstu} doesn't exceed how much the supplier can deliver, as well as allowing the suppliers to not have to deliver more parts than is needed in the supply chain.

Constraint (5.6) ensures start and stop of production only can happen once. The inventory capacities for storage of parts are covered in constraints (5.7). Lastly, constraints (5.8) and (5.9) represent the non-negativity and integer constraints for the decision variables.

5.3.3 Producer subset of the model

$$C_{pu} = \sum_{d\in D}\sum_{t\in T}(H^{I}_{dp} l_{dptu}) + \sum_{k\in K}\sum_{t\in T}(H^{O}_{kp} l_{kptu} + C_{kp}\sum_{v\in V} x_{kpvtu}), \quad p \in P, u \in U, \quad (5.10)$$

$$l_{dptu} = l_{dp(t-1)u} + f_{dptu} - \sum_{k\in K}(A_{dk} q_{kptu}), \quad d \in D, p \in P, t \in T, u \in U, \quad (5.11)$$

$$l_{kptu} = l_{kp(t-1)u} - \sum_{v\in V} x_{kpvtu} + q_{kp(t-T_{kpu})u}, \quad k \in K, p \in P, t \in T, u \in U, \quad (5.12)$$

$$\sum_{k\in K} q_{kptu} \le M^{prod}_{p}, \quad p \in P, t \in T, u \in U, \quad (5.13)$$

$$\sum_{d\in D} A_{d} l_{dptu} \le M^{I}_{p}, \quad p \in P, t \in T, u \in U, \quad (5.14)$$

$$\sum_{k\in K} A_{k} l_{kptu} \le M^{O}_{p}, \quad p \in P, t \in T, u \in U, \quad (5.15)$$

$$l_{dptu} \ge 0, \quad d \in D, p \in P, t \in T, u \in U, \quad (5.16)$$

$$l_{kptu} \ge 0, \ integer, \quad k \in K, p \in P, t \in T, u \in U, \quad (5.17)$$

$$f_{dptu} \ge 0,, \quad d \in D, p \in P, t \in T, u \in U, \quad (5.18)$$

$$q_{kptu} \ge 0, \ integer, \quad k \in K, p \in P, t \in T, u \in U, \quad (5.19)$$

The total producer costs are related to inbound unit inventory holding costs per part $d \in D$ that is stored at each producer $p \in P$, as well as the outbound unit inventory holding costs per component $k \in K$ that is stored at each producer $p \in P$ and the unit production costs for each component $k \in K$ at each producer $p \in P$ (5.10). Constraint (5.11) ensures inbound inventory balancing of parts. The variables $l_{ds(t-1)}$ are set to zero when (t-1) < 0. Likewise, constraints (5.12) gives outbound inventory balancing of components. Constraint (5.13) guarantees that the production quantity at each producer does not exceed the production capacity. Further, the inbound inventory capacities for storage of parts are covered in constraints (5.14), and the outbound inventory capacities for storage of components are covered in constraints (5.15). Lastly, constraints (5.16-19) represent the non-negativity and integer constraints for the decision variables.

5.3.4 Port subset of the model

$$C_u^{port} = \sum_{k\in K}\sum_{t\in T} H_k^{port} l_{ktu}^{port}, \qquad u \in U, \quad (5.20)$$

$$l_{ktu}^{port} = l_{k(t-1)u}^{port} + f_{ktu}^{port} - i_{ktu}^{port}, \qquad k \in K, t \in T, u \in U, \quad (5.21)$$

$$\sum_{k\in K} A_k l_{ktu}^{port} \le M^{port}, \qquad t \in T, u \in U, \quad (5.22)$$

$$\sum_{\boldsymbol{\tau}=1}^{t} D_{k\boldsymbol{\tau}} \ge \sum_{\boldsymbol{\tau}=1}^{t} i_{k\boldsymbol{\tau}u}^{port}, \qquad k \in K, t \in T, u \in U, \quad (5.23)$$

$$l_{ktu}^{port} \ge 0, \ integer, \qquad k \in K, t \in T, u \in U, \quad (5.24)$$

$$f_{ktu}^{port} \ge 0, \ integer, \qquad k \in K, t \in T, u \in U, \quad (5.25)$$

$$i_{ktu}^{port} \ge 0, \ integer, \qquad k \in K, t \in T, u \in U, \quad (5.26)$$

The total port costs presented in constraint (5.20) consist of the unit inventory holding costs per component $k \in K$ that are stored in the port. Constraint (5.21) cover the inventory balancing of components in the port. Further, the port's storage capacity is respected in constraint (5.22). Constraint (5.23) ensures that the number of components used in installation doesn't happen before they are demanded by the installation schedule. Lastly, constraints (5.24-26) guarantee non-negativity and integer constraints for the decision variables.

5.3.5 Transportation subset of the model

$$C^{transport} = \sum_{s\in S}\sum_{p\in P}\sum_{v\in V}\sum_{t\in T} C_{spvt}^{book} y_{spvt} + \sum_{p\in P}\sum_{v\in V}\sum_{t\in T} C_{pvt}^{book} y_{pvt}, \quad (5.27)$$

$$f_{dptu} = \sum_{s \in S} \sum_{v \in V} x_{dspv(t-T_{spvtu})u}\ , \qquad d \in D, k \in K, p \in P, t \in T, u \in U, \quad (5.28)$$

$$f^{port}_{ktu} = \sum_{p \in P} \sum_{v \in V} x_{kpv(t-T_{pvtu})u}\ , \qquad k \in K, t \in T, u \in U, \quad (5.29)$$

$$\sum_{d \in D} x_{dspvtu} \leq U_{spv} y_{spvt}\ , \qquad s \in S, p \in P, v \in V, t \in T, u \in U, \quad (5.30)$$

$$\sum_{k \in K} x_{kpvtu} \leq U_{pv} y_{pvt}\ , \qquad p \in P, v \in V, t \in T, u \in U, \quad (5.31)$$

$$\sum_{\boldsymbol{\tau}=t}^{(t+T_{spvtu}+1)} y_{spv\boldsymbol{\tau}} \leq 1\ , \qquad s \in S, p \in P, v \in V, t \in T, u \in U, \quad (5.32)$$

$$\sum_{\boldsymbol{\tau}=t}^{(t+T_{pvtu}+1)} y_{pv\boldsymbol{\tau}} \leq 1\ , \qquad p \in P, v \in V, t \in T, u \in U, \quad (5.33)$$

$$x_{dspvtu} \geq 0, \qquad d \in D, s \in S, p \in P, v \in V, t \in T, u \in U, \quad (5.34)$$

$$x_{kpvtu} \geq 0,\ integer, \qquad k \in K\ p \in P, v \in V, t \in T, u \in U, \quad (5.35)$$

$$f_{dput} \geq 0, \qquad d \in D, p \in P, t \in T, u \in U, \quad (5.36)$$

$$f^{port}_{ktu} \geq 0,\ integer, \qquad k \in K, t \in T,\ u \in U, \quad (5.37)$$

$$y_{spvt} \in \{0, 1\}, \qquad s \in S, p \in P, v \in V, t \in T, \quad (5.38)$$

$$y_{pvt} \in \{0, 1\}, \qquad p \in P, v \in V, t \in T, \quad (5.39)$$

The total transportation costs consist of the transportation booking cost for all vessels from suppliers to producers, as well as the transportation booking cost for all vessels from producers to port (5.27). Constraints (5.28) and (5.29) ensure flow balancing of parts and components in suppliers, producers and port. Further, constraints (5.30) and (5.31) cover the maximum number of parts and components that can be transported by a transportation vessel in one time period. Constraints (5.32) and (5.33) ensure that when a ship is booked it is occupied for the duration of the transportation time including one time period to get back to either supplier or producer, taking measures to stay within the ranges of the time period set when approaching the last periods. Lastly, constraints (5.34)-(5.37) guarantee non-negativity and integer constraints for the relevant decision variables, and constraints (5.38) and constraints (5.39) state the binary variables.

6. Matheuristic

As the model is tested for an increasing number of time periods and several scenarios the complexity of the problem increases as well, making it harder and more time consuming to find satisfactory solutions. This results in Fico Xpress no longer being able to solve the model within a reasonable amount of time. This trend is made evident in Section 7.X. In order to mitigate this complication, and help the model in the process of finding a solution with a small enough optimality gap, a matheuristic has been constructed.

6.1 Heuristic overview

The fundamental idea behind the matheuristic is to create a new problem with lower complexity so that the model runs easier in the first iterations. Then exploit the results the model provides to make better and better estimations for the timing of start and stop of the production. These estimations are used to solve a new problem, where the complexity remains manageable even though the initial measures, that were taken to decrease complexity, are removed step by step. The steps carried out in the matheuristic is shown algorithmically in figure X.

The initial measures taken to aid the solution process of the model is first to relax all the second stage decision variables with an integer domain in the original two-stage stochastic optimization model (line 1 in the algorithm). The second measure taken disregards some of the decision variables from the first stage. To decrease the complexity, the variables deciding the timing of production start at each supplier, g_{st}^{start}, are only created in the first and then every fifth period through the planning horizon. Similarly, the variables that decide the timing of production stop at each supplier, g_{st}^{stop}, are only created in every fifth period (line 2). This measure concerns all suppliers.

Algorithm 1: Matheuristic

1: Relax all second stage decision variables

2: **if t** ~= 1 or **t** mod 5 ~= 0 **then** $g_{st}^{stop} = 0$
if t mod 5 ~= 0 **then** $g_{st}^{stop} = 0$

3: **Solve**

4: **return** t_s^{start} and t_s^{stop}, when $g_{st}^{start} = 1$ and $g_{st}^{stop} = 1$

5: **if t** $>$ (t_s^{start} + 4) **then** $g_{st}^{start} = 0$
if t $<$ (t_s^{start} - 4) **then** $g_{st}^{stop} = 0$

6: **Solve**

7: **return** all values g_{st}^{start}, g_{st}^{stop}, y_{spvt}, y_{pvt}

8: Fix all second stage decision variable to returned values: g_{st}^{start}, g_{st}^{stop}, y_{spvt}, y_{pvt}

9: Remove relaxations on second stage decision variables

10: **Solve**

When the model is run, with the newly introduced modifications (line 3), the model provides values for the first stage decision variables (line 4). These results are assessed and used to determine limited time intervals, each supplier can only start and stop production within the designated and determined intervals (line 5).

To clarify, starting with t_s^{start}, the time period production was set to start at supplier s in the first solution of the model. The determined time interval goes from time period 1 up to and including t_s^{start}, as well the next four periods. The four additional time periods are added since they were not available for selection in the first running of the model. Similarly, using

t_s^{stop}, the time period production was set to stop at supplier s in the first solution of the model. The determined time interval starts four periods before t_s^{stop} and stops at the last time period. This is subsequently done for every supplier in the problem. Since these intervals are dependent on the supplier the limitations are achieved through the means of constraints for each individual supplier. A mathematical formulated example is shown below.

```
forall (s in Suppliers, t in Periods) do
    if s = 1 and t < 14 then
        g_st^start = 0;
    end - if
    if s = 1 and t > 25 then
        g_st^stop = 0;
    end - if
end - do
```

After the model is run with the limited intervals (line 6), the values for the first stage decision variables the solution provides are fixed (line 8). As a reminder this includes production start, g_{st}^{start}, production stop, g_{st}^{stop}, the timing of booked transportation vessels between suppliers and producers, y_{spvt}, as well as between producers and installation port, y_{pvt}. In addition the relaxations on the first stage decision variables are removed (line 9). With the first stage decision variables fixed and the relaxations removed the model is run one last time to obtain the final results (line 10).

7. Computational study

The purpose of the computational study is to test the model presented in Chapter 5, with and without the implementation of the matheuristic presented in Chapter 6. Section 7.1 presents the input data used for testing the model. Section 7.2 presents the testing of the original model without the use of matheuristic, while section 7.3 presents the testing of the model with the matheuristic. Finally, section 7.4 aims to summarize and discuss interesting results, in pursuit of any managerial insight the testing might provide.

The model is implemented in commercial solver FICO Xpress IVE 8.10. All instances were run by a 12th Gen Intel(R) Core(TM) i5-12500H, 2.50 GHz processor and 16,0 GB (15,7 GB usable) RAM.

7.1 Input data

This section aims to describe the input data used in all the test instances used to test the model. The input data is primarily based upon the information and sources provided in Chapter 2. The presented input data covers data related to the parts and components the suppliers and producers provide, time and vessels, costs and scenarios and how uncertainty impresses the different scenarios.

7.1.1 Parts and components

The flow of parts and components in the supply chain is dependent on how many parts each supplier can produce in each period. This number of parts determines how many parts can be transported to producers and is set by the data input. Since an offshore wind turbine consists of thousands of parts, these parts are accumulated so that one part in data input represents several parts in reality. This measure is taken to cope with excessive complexity in the problem, so that other aspects of the problem can be studied more closely. Ultimately, these accumulations are constrained by the most vital and scarce parts that determines the availability of each accumulation of parts.

The data input focuses on the top structure of the wind turbine, which consist of three components: Nacelle, tower and rotor. This focus was set based on the tests conducted. The solver started to struggle when the complexity increased and increasing the number of scenarios was prioritized over increasing the number of components. This is emphasized in section 7.2. The accumulated parts represent the parts needed to produce these three components and ranges in the data input from 3 - 6, corresponding to 1 - 2 accumulations of parts per component. As pointed out in Chapter 2, there are a few dominant suppliers and producers in the market, which suits the nature and size of OWF-projects. Therefore, the number of suppliers and producers both ranges from 1 - 3 in the data input.

The cost of parts and components are based on the price of components described in Chapter 2. A nacelle cost £4 million, a tower cost £700 000 and a rotor cost £1.7 million. The production costs of parts of components ranges from 120 - 1200 in the data input. All costs related to parts and components then sum up to approximately the mentioned cost for the finished components.

7.1.2 Costs

All data input regarding costs represents $1000. The set costs are not always directly derived from real life costs, this is in some cases caused by lack of finding accurate estimates and in other cases a result of the acquired data is not straightforward to implement in the data sets, so some adjustments have been made to create a combined realistic picture of how the costs affect the model. An example is the costs of parts and components that accumulate to the cost of an offshore wind turbine.

In addition to the mentioned cost of parts and components the data input also sets costs for inventory holding, booking of transportation vessels and penalty costs for not meeting the demand of the installation schedule. In pursuit of finding inventory holding costs that reflect a realistic portion of the total cost a calculator was used and estimated that approximately 30% of total costs are inventory holding costs (Shipbob). The inventory holding costs range from 17 - 90 per part or component each period, depending on the size of the part or component in question and where it is stored in the supply chain. The booking costs are mainly set to 100 in the data sets.

As mentioned in Chapter 2 OWF-projects are of a finite nature, with strict contracts. Any disruption or delays that lead to any contract extension may prove very costly. The cost penalty for not delivering components in time to adhere to the installation schedule is set to 1000 to encourage the model to deliver in time. In the last period the penalty cost is set to 10000 to express the cost of any potential contract extension.

7.1.3 Time

The test instances use a time discretization of 1 week. The number of time periods in the data input ranges from 30 - 65. Which corresponds to a 7 - 16 months planning horizon for the projects. The data input sets the number of periods it takes to produce each component at each producer. It also sets the transportation time for every booked vessel in each period both from supplier to producer and from producer to port. The number of time periods differ from scenario to scenario.

7.1.4 Scenarios and uncertainty

The number of scenarios run in the model ranges from 1 - 7. The differences in these scenarios mainly lie in how much disruption and delay that is realized. The uncertainty is rooted in both production and transportation. Both are set by the data input. Downtime in production is represented by setting the available production to 0 for every period when the supplier can't produce parts. The uncertainty regarding transportation time is expressed by making the time it takes to transport parts or components with a transportation vessel to a higher number of periods than what is the standard, which usually is one time period. To make sure the model doesn't cheat by just skipping one time period, the extended transportation time will decrease incrementally by one, each following time period until it is back to standard or another delay occurs. The test instances can contain no disruption or delays, as well as either disruption in production, delay in transportation time or both.

When running multiple scenarios there is always a best case scenario that is weighted 0.5, the rest of the scenarios that introduce uncertainty, are weighted 0.5 divided by the number of scenarios, excluding the best case scenario.

7.1.5 Test instances

This section provides an overview of the test instances run on both with and without the use of the matheuristic in table 7.1 and 7.2, respectively.

Table 7.1: Test instances run on the original model

Test instance	Suppliers	Producers	Parts	Components	Vessels	Periods	Scenarios	Disruption /delay
T1	1	1	3	3	3	30	1	No/No
T2	2	2	6	3	3	30	1	No/No
T3	3	3	6	3	3	30	1	No/No
T4	2	2	6	3	10	30	1	No/No
T5	2	2	6	3	3	30	1	Yes/No
T2S3	2	2	6	3	3	30	3	Yes/No
T6	2	2	6	3	3	65	1	No/No
T6S5	2	2	6	3	3	65	5	Yes/Yes

Table 7.2: Test instances run with matheuristic

Test instance	Suppliers	Producers	Parts	Components	Vessels	Periods	Scenarios	Disruption /delay
T3	3	3	6	3	3	30	1	No/No
T6	2	2	6	3	3	65	1	No/no
T7	2	2	6	3	3	65	1	Yes/Yes
T8	2	2	6	3	3	65	1	No/Yes
T9	2	2	6	3	3	65	1	Yes/No
T6S5	2	2	6	3	3	65	5	Yes/Yes
T6S7	2	2	6	3	3	65	7	Yes/Yes
T6S7_2	2	2	6	3	3	65	7	Yes/Yes
T6S7_3	2	2	6	3	3	65	7	Yes/No
T6S7_4	2	2	6	3	3	65	7	No/Yes

7.2 Original model

All tests are done with a time limit of 3 hours (10800 s). Due to experiencing a tailing off effect in a lot of the test instances there is set a stop criterion that stops the running of the model when the optimality gap dips below 1%. The weights of different scenarios are given by w in parentheses for each scenario. Whether the scenarios are affected by production disruption or delay in transportation is indicated by yes or no in the result table 7.3 and 7.4.

First, the original mathematical model, presented in Chapter 5, is tested. Table 7.3, presents the results of each test instance. As the results show, the model encounters problems fairly quickly. Except for transportation vessels, any increase in dimension in data input increases the computational time significantly. Instance T3 and T6S5 are not solved with an optimality gap smaller than 1% within 3 hours.

Since the results indicate that the number of vessels doesn't affect the solution by a substantial degree and any other increase in dimension increases the solution time, the priority in the next section is to increase the number of scenarios. This priority is made to obtain a greater insight in how the model handels as many different sources of uncertainty as possible.

Table 7.3: Results from test instances run on the original model

Test instance	Components delivered / Demand	Start of production	End of production	Time [s]	Gap (%)	Objective value	Disruption/ delay
T1	66 / 66	$t_1^{start} = 12$	$t_1^{stop} = 20$	1.6	0	112400	No/No
T2	66 / 66	$t_1^{start} = 18$ $t_2^{start} = 12$	$t_1^{stop} = 24$ $t_2^{stop} = 14$	70	0.86	121624	No/No
T3	66 / 66	$t_1^{start} = 14$ $t_2^{start} = 22$ $t_3^{start} = 10$	$t_1^{stop} = 18$ $t_2^{stop} = 26$ $t_3^{stop} = 11$	10800	3.87	119265	No/No
T4	66 / 66	$t_1^{start} = 18$ $t_2^{start} = 12$	$t_1^{stop} = 24$ $t_2^{stop} = 14$	84	0.36	121464	No/No
T5	66 / 66	$t_1^{start} = 12$ $t_2^{start} = 18$	$t_1^{stop} = 14$ $t_2^{stop} = 24$	48	0.37	122014	Yes/No
T2S3	scenario 1: (w = 0.5) 66 / 66 scenario 2: (w = 0.25) 66 / 66 scenario 3: (w = 0.25) 66 / 66	$t_1^{start} = 12$ $t_2^{start} = 18$	$t_1^{stop} = 14$ $t_2^{stop} = 24$	162	0.38	122030	Yes/No

T6	219 / 219	$t_1^{start} = 42$ $t_2^{start} = 19$	$t_1^{stop} = 54$ $t_2^{stop} = 33$	1287	0.96	440362	No/No
T6S5	scenario 1: (w = 0.5) 219 / 219 scenario 2: (w = 0.125) 219 / 219 scenario 3: (w = 0.125) 201 / 219 scenario 4: (w = 0.125) 219 / 219 scenario 5: (w = 0.125) 218 / 219	$t_1^{start} = 48$ $t_2^{start} = 16$	$t_1^{stop} = 54$ $t_2^{stop} = 36$	10800	6.84	478049	Yes/Yes

7.3 Model with heuristic

Table 7.4 shows the results of the test instances run with the use of the matheuristic. This section aims to compare how the matheuristic has changed the model, and research how the different scenarios and uncertainties affect the solution.

Table 7.4: Results from test instances run with the matheuristic

Test instance	Components delivered / Demand	Start of production	End of production	Time [s]	Gap (%)	Objective value	Disruption /delay
T3	66 / 66	$t_1^{start} = 18$ $t_2^{start} = 14$ $t_3^{start} = 10$	$t_1^{stop} = 24$ $t_2^{stop} = 16$ $t_3^{stop} = 11$	1: 13 2: 34 3: 0.2	1: 0.42 2: 0.66 3: 0	118067	No/No
T6	219 / 219	$t_1^{start} = 19$ $t_2^{start} = 36$	$t_1^{stop} = 29$ $t_2^{stop} = 51$	1: 44 2: 55 3: 0.2	1: 0.37 2: 0.32 3: 0	443738	No/No
T7	219 / 219	$t_1^{start} = 43$ $t_2^{start} = 16$	$t_1^{stop} = 54$ $t_2^{stop} = 41$	1: 50 2: 5.5 3: 0.1	1: 0.57 2: 0.93 3: 0	502382.7	Yes/Yes
T8	219 / 219	$t_1^{start} = 34$ $t_2^{start} = 16$	$t_1^{stop} = 50$ $t_2^{stop} = 25$	1: 32 2: 132 3: 0.2	1: 0.23 2: 0.23 3: 0	472078	No/Yes
T9	219 / 219	$t_1^{start} = 16$ $t_2^{start} = 29$	$t_1^{stop} = 31$ $t_2^{stop} = 56$	1: 7 2: 33 3: 0.1	1: 0.77 2: 0.85 3: 0	499498	Yes/No

T6S5	scenario 1: (w = 0.5) 219 / 219 scenario 2: (w = 0.125) 219 / 219 scenario 3: (w = 0.125) 203 / 219 scenario 4: (w = 0.125) 219 / 219 scenario 5: (w = 0.125) 219 / 219	$t_1^{start} = 38$ $t_2^{start} = 15$	$t_1^{stop} = 53$ $t_2^{stop} = 28$	1: 3697 2: 1244 3: 3	1: 0.94 2: 0.65 3: 0	465373	Yes/Yes
T6S7	scenario 1: (w = 0.5) 219 / 219 scenario 2: (w = 0.0833) 219 / 219 scenario 3: (w = 0.0833) 187 / 219 scenario 4: (w = 0.0833) 219 / 219 scenario 5: (w = 0.125) 219 / 219 scenario 6: (w = 0.0833) 216 / 219 scenario 7: (w = 0.0833) 219 / 219	$t_1^{start} = 11$ $t_2^{start} = 44$	$t_1^{stop} = 27$ $t_2^{stop} = 58$	1: 925 2: 1712 3: 3.8	1: 0.68 2: 0.98 3: 0	552139.9	Yes/Yes

T6S7_2	scenario 1: (w = 0.5) 219 / 219 scenario 2: (w = 0.0833) 219 / 219 scenario 3: (w = 0.0833) 212 / 219 scenario 4: (w = 0.0833) 219 / 219 scenario 5: (w = 0.125) 219 / 219 scenario 6: (w = 0.0833) 177 / 219 scenario 7: (w = 0.0833) 219 / 219	$t_1^{start} = 16$ $t_2^{start} = 40$	$t_1^{stop} = 35$ $t_2^{stop} = 52$	1: 2558 2: 10800 3: 4.6	1: 0.66 2: 1.53 3: 0	553988	Yes/Yes
T6S7_3	scenario 1: (w = 0.5) 219 / 219 scenario 2: (w = 0.0833) 219 / 219 scenario 3: (w = 0.0833) 209 / 219 scenario 4: (w = 0.0833) 206 / 219 scenario 5: (w = 0.125) 211 / 219 scenario 6: (w = 0.0833) 216 / 219 scenario 7: (w = 0.0833) 219 / 219	$t_1^{start} = 11$ $t_2^{start} = 30$	$t_1^{stop} = 24$ $t_2^{stop} = 58$	1: 5579 2: 2760 3: 0.4	1: 0.60 2: 0.50 3: 0	689223.8	Yes/No

T6S7_4	scenario 1: (w = 0.5) 219 / 219 scenario 2: (w = 0.0833) 219 / 219 scenario 3: (w = 0.0833) 219 / 219 scenario 4: (w = 0.0833) 219 / 219 scenario 5: (w = 0.125) 219 / 219 scenario 6: (w = 0.0833) 219 / 219 scenario 7: (w = 0.0833) 219 / 219	$t_1^{start} = 30$ $t_2^{start} = 15$	$t_1^{stop} = 49$ $t_2^{stop} = 22$	1: 10800 2: 10800 3: 0.7	1: 1.08 2: 10.6 3: 0	468841.7	No/Yes

7.3.1 The use of the matheuristic compared to the original model

The use of matheuristic creates a new problem that is used to get an estimated solution for the objective function. Some of the test instances are run again with the use of the matheuristic, it may be interesting to compare the optimal solutions from the original model with the estimations acquired with the use of the matheuristic. The instances that are run with both models are T3, T6 and T6S5. First of all, it can be observed that the running time of the model has been reduced substantially, and the gap reaches the stop criterion of 1%.. Although the solution time has been reduced it seems that the matheuristic provides a good estimation of the objective value, as it is very close to the values acquired through the original model while delivering the same number of components to the port. In T6S5 solving with the matheuristic delivered a few more of the components demanded by the installation schedule.

The matheuristic seems to differ some from the original model, in terms of what time periods to start and stop production, but the duration of production seems to be quite similar.

In addition to acquiring good estimations in a substantially reduced solving time, it also allows the model to run a few more scenarios, to obtain a broader picture of how the model deals with uncertainty. Although the test instances indicate that the model starts having more difficulties when reaching seven scenarios, any further increase of scenarios seems unnecessary.

Table 7.5: Original model compared to use of matheuristic

Test instance	Objective value	Start of production	End of production	Solving time (gap%)
T3, original model	119265	$t_1^{start} = 14$ $t_2^{start} = 22$ $t_3^{start} = 10$	$t_1^{stop} = 18$ $t_2^{stop} = 26$ $t_3^{stop} = 11$	10800 (3.87)
T3, with matheuristic	118067	$t_1^{start} = 18$ $t_2^{start} = 14$ $t_3^{start} = 10$	$t_1^{stop} = 24$ $t_2^{stop} = 16$ $t_3^{stop} = 11$	47 (0.42/0.66)
T6, original model	440362	$t_1^{start} = 42$ $t_2^{start} = 19$	$t_1^{stop} = 54$ $t_2^{stop} = 33$	1287 (0.96)
T6, with matheuristic	443738	$t_1^{start} = 19$ $t_2^{start} = 36$	$t_1^{stop} = 29$ $t_2^{stop} = 51$	99.2 (0.37/0.32)

T6S5, original model	478049	t_1^{start} = 48 t_2^{start} = 16	t_1^{stop} = 54 t_2^{stop} = 36	10800 (6.64)
T6S5, with matheuristic	465373	t_1^{start} = 38 t_2^{start} = 15	t_1^{stop} = 53 t_2^{stop} = 28	4944 (0.94/0.65)

7.3.2 The effect of uncertainty in the model

To see how the uncertainty has affected the model. The best case deterministic solution, T6, without any production disruption or transportation delay has to be compared to the other deterministic solutions that do include production disruption and/or transportation delay, T7, T8, T9. All deterministic solutions are also compared to the stochastic test instances with several scenarios that introduce uncertainty.

First the best case instance, T6, is compared to the other deterministic instances. T7 is exposed to production disruption and transportation delay, T8 is exposed to only transportation delay, opposed to T9 that is only exposed to production disruption. It can be observed that in every case the model manages to meet the demand of components, although, in T7, T8 and T9 we can see an increase in total costs when the supply chain is exposed to disruption and delays. There is no clear tendency that the production starts any earlier to cope with any disruption or delay, but an interesting observation is that for the two instances that introduce production disruption the duration of production is higher. T6 and T8 both produce for a total 23 time periods, while T7 and T9 produce for a total of 33 and 40 periods, respectively. This unexpected adaptation could be due to poor scenario generation or mathematical formulation, that leads to production in late periods are advantages under production disruption. Which was not the sought after mechanism, that seeked to enable earlier start to generate buffers of parts and components to cope with the risk of uncertainty and ultimately penalty costs.

When several scenarios are introduced, so are uncertainty. T6S7, T6S7_2, T6S7_3 and T6S7 are all run with seven scenarios. T6S7 and T6S7_2 are both exposed to production disruption and transportation delay, while T6S7_3 is only exposed to production disruption and T6S7_4 is only exposed to transportation delay. For this number of scenarios the solver had a harder time solving the problem within the 3 hour time limit, especially T6S7_4 which had a 10.6% gap. This makes it more challenging to draw definitive conclusions from the test instance.

All the instances with seven scenarios naturally had an increase in total costs compared to, T6, the best case instance. A contributor to this is that several of the instances fail to adhere to the demand of the installation schedule and are therefore penalized by the penalty cost. That, as mentioned, represents the cost of contract extensions. Again, there is no clear tendency that the supplier starts production earlier in order to build up an inventory buffer to cope with production disruption or transportation delay. Yet, the duration of production does increase to 28 and 29 time periods compared to the 23 of the best case instance to, for all instances except T6S7_4. The differences from this instance compared to the others, is that it is only exposed to transportation delay and has a significantly bigger gap for the objective value than the other instances.

7.3.3 Test with fixed first stage variables

It can be difficult to quantify if the two-stage stochastic approach makes the model more robust than by just solving the model deterministically for the best case scenario. An interesting way to try to remedy this is to compare the number of components delivered. More specifically, the delivery of test instances T6, T7, T8 and T9. These are all included as scenarios in test instance T6S7_2. The number of components delivered in the four instances are shown in table 7.4, in column T6S7_2, as scenario 1 (T6), 3 (T7), 6 (T9) and 7 (T8). These values are compared to the values obtained when fixing all first stage decision variables from T6, the best case instance, and run all four scenarios with the fixed variables.The first stage decision variables are the only variables that are assumed to have been set before the project starts. This is done to try to indicate what consequences not taking uncertainty into account will have when setting up the supply chain.

Table 7.6: Comparison of components delivered

Test with	Components delivered / Demand **(with T6 fixed variables)**	Components delivered / Demand **(in T6S7_2)**	Disruption/delay
T6	219 / 219	219 / 219	No/No
T7	168 / 219	212 / 219	Yes/Yes
T8	173 / 219	219 / 219	No/Yes
T9	120 / 219	177 / 219	Yes/No

Table 7.6 shows a clear tendency that the service rate is significantly higher when taking uncertainty into account. Nevertheless, any conclusions must be drawn with caution. This is due to the fact that the scenarios from T6S7_2 are weighted by scenario probability when solved. This can undermine the cost of maintaining such a high number of components delivered under production disruption and transportation delay.

7.4 Summary

To summarize the computational study, the original model started to struggle when the complexity of the problem increased. A matheuristic was developed to remedy the struggles and to enable the model to cope with an increasing number of scenarios. The new model substantially decreased the solving time, while obtaining good estimations, compared to the original model. The new model allowed the number of scenarios to increase, but also started to struggle with the increasing complexity.

It proved difficult to draw definitive conclusions from the results, although there were some tendencies that could be interpreted. It was originally assumed that with the introduction of uncertainty the production at suppliers would start earlier, in order to build up inventory buffers of parts and components to decrease penalty costs of potential disruption or delay. This proved not to be the case. However, under exposure to production disruption the duration of production was prolonged into later time periods of the planning horizon. During a test, with fixed first stage decision variables from the best case scenario and an instance run with several scenarios, compared the number of delivered components. This showed a clear tendency of a higher service level, when several scenarios introducing uncertainty were taken into account. However, it was pointed out, that due to scenario weights, might dilute the one aspect of the trade-off that implies increased inventory holding costs.

8. Concluding Remarks

In this thesis, a mathematical model has been formulated to study an offshore wind farm supply chain optimization problem. The problem is a Multi-Product, Multi-Period (MPMP) supply chain optimization problem under uncertainty and the model is formulated as a two-stage stochastic model. The model contains decisions regarding choice of suppliers and producers of offshore wind turbine parts and components, and when to start and stop production, as well as when to book transportation vessels. Additionally, decisions are made regarding flow and storage of wind turbine parts and components in the supply chain. The decisions are made with the objective to find the minimal total cost of the supply chain network. To mitigate increasing solution time, a matheuristic was developed. A commercial solver has been utilized to solve the model exactly, yielding the results presented in Chapter 7.

The main contribution to the literature was to take uncertainty into account when solving a MPMP supply chain optimization problem for the offshore wind industry. Similar approaches have been developed in general research, but they differ in which capacities and uncertainties were taken into account, as this thesis handles production disruption and delay in transportation. Another aspect that sets this thesis apart from the literature is penalty costs that penalizes any shortcomings of demand installation schedule that could trigger costly contract extensions.

The result did present some tendencies to how uncertainty was dealt with. When exposed to production disruption the production at suppliers did not seem to start earlier, as originally assumed, in order to generate inventory buffers of parts and components to cope with potential disruption and delays. However, the duration of production did continue further into the planning horizon. The results also showed a tendency to have a higher number of components delivered when run with several scenarios, which indicates that the model is more robust when dealing with uncertainty.

As repeatedly mentioned throughout this thesis, there is very little research on the offshore wind farm supply chain. The complexity of the supply chain of the supply chain leaves great potential to improve the chain and reduce costs significantly. These factors, combined with the hold-ups at port mentioned in the introduction, underscore the need and value of offshore wind farm supply chain optimization that can deal with uncertainty.

9. Future Research

For potential future research there are several interesting aspects that could be added and implemented in this model. Namely, increased detail and dimensions in data input and increased efficiency in the solving methods.

The increased dimensions could be:

- including more suppliers and producers into the supply chain to have a wider competitor field.
- increase the number of parts and components to get a better picture of the complexity and all flowing product in the supply chain

The increased detail could be:

- include geographical positions to the suppliers and producers to better evaluate transportation costs and duration

- accumulate and test data from a specific future project
- do more research on how uncertainty is realized and dealt with in the supply chain and add resource actions into the model

To achieve all the mentioned improvements it is vital that the model becomes more efficient. To handle these extensions better heuristics could be developed, to gain valuable insight in a shorter amount of time.

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