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A Heuristic Approach to Creating an Annual Delivery Program for an LNG Producer with Transshipment

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Purpose of Master's Thesis

The purpose of this thesis is to create an Annual Delivery Program (ADP) for an LNG producer and its customers. The ADP describes delivery schedules to customers located in different continents. Due to limited availability of routes from the producer to the customers, the cargo can be delivered either directly or via a transshipment port.

The deliveries are determined based on annual demand stated in long-term contracts. The annual demand must be fulfilled for each long-term customer and is further divided into periodic demand. The periodic demand allows over- and under-deliveries. Both over- and under-delivery are penalized. Excess LNG can be sold in the spot market.

The producer seeks to minimize the costs of operation when fulfilling the long-term contracts. Selling LNG in the spot market can be considered as a negative cost. In addition, inventory constraints are considered at the producer and the transshipment port. The problem of creating an ADP can be categorized as a Maritime Inventory Routing Problem (MIRP).

MIRPs are difficult to solve. So far in the existing literature, similar problems have been solved with exact methods and heuristics. Heuristics are able to solve larger instances and provide good solutions. This thesis therefore focus on heuristics in order to create an ADP.

Preface

This Master's thesis is the concluding work of our Master of Science at the Norwegian University of Science and Technology. Our field of specialization is Managerial Economics and Operations Research at the Department of Industrial Economics and Technology Management.

This thesis was written during the spring semester of 2018 and is a continuation of our specialization work from the fall semester of 2017 (Bugge and Thavarajan, 2017).

We would like to express our deepest gratitude to our supervisors, Peter Schütz and Ruud Egging, for excellent feedback and guidance. We appreciate your sincere enthusiasm towards the thematics in the thesis. The thesis has been written in cooperation with Tieto, and we would like to thank Jørgen Glomvik Rakke for actively contributing with his insights, and Lars Petter Bjørgen for his valuable inputs.

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Abstract

In this thesis, an Annual Delivery Program (ADP) planning problem is studied. The objective of the ADP planning problem is to create a cost-efficient delivery schedule for a liquefied natural gas (LNG) producer, who has a fleet of heterogeneous vessels. The fleet of vessels consists of ice-going vessels and conventional vessels. The LNG producer has entered long-term contracts with customers in different parts of the world, and is committed to fulfill the demands stated in the contracts.

Voyages to the customers are either direct or via a transshipment port. The direct voyages to the customers in Asia depend on the opening periods of the Northern Sea Route. If the NSR is closed, the ice-going vessels travel to the transshipment port to transfer the cargo onto a conventional vessel, which then continues the journey via the Suez Canal. Only ice-going vessels are permitted to use the NSR.

The size of the storage tank at the transshipment port is a challenging factor in the ADP planning problem, and thus partial loading is implemented to avoid a bottleneck caused by residual LNG left in the tank. Partial loading only applies to the ice-going vessels sent from the producer's port, and the filling levels in the vessel tanks are regulated to reduce the effects of sloshing.

The ADP planning problem can be classified as an industrial shipping problem with decision making on a tactical planning level. Relevant literature is presented to illustrate how certain properties of the problem, such as partial loading, is implemented in other works, and how different solution methods have been used to solve LNG inventory routing problems (LNG-IRP). The ADP planning problem is a maritime inventory routing problem (MIRP). MIRPs are numerically complex to solve and usually require heuristic solution methods to produce good solutions.

A mixed integer programming (MIP) formulation of the ADP planning problem is developed based on the aforementioned factors, where partial loading and boil-off considerations are explicitly handled in the model formulation for some of the vessels.

Because of the long planning horizon of the ADP planning problem, a rolling horizon heuristic (RHH) is proposed to solve the problem. Several strategies for the different periods within a sub-horizon are tested to solve the ADP planning problem efficiently. In addition to the RHH, an aggregation and disaggregation heuristic (ADH) is proposed as an alternative approach to solving a reduced size of the problem. The intention behind both methods is to reduce the complexity of the problem during the solution process, by either solving the problem in shorter sub-horizons or by reducing the number of nodes in the network. The solution methods are combined to create an ADP quickly. Results from these solution methods are compared with a solution from a corresponding case solved by exact method.

The RHH obtains the best result for the ADP planning problem. The heuristic improves both the ADP-objective and computational time compared to the exact solution method. When the ADH is combined with the RHH to solve the aggregated case, the computational time can be decreased further. Despite the improved solution time, the RHH-ADH did not improve the solution compared with the exact solution method.

The results show that the performance of the ADH depends on several factors; the chosen aggregation strategy, the solution method used for solving the aggregated case, and the amount of over- and under-deliveries in the solution for the aggregated case.

Sammendrag

Denne masteroppgaven omhandler et årlig leveringsprogram–planleggingsproblem (ADP-planleggingsproblem). Målet med et slikt problem er å lage en kostnadseffektiv leveringsplan for en flytende naturgassprodusent (LNG-produsent) som har en heterogen flåte. Flåten består av isgående skip og konvensjonelle skip. LNG-produsenten har inngått langtidskontrakter med kunder over hele verden, og er forpliktet til å tilfredsstille etterspørselen som er spesifisert i kontraktene.

En sjøreise kan enten gå direkte til kundene eller via en omlastningshavn til kundene. Direkteturer til kunder i Asia avhenger av åpningstidene til den nordlige sjørute (NSR). Dersom NSR er stengt må de isgående skipene reise til omlastningshavnen for å overføre last til konvensjonelle skip. De konvensjonelle skipene fortsetter seilasen til Asia gjennom Suez-kanalen. Det kun er tillatt å bruke isgående skip i NSR.

Størrelsen på lagertanken i omlastningshaven er en utfordring i ADP- planleggingsproblemet. Delvis lasting er innført for å unngå en flaskehals-problematikk som skyldes gjenværende mengder av LNG i lagertanken. Delvis lastning er kun aktuelt for de isgående skipene som seiler mellom produsenten og omlastningshavnen. Selv om skipene kan lastes delvis kreves det at mengden last ombord er over et minimumskrav for å redusere effektene av sloshing.

ADP-planleggingsproblemet kan klassifiseres som et industrielt skipsfartsproblem, med beslutningstaking innenfor en taktisk planleggingshorisont. Relevant litteratur er presentert for å illustrere hvordan visse aspekter av problemet er implementert i annen litteratur. I tillegg er det ønskelig å vise hvordan ulike løsningsmetoder er benyttet for å løse kombinerte LNG lagerstyrings- og ruteplanleggingsproblemer. ADP-planleggingsproblemet er et kombinert maritimt lagerstyrings- og ruteplanleggingsproblem (MIRP). MIRP er numerisk komplekse og krever ofte en heuristisk løsningsmetode for å kunne gi gode løsninger.

Et blandet heltallsprogram er formulert basert på ADP-planleggingsproblemet. Denne formuleringen inkluderer tidligere nevnte faktorer, der delvis lastning og avdamping av LNG er en eksplisitt del av modellformuleringen for noen av skipene.

Grunnet den lange planleggingshorisonten for ADP-planleggingsproblemet er en rullende horisont-heuristikk (RHH) foreslått for å løse problemet. Flere strate-

gier for de ulike periodene innenfor en sub-horisont er testet for å kunne få en effektiv løsningsprosess. I tillegg til RHH, er en aggregering og disaggregeringsheuristikk (ADH) utviklet for å løse en mindre instans av problemet. Intensjonen med begge metodene er å redusere kompleksiteten til problemet, enten ved å løse det i mindre sub-horisonter eller ved å redusere antall noder i nettverket. Løsningsmetodene kombineres for å raskt kunne produsere en ADP. Resultatene fra begge løsningsmetoder sammenliknes med en løsning fra tilsvarende probleminstans løst med eksakt metode.

RHH gir de beste resultatene for ADP-planleggingsproblemet. Heuristikken forbedrer både målfunksjonen til ADP og løsningstiden sammenliknet med eksakt metode. Dersom ADH kombineres med RHH (RHH-ADH) for å løse den aggregerte probleminstansen, kan løsningstiden reduseres ytterligere. Til tross for en forbedret løsningstid gir ikke RHH-ADH en bedre løsningsverdi sammenliknet med den eksakte løsningsmetoden.

Ytelsen til ADH avhenger av flere faktorer; valg av aggregeringsstrategi, løsningsmetode brukt for å løse den aggregerte probleminstansen, og mengden over- og underlevering i løsningen til den aggregerte instansen.

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Chapter 1

Introduction

The demand for liquefied natural gas (LNG) has increased significantly during the past decade. In 2017, global imports peaked at 289.8 million tons (MT) (GIIGNL, 2018). Natural gas is increasingly used as an energy source in electric power and industrial sector, and emits almost half as much CO_2 per unit of energy compared to coal (EIA, 2017a,b). By converting natural gas to liquid state, the volume is reduced by a factor of 1:625, which enables the transportation of large amounts of natural gas more efficiently.

Increasing contribution from the supply side in recent years has motivated buyers to push for more flexibility in existing long-term contracts, such as more frequent re-negotiations on pricing terms, delivery quantities and destination flexibility (Gloystein, 2018). With new participants entering the demand side of the LNG markets, the demand side is becoming increasingly more diverse and complex.

In the capital intensive LNG industry, LNG producers typically enter contracts with a duration of around 20 years to minimize the risks from investment and guarantee return on the investments. But with a growing LNG demand and buyers pushing for more flexibility, the traditional, rigid contracting schemes are now challenged by developments in short-term trades and sales in spot markets. More frequent re-negotiations on contractual terms may further complicate the delivery schedule processes of the LNG producers.

The LNG producers usually plan the deliveries up to a year ahead. The result of the scheduling processes is an Annual Delivery Program (ADP), which is a delivery schedule with a 12 month horizon. Since the producers are responsible for large parts of the value chain, inventory constraints in different parts of the value chain are taken into account during scheduling to minimize idle capacities in the chain Tusiani and Shearer (2007).

The scheduling processes have for a long time been carried out manually, mostly based on experience and industry know-hows. Now that the changes in market dynamics are confronting the traditional industry practices, LNG producers see the monetary benefits in creating delivery schedules to satisfy the customer terms and at the same time, utilize central parts the LNG value chain.

Such a complex task necessitates the development of decision support tools that create optimal delivery schedules with the above-mentioned factors in mind. It it common to create ADPs in-office during contract negotiations, and thus speed and quality are essential for such a decision support tool.

In this Master's thesis, the goal is to develop a decision support tool that creates an ADP for an LNG producer situated in north of the Arctic Circle. Despite the challenging arctic conditions, around 30% of undiscovered natural gas resources are expected to be located within the Arctic Circle, making it an area of interest for LNG producers. Climate changes have lead to a reduction in sea ice levels over the years, thus enabling longer navigation periods along the Northern Sea Route (NSR).

The LNG producer has entered long-term contracts with customers in Europe and Asia. The location of the production facilities enables the opportunity of using the NSR to reach the customers in Asia in a shorter amount of time.

Due to sea ice, navigation in the NSR is subject to strict regulations. This entails that vessels are permitted to sail along the route as long as they fulfill the technical requirements. The producer operates with heavily equipped, costly, ice-going vessels that fulfill these requirements. They are necessary to use along the ice-covered parts of the routes. When the NSR is closed, the ice-going vessels need to use the conventional Suez route to reach the customers in Asia. To avoid using the ice-going vessels more than necessary, the producer has invested in a storage tank at a transshipment port in Europe to transfer cargo onto less expensive, conventional vessels.

The ADP planning problem is an industrial shipping problem with a tactical planning horizon, and falls under the category of maritime inventory routing problems (MIRPs). MIRPs are hard to solve due to the numerical complexity, and existing literature on MIRPs and ADPs solve the problems with the use of exact methods or heuristical approaches. The seasonal availability of NSR, voyages via a transshipment port and large distances between the producer and customers, introduce additional complexity to the ADP planning problem. Therefore, in this Master's thesis, we develop solution methods to improve the computational time of solving the ADP planning problem.

Rolling horizon heuristics have been applied in the existing ADP literature, and are able to solve scheduling problems with long time horizons efficiently. To the extent of our knowledge, aggregation and disaggregation techniques are not widely used in recent MIRP literature. The combination of both solution methods is thus a novel twist to existing solution methods in the ADP literature.

The structure of the Master's thesis is as following: in Chapter 2 several aspects of the LNG industry and the ADP planning problem are described, before reviewing existing literature in Chapter 3. Chapter 4 presents a problem description of the ADP planning problem, which is then formulated as a mathematical model in Chapter 5. The two solution approaches that we use to solve the ADP planning problem are described in 6. Relevant data and case instances are presented in Chapter 7, before presenting the results and a discussion on the different solution methods in Chapter 8. Chapter 9 concludes the study we have carried out, and Chapter 10 presents possible extensions for further research.

Due to a confidentiality agreement between the authors and Tieto, case specific data and information are withheld from the thesis. Even though parts of the case instances and data have been constructed by the authors, these are omitted to avoid any implications.

Chapter 2

Background

Before introducing the ADP planning problem, an introduction to relevant concepts for the problem is presented in this chapter. Most of the information is based on the report by Bugge and Thavarajan (2017) and has been adapted to this thesis. First, the current state of the LNG industry is presented in Chapter 2.1. An overview of the LNG value chain is then presented in Chapter 2.2. Contracts and developments in short-term trade play an important part in the trading aspect and are discussed in Chapter 2.3, before proceeding to ADPs in Chapter 2.4. Lastly, Chapter 2.5 discusses the specific properties of the case and introduces challenges related to the ADP planning problem.

2.1 LNG Market

There is an increasing demand in energy. The U.S. Energy Information Administration (2017) presents an assessment on the developments of the global energy markets based on a reference case with a timespan from 2015 to 2040. During this time horizon, the report expects an increase of 28% in world energy consumption. Renewables turn out to be the fastest growing source of energy, with an increase in global consumption by 2.3% per year. Among the fossil fuels, natural gas is the fastest growing energy source and is projected to increase by 1.4% annually in global consumption. Due to stable long-term economic growth in non-OECD countries, these countries are expected to be the main drivers for the increasing energy demand (EIA, 2017a).

2.1.1 Imports

In 2017, the global LNG imports peaked at 289.8 million tons (MT), a substantial increase from 263.6 MT the previous year. As shown below in Figure 2.1, the Asia-region has a 72.9% market share in global imports in 2017 and is driving the demand growth. Japan remains the leading importer of LNG, contributing with a market share of 28.8% in 2017 (GIIGNL, 2018). China's energy demand is changing. Air pollution is a serious problem in China, and the authorities are trying to reduce the emissions. As of 2017, the Chinese Government imposed strict regulations known as the "2+26"-policy. The policy was enforced in the winter months of 2017 and 2018 and reduced the coal consumption, which is a major energy source in both industrial and private sector (Tremblay, 2017). The country chose to rely more on LNG imports. In fact, GIIGNL (2018) reports an increase in the country's imports by 42.3% in 2017, thus overtaking the position as the second leading importing country of LNG in Asia from South Korea. Since LNG as an energy source has lower CO_2 emissions compared to coal and other fossil fuels, it is not unlikely that the demand for LNG will increase in the future, especially for China (EIA, 2017b). In Europe, the net LNG imports increased by 7.5 MT mainly due to increased demand for power generation (GIIGNL, 2018).

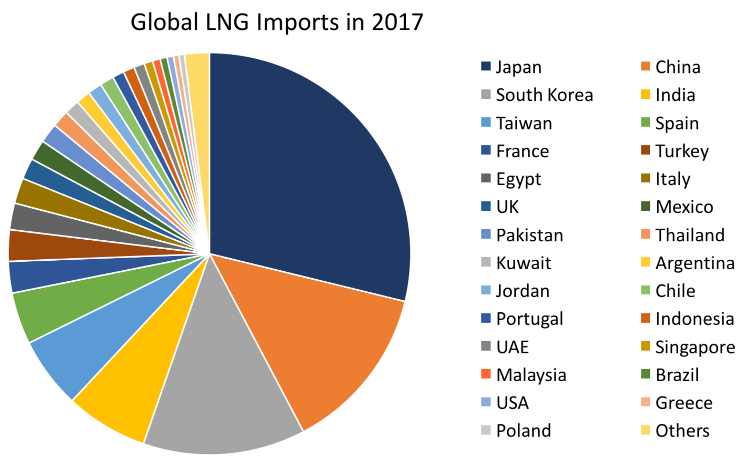

Figure 2.1: Overview of global net imports in 2017. Based on data from GIIGNL (2018).

2.1.2 Exports

GIIGNL (2018) reports 2017 as the year with the strongest supply growth since 2010, with 289.8 MT in global exports. The number of exporting countries increased to 20, and a total of five new onshore liquefaction trains were commissioned in Australia, the US, and Russia. Australia increased the global LNG supply by 10.7 MT, while the US contributed with an additional 9.6 MT. Qatar has been a leading exporter of LNG for several years. In 2017, the country supplied 26.7% of global LNG, compared to 30% from the previous year, due to maintenance. The US has increased its export as a result of new liquefaction plants coming online and supplied 25 countries in 2017, compared to 13 in the previous year. Following the initiations of new projects in 2016, Australia remains the second largest LNG exporter globally, contributing with 55.56 MT in 2017, an increase by 10.7 MT from the previous year. With the initiation of the first of three new trains in Russia, the country stood for 11.49 MT in 2017. The report is expecting an increase in the supply share from the Atlantic Basin, mainly due to the initiation of several projects in the US.

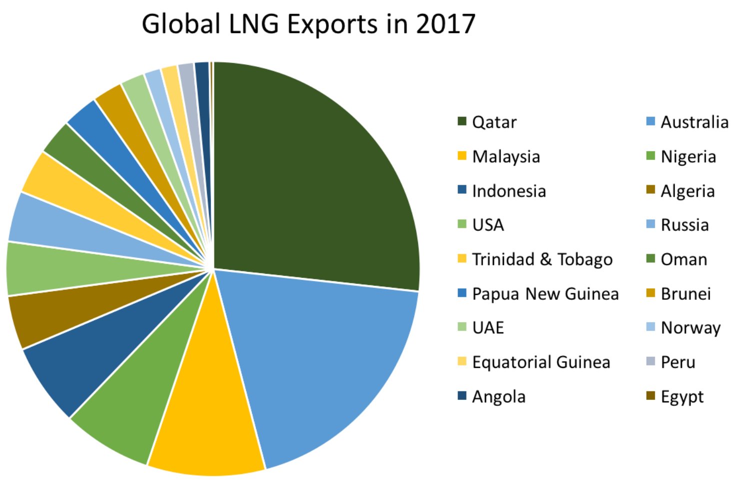

Figure 2.2: Overview of global net exports in 2017. Based on data from GIIGNL (2018).

2.2 Value Chain

The LNG value chain concerns the whole process from the extraction of natural gas in the wells to regasification processes, before reaching the end user. After the gas is produced from the well, it is transported to a process facility (Pettersen, 2016). Here, water and other substances are separated from the gas, before sending the gas into trains where it goes through different purifying processes. A train is the compression facility used to convert the gas to liquid state (Tusiani and Shearer, 2007). After the purification processes, the gas is liquefied, and sent to the storage tanks. From here, LNG is loaded onto LNG vessels and transported to the end user. During the voyage, LNG is stored in tanks that are designed to preserve the temperature of the liquid at $-163°C$. Despite good insulation of the tanks, there is some heat input from the surroundings that leads to boiling and causes evaporation. This is called natural boil-off. The boil-off gas increases the pressure in the tanks and has to be removed in order to keep the pressure stable (Zakaria et al., 2012). The boil-off gas can be handled in several ways, and the most common solution is to use it as fuel for the LNG vessel. The amount of natural boil-off is normally around 0.10% to 0.15% of the ship volume per day (Mokhatab et al., 2014). It is also possible to force some of the LNG to evaporate, in order to decrease the bunker fuel consumption (Dodds, 2014). To preserve the temperature in the tank after delivery, some LNG is left in the vessel (Tusiani and Shearer, 2007).

When the vessel arrives at the destination port, the LNG is converted back to gas in regasification processes. First, short pipelines transfer the LNG from the vessel to a storage tank located at the port. From the storage tank, the LNG is then transported to a regasification system. In this system heat exchangers are used to increase the temperature of the LNG to $0°C$, and the liquid becomes vaporized. The gas is then fed into the transmission system or delivered directly to the end user (Kantharia, 2016).

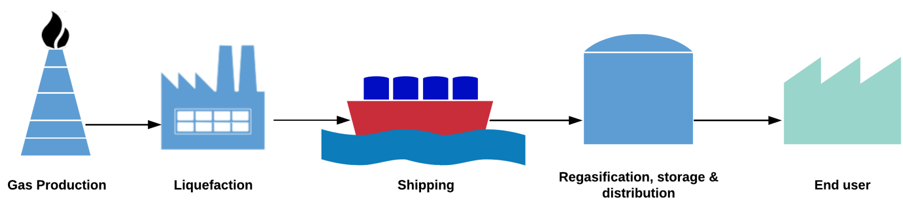

Figure 2.3: The LNG value chain

The liquefying and regasification processes are energy consuming, but by transforming the gas into liquid, the volume of the gas is reduced by a factor of 1:625 (Fredheim and Solbraa, 2016). This makes transportation of LNG easier and makes it possible to deliver to a larger geographical area, compared to transportation of gas through pipelines. An LNG producer invests in large parts of the LNG value chain, since the operations require production facilities, vessels, and receiving terminals. This leads to high investment costs, but the additional transportation costs are lower compared to the cost of pipelines. Therefore, LNG transportation is more profitable than pipelines (Pettersen, 2016).

2.3 Contracts and Trading

The LNG trade has for a long time been characterized by long-term contracts. There are mainly two types of contractual obligations: long-term and short-term. Long-term contracts have a duration of typically 5 to 20 years, while short-term contracts typically last less than 5 years (International Gas Union, 2017). The LNG-business is capital intensive due to high investment costs in facilities, equipment and vessels. By entering long-term contracts, the producers are secured more steady cash-flows in a longer time horizon.

During negotiations, buyer and seller agree on a fixed volume of LNG to be delivered annually, which is specified as an annual contractual quantity (ACQ) in the contracts. However, the deliveries are not always met exactly. Differences in vessel tank capacities and maintenance are examples of how a producer might deviate from the ACQ. ACQs are normally specified as "take-or-pay", which means that the buyer is obligated to pay for the cargo to be delivered even if not taken. So, in the unfortunate case where under-delivery occurs, i.e. due to plant maintenance, the buyer still pays for the shortfall. The producer would then have to deliver the missed volume later or the following year. When over-delivery occurs, for instance as a result of improved plant performance, the contracts normally contain clauses that specify which party has the preferential rights to claim the excess LNG. Over-delivery is profitable for buyer and seller (Tusiani and Shearer, 2007). According to Gloystein (2018), most Asian long-term contracts state the destination of the LNG cargo explicitly, which would prevent Asian buyers from selling LNG, or more specifically excess LNG, to third parties.

2.3.1 Short-term Trading

Sales in spot markets and contracts with short-term commitments have become more common in the past decade and challenge the traditional long-term contracts. Spot markets are characterized by the immediate trade of commodities or "trade on the spot". The price of the commodities is determined by the market. Figure 2.4 shows the global spot and short-term trades in recent years.

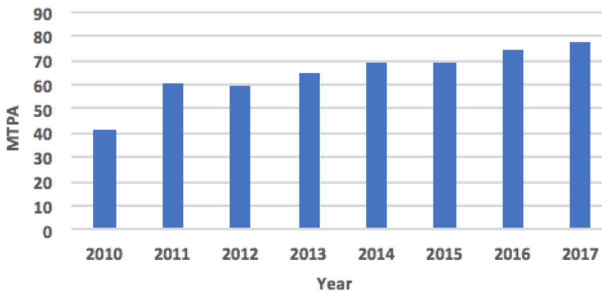

Figure 2.4: Spot and short-term trade in recent years. Volumes given in million tonnes per annum (MTPA). Recreated from GIIGNL (2018).

After the Fukushima crisis in 2011, Japan had to resort to alternative energy sources to fulfill their demand. This led to a substantial increase in spot sales and prices spiked. In 2016, spot contracts accounted for 28% of total LNG imports (GIIGNL, 2017). The average Northeastasian spot price in 2016 was $5.52 per million British thermal units (MMbtu), as a result of decreasing spot prices the first half of the year, followed by a surge upwards in spot prices due to cold weather and supply disruptions (International Gas Union, 2017). International Gas Union (2017) anticipated weakened spot prices in 2017, due to oversupply in the market. However, after a colder than usual winter in 2017 and China resorting to spot purchases at the end of the year, the increase in spot price at the end of the year was stronger than anticipated (GIIGNL, 2018).

Buyers push for more flexibility in the contract terms of existing long-term contracts. The most common clauses subject to re-negotiations are “take-or-pay”, destination, and prices. The ”take-or-pay” clause may become problematic for customers who experience unusually low demand and need to pay for an over-delivery. With fixed destinations in the contracts, customers cannot sell excess LNG to third parties or in a spot market.

Short-term contracting creates opportunities for more frequent re-negotiations compared to long-term contracts. The LNG producers rely on the long-term contracts to invest in the LNG-business, so frequent re-negotiations and more flexible contract terms may become more common in the future long-term contracts.

2.4 Annual Delivery Program

Scheduling is crucial in the trading world. An LNG producer is involved with several parts of the value chain, such as production, loading and vessel routing operations. When an LNG producer enters long-term contracts with different customers around the world, the delivery schedules should be created to take both contract specifications and value chain management into consideration. Failure to optimize the delivery schedules can result in big losses for both producer and customer. Neither party wishes to leave idle capacity unused (Tusiani and Shearer, 2007). This motivates LNG producers to create delivery schedules that take inventory management, loading operations, vessel routing and scheduling, and contract specifications into account.

An ADP is a complete sailing schedule that considers the above-mentioned factors with a planning horizon of typically 12 to 18 months. The ADP is a result of the planning problem the LNG producer faces, and is created with regards to the Annual Contractual Quantities (ACQ) in the long-term contracts. It provides information about every voyage such as the loading location, departure date, arrival date at the customer's terminal and which vessel to use. The initial ADP is created in-office and used during contract negotiations with the customers. If the customers do not accept the suggested delivery dates given by the initial ADP, the plan is adapted until both parties agree on the delivery dates (Rakke et al., 2011). Aside from the contractual obligations, an ADP can be adjusted to include the possibility of selling excess LNG in the spot markets. The ADP planning problem would in this case produce an ADP with suggested departure dates for spot voyages. It is then up to the decision maker to decide whether the suggested spot sales should take place or not.

2.5 Arctic LNG

The problem described in this paper concerns an LNG producer located north of the Arctic Circle. The upstream part of the LNG value chain is here challenged by harsh climate conditions most of the year and restricted transportation opportunities, which in turn lead to high transportation costs. Despite these challenges, around 30% of undiscovered natural gas resources are expected to be located in the Arctic Circle, making it an area of interest for LNG producers (EIA, 2012).

The climate change during the past decades has decreased the level of sea ice in the Arctic. This enables the possibility of using the Northern Sea Route (NSR) to reach customers in Asia quicker and more cost-efficient compared to using the conventional routes via the Suez Canal (Schøyen and Bråthen, 2011). In order to transport LNG from the Arctic to customers, LNG carriers specially designed to handle the Arctic ice waters, known as ice-going vessels, pick up LNG at the production port. Depending on the ice conditions, the vessels are able to use NSR from the producer to customers in Asia. When the NSR is closed, the LNG producer needs to use the conventional route.

Ice-going vessels are expensive to operate. Therefore, the producer has chosen to use transshipment to transfer the cargo onto a less expensive vessel when the ice-going vessel is no longer needed. The ice-going vessels travel to a transshipment port in Europe and unload the cargo into a storage tank. The cargo is then picked up by a chartered conventional vessel and continues the voyage to the customer.

2.5.1 The Northern Sea Route and Vessels

The Northern Sea Route (NSR) is located in the Arctic waters and is part of the Northeast Passage, as shown in Figure 2.5. The NSR is approximately 4.800 km long, and is 40% shorter than the conventional route through the Suez Canal. The route is covered by sea ice most of the year, so the possibility of using the NSR is subject to seasonality. The time windows denoting when the route is open depends on the prevailing ice conditions, and may vary from year to year. From the second half of November to the beginning to July, the ice conditions are usually bad and the route is hence closed (CHNL, 2018d).

Navigation in the NSR is controlled by the Northern Sea Route Administration (NSRA), which is under the jurisdiction of the Russian Government. To ensure safe navigation, strict regulations are imposed upon the vessels that travel in sea ice. Vessels are permitted to navigate the route as long as they fulfill the technical requirements.

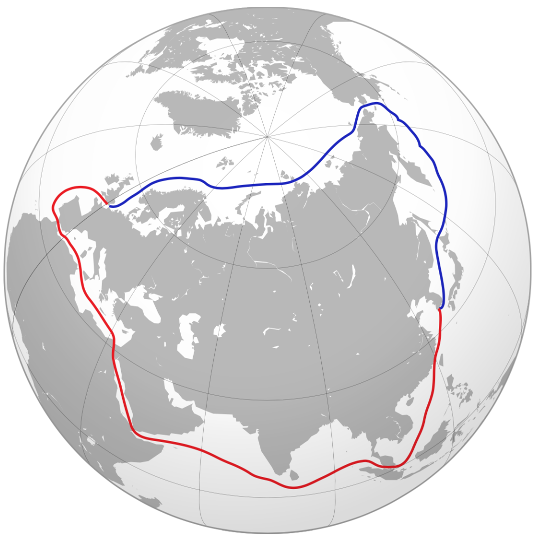

Figure 2.5: The red route shows the conventional route, while the blue shows the Northeast Passage. The NSR is part of the blue route. By Collin Knopp-Schwyn and Turkish Flame, CC BY 4.0, https://commons.wikimedia.org/w/index.php?curid=7865628. Downloaded 14.05.2018

According to the guidelines of the NSRA, only vessels that have a specific ice class (or higher) are permitted to travel the NSR. An ice class denotes technical characteristics that a vessel should possess when traveling in sea ice, such as strengthened hull. The higher the ice class, the more heavily equipped and more qualified it is to handle tough sea ice conditions. The ice-going vessels we consider in this thesis are built according to two different ice classes. Vessels of the highest ice class are permitted to use the NSR in the whole opening period, while vessels of the lower ice class have a shorter navigation period. The latter is also required to use icebreaker convoys when the ice conditions are at the worst when NSR is open. This does not apply to the vessels with the highest ice class, since they are built based on a double acting concept. The double acting concept enable the ship to use astern movement to break the sea ice when the ice conditions are challenging.

2.5.2 Storage Limitations at the Transshipment Port

The vessels that are sent from the production port are ice-going and have high operational costs. They are only needed in parts of the route that are covered by ice, since conventional vessels are unable to handle these conditions. Therefore, the LNG producer is using transshipment as a way to cut operational costs by switching to a conventional vessel when the ice-going vessel is no longer needed. As of now, the current practice is ship-to-ship (STS) transfers, but transshipment is going to replace STS soon. The producer has invested in a storage tank at a transshipment port in Europe for this purpose (J. G. Rakke, personal communication, May 15th, 2018). The size of the storage tank is roughly equal to the size of one of the largest icebreakers in the global LNG fleet. During transshipment, the arriving icebreaker unloads the cargo into the storage tank. This is later picked up by a conventional vessel and transported to a customer. The common industry practice is to fully load and unload a vessel. If the capacities of the ice-going vessels and conventional vessels differ, there might be some residual left in the storage tank after a while.

If the residual is large enough to prevent unloading a full ship load, and too small to be loaded onto a conventional vessel, the producer might unload the ship load partially. This implies that the vessel is fully loaded at the production port and unloads enough to fill the storage tank at the transshipment port up to maximum capacity. The vessel then travels back to the production port with a partially loaded tank, and pick up LNG to refill the vessel tank fully. The vessel would then be rerouted to a new destination (J. G. Rakke, personal communication, May 15th, 2018).

Partial ship loads introduce a technical challenge for the vessel tanks. Partial ship loads increase the risk of sloshing in the vessel cargo tanks. Sloshing occurs because of increased fluid movement inside the tanks, which creates high impact pressure on the tank surface (DNV GL AS, 2016). When the filling levels are more than 70 percent or less than 10 percent of the tank volume during a voyage, the sloshing impact may damage the structure of the tanks (Kuo et al., 2009). The producer might in this case risk to have an amount of cargo on the return trip that could increase the sloshing impact. The producer would in this case only unload enough to avoid a considerate sloshing risk.

Chapter 3

Literature Review

In this chapter, we present an overview of existing literature within maritime transportation and LNG inventory routing problems (LNG-IRP). The general classifications within maritime transportation problems are first presented in Section 3.1 and 3.2, before introducing LNG-IRPs. Section 3.4 presents split-deliveries in industrial shipping problems, and how the sloshing risk is handled in the LNG-IRPs. Since we use heuristics to solve the Annual Delivery Program (ADP) planning problem, Section 3.6 presents literature that use rolling horizon approaches to solve similar scheduling problems.

For a comprehensive review on maritime transportation problems, see Christiansen et al. (2007).

3.1 Shipping Modes

The literature on maritime transportation problems commonly categorize the problems according to the following modes of operations: liner, tramp or industrial (Lawrence, 1972).

Within liner shipping, the operations depend on published schedules, where voyages are planned by fixing vessels to routes, just like a bus schedule. The liner operator usually controls the fleet of vessels. In tramp shipping, the operator controls a fleet of vessels and picks up and delivers available cargos, similar to taxi services. Unlike the two former modes, the operator in industrial shipping controls both the fleet of vessels and cargo. Industrial operators are usually manufacturers that ship materials from a production area to a consumption area. They normally seek to minimize the costs of operations, which is different from liner and tramp operators, who usually seek to maximize profits (Christiansen et al., 2007).

A maritime transportation problem may have characteristics from several modes of operations, so this categorization is not necessarily strict. The ADP planning problem in this thesis bears resemblance to the industrial case the most. The operator is an LNG producer who owns a heterogeneous fleet of vessels used to ship LNG to long-term customers, and seeks to minimize the operational costs.

Hence for the remainder of this chapter, only literature concerning industrial operations is described.

3.2 Planning Levels

The literature on maritime transportation may further be classified according to planning levels. Each planning level deals with decision making in different time horizons. Christiansen et al. (2007) use a general classification of planning levels, where the planning horizon considered in maritime problems indicates whether the problems are strategic, tactical or operational. Note that decisions made on a planning level can create implications for the business on the other levels. For the ADP planning problem, the literature on tactical planning level is the most relevant, and hence there is less emphasis on the two other levels. We briefly describe problems on a strategic or operational level to highlight the diversity of the planning problems that exists in the LNG value chain.

The strategic planning level address decision making that create long-term implications on the business, with a time horizon commonly from 15 years and above. Fleet size and mix problems and contract analysis are typical examples of problems with a strategic time horizon. In a fleet size and mix problem, the decision maker seeks to determine the optimal fleet for the operations. This usually entails an extension or reduction of the existing fleet of vessels, and rarely an investment of a new fleet of vessels. In a contract analysis problem, the negotiable terms in a potential contract are analyzed, and based on this, the aim is to determine whether the decision maker should accept or decline the contract. Recall from Section 2.3 that the LNG industry is capital intensive and LNG producers typically enter long-term contracts with a time horizon of 20-30 years. In the context of the LNG value chain, the two planning problems mentioned so far can be interconnected, in the sense that the expiry or acceptance of new long-term contracts might lead to an adjustment of the existing fleet of vessels.

The decisions made on the operational level have a short-term impact on the business. Christiansen et al. (2007) and Christiansen et al. (2013) provide an overview of common operational problems encountered in a maritime setting and discuss these in depth. Disruption management, speed selection, operational scheduling and booking of single orders are examples of typical short-term decisions. Within the context of the LNG industry, a typical short-term decision is to re-route a voyage to the spot market. These decisions are usually made three to four months in advance (Rakke et al., 2011).

Problems on a tactical planning level concern decision making on a medium-term basis, usually around a year or two. Routing and scheduling problems normally fall into this category. Routing problems deal with the assignment of port sequences for a fleet of vessels, while scheduling adds temporal aspects to the problems. Within industrial shipping, it is not uncommon to take inventory management into account when scheduling. Problems that combine the routing and scheduling aspect with inventory management in maritime transportation, are known as Maritime Inventory Routing Problems (MIRP). MIRPs have been studied extensively in the past decade and are numerically complex to solve with exact methods. Hence, the focus has been on developing heuristics or other tailor-made approaches to solve the problems. For a more in-depth discussion on MIRPs, we recommend the comprehensive reviews by Christiansen et al. (2013) and Christiansen et al. (2007).

The LNG producer is committed to make deliveries based on the contractual terms, in addition to managing large parts of the LNG value chain. The routing and scheduling problems that take these aspects into account are referred to as LNG inventory routing problems (LNG-IRP) and fall into the category of MIRPs.

Goel et al. (2012) address an LNG-IRP problem, which is formulated as an integer multi-commodity network flow problem. The problem shares similar characteristics to our ADP planning problem, such as seasonal travel times, heterogeneous fleet of vessels, inventory constraints at the producer's, and restricted berth capacity. Additionally, inventory management at the customers is considered. The authors develop a Large Neighborhood Search (LNS) to find good solutions fast. The LNS consists of three components: a construction heuristic, a time window improvement heuristic and a two-ship improvement heuristic. Based on the results, the authors consider the proposed solution method to be computationally efficient.

Shao et al. (2015) attempts to improve the solutions from the abovementioned problem, by developing a hybrid heuristic strategy. The construction heuristic is created based on a greedy randomized adaptive search procedure (GRASP) and a rolling time horizon approach, while the improvement heuristic consists of a suite of singleton swaps. The hybrid heuristic strategy finds better solutions for the problem instances, compared to Goel et al. (2012).

Based on the discussions on shipping modes and planning levels so far, we can categorize our ADP planning problem as an industrial shipping problem, with decision making on a tactical planning level.

3.3 Annual Delivery Program

Unlike the LNG-IRPs discussed so far, the planning horizon of the ADPs are much longer. The distinction between the two problem types is not necessarily strict. In the literature, the ADP planning problems specifically deal with a tactical planning horizon, whereas the LNG-IRPs consider a shorter time horizon, but decision making on a tactical level. In a way, ADPs fall under the category of LNG-IRP, but schedules for a longer time horizon. Most of the ADPs discussed in this section are quite similar to the ADP planning problem in this thesis.

Halvorsen-Weare and Fagerholt (2013) are the first in the literature to solve an ADP planning problem. Unlike our ADP planning problem, there are no revenues associated with spot sales. The authors argue that spot sales should only take place to control the inventory levels. They first formulate the problem as an arc-flow formulation, before decomposing it into a feasibility scheduling problem and routing subproblems. The routing subproblems are solved with branch-and-bound. For the real-life instances, branch-and-bound is unable to solve the subproblems, and hence a multi start search heuristic is used.

In Halvorsen-Weare et al. (2013), a cargo-based approach to the ADP planning problem described above is presented. With this formulation, the authors argue that the instances used for comparison are solved to optimality within a CPU time of 30 minutes, while the arc-flow formulation in Halvorsen-Weare and Fagerholt (2013) can only solve small instances. Uncertainty in the daily production rates and sailing times is introduced to the problem. The authors develop a simulation with a re-course procedure to test four different robustness strategies. Different from our problem, no penalty costs incur in case of deviations in deliveries. Instead, the authors implement hard constraints with time windows to enforce the delivery dates.

Stålhane et al. (2012), Rakke et al. (2012) and Andersson et al. (2015) all study the same ADP planning problem, but develops different of solution methods to effectively create an ADP for one of the largest LNG producers in the world. The objective is to create an ADP that minimizes the costs from fulfilling the long-term contracts, while maximizing the revenue from spot sales. The deviations from contractual demands are punished in the objective. In Stålhane et al. (2012) a multi-start local search heuristic is created and performs well on large case instances. While our ADP planning problem penalizes over- and under-deliveries, Stålhane et al. (2012) only penalize the under-deliveries. Rakke et al. (2012) formulate the problem based on delivery patterns and use a branch-and-price approach to solve it. Symmetry breaking constraints and three types of valid inequalities are added to the formulation to remove symmetric solutions and strengthen the LP-relaxation respectively. The delivery inequalities cut off partial deliveries in the LP-relaxation, the loading inequalities limit the number of loading processes in a given time interval, while the timing inequalities prevent vessels from departing with partial loads.

The authors report better lower bounds than in Stålhane et al. (2012). Andersson et al. (2015) use the inequalities in their branch-and-cut method to improve the lower bounds.

The ADP planning problems mentioned so far do not incorporate partial loading or split-delivery. In the next section, industrial problems that deal with partially filled tanks are presented.

3.4 Partial Loading

The ADP planning problem in this thesis incorporates partial loading for the voyages from the producer's port to the transshipment port. Due to the occurence of a bottleneck at the transshipment storage tank, Bugge and Thavarajan (2017) are not able to solve the ADP planning problem for the whole planning horizon. Thus, in this thesis we implement partial loading to solve the inventory bottleneck. Some of the literature on LNG-IRPs implement split-deliveries and deal with partial filling levels. If there is a considerable difference between the customer demands and the vessel capacities, split-delivery can used as a way of avoiding substantial over- and under-deliveries. We first present split-delivery as an extension to industrial shipping problems in general, before LNG-IRPs with split-delivery are introduced. The underlying assumption for the LNG-IRPs with split-deliveries is that the vessels have several distinct cargo tanks, so that individual cargo tanks can be fully unloaded as a split-delivery. This is an attempt to minimize the sloshing risk with partial filling levels.

In Christiansen (1999), an inventory pickup and delivery problem with time windows (IPDPTW) is described. Since the problem takes inventory management into account, it resembles a MIRP. The IPDPTW concerns an ammonia producer that transports a single product type between the production port and different consumption ports. The loading quantities can vary, and cargo may be split among different consumption ports during a single voyage, which is a split-delivery extention. Christiansen (1999) decomposes the problem and solves the decomposed model with Dantzig-Wolfe. Due to the complexity of the problem, the solution method is only able to solve small case instances.

In Lee and Kim (2015) an industrial ship routing problem with split delivery is solved with the use of an adaptive large neighborhood search (ALNS) heuristic. The problem concerns a steel manufacturing company that ships different types of cargo from the multiple supplier ports to a set of delivery ports. Each cargo has a time window for pick-up and delivery. Split loading of a cargo is possible, as long as the time windows of the cargo at the pickup and delivery port is not violated. Tramp ships are chartered for spot sales. The authors argue that split delivery is necessary for this problem due to demands being larger than the vessel capacities. Local search heuristics are applied to reduce the number of tramp vessels chartered, and to merge unnecessarily split cargos given by an initial solution. The solution framework produces near optimal solutions on the data instances, but the computational time remains an area of improvement. Unlike the problem described above, inventory levels are not taken into consideration.

Grønhaug and Christiansen (2009) are the first to study an LNG-IRP in the literature and formulate both arc-flow and path-flow formulations. A path denotes a geographical route and schedule for a vessel. The path incorporates ship inventory management, boil-off and the amount of cargo picked up and unloaded at ports. The problem bears some similarities to our ADP planning problem, but considers additional parts of the LNG value chain, such as determining the LNG production volumes and the level of demand fulfillment. The planning horizon is two months, which is much shorter than the planning horizon of our ADP planning problem. Since the vessels in their problem have several cargo tanks, split delivery is permitted, as long as only whole cargo tanks are unloaded. These characteristics makes the LNG-IRP complex to solve. The authors use branch-and-bound as a solution method, but because of the complexity of the problem, only small problem instances are solved. The arc-flow formulation finds the initial solution faster than the path-flow formulation, while the path-flow formulation solves the instances faster.

Grønhaug et al. (2010) solve a similar LNG-IRP with split-deliveries, but this time, with Branch-and-Price. The problem is decomposed into a master problem that handles inventory routing, and subproblems that handle the ports and ships. Dynamic programming is used to solve the subproblems. This solution method yields better solutions than the approach by Grønhaug and Christiansen (2009).

Mutlu et al. (2016) implement split-delivery in their ADP planning problem and aim to develop a comprehensive ADP for an LNG producer. The authors argue that incorporating split-deliveries leads to substantial cost reductions in the upstream LNG supply chain, and their results strengthen their claim. They further use the guidelines by the American Bureau of Shipping to regulate the filling levels in order to minimize the sloshing risks. Since commercial solvers cannot provide a feasible solution to the real-life instances, a vessel routing heuristic is created to construct multiple solutions that can be improved with the use of commercial solvers. Similarly to Halvorsen-Weare and Fagerholt (2013), spot revenues are excluded from the objective, since the purpose of spot sales in this problem is to control the inventory levels. Contractual deviations are handled in the objective, where a penalty cost incurs for every under- or over-delivery. For deliveries made outside of a specified delivery time window, a piece-wise increasing penalty cost incurs. Furthermore, valid inequalities are added to the formulation to reduce binary flow variables, making this ADP planning problem possibly the most comprehensive in the ADP-literature so far.

3.5 Transshipment

The literature on transshipment in industrial maritime transportation problems is scarce. To the extent of our knowledge, we are only aware of one paper addressing a MIRP with transshipment. None of the ADPs and LNG-IRPs mentioned so far includes transshipment, and thus our thesis contributes with the aspect of transshipment in LNG inventory routing problems.

Shen et al. (2011) consider a distributor who ships crude oil from a supply center to several customers. The objective is to determine the numbers of tankers to rent, number of tankers to dispatch on each route, and quantity of crude oil through the pipelines. The problem is complex due to the inclusion of both pipelines and tankers, multiple routes, and several transshipment ports. Like our ADP planning problem, the planning horizon considered is 12 months. The distributor controls the inventory levels at the transshipment ports and at the customer ports. The authors solve the problem with the combination of Lagrangian relaxation and a rolling horizon approach, and finds good solutions. They also solve a variant of the original model that includes partial loading for voyages to the transshipment ports, in the cases where the capacity of the storage tanks is limiting. The heuristic performs better when solving the partial ship load variant compared to the original problem with full ship loads, due to flexibility in cargo sizes. Unlike our ADP planning problem, they do not take any sloshing risk into consideration when formulating the partial load variant.

3.6 Solution Methods

Rolling horizon heuristics (RHH) are widely used to solve scheduling problems in the literature. The concept of RHH is to solve a planning problem in sub-horizons, and iteratively re-optimize when new information becomes available. For planning problems with long time horizons, this method might provide some computational efficiency.

Mercé and Fontan (2003) use a RHH approach to solve a multi-item capacitated lot sizing problem. Two variants of the RHH is developed, which differ in the choice of freezing strategies. The first freezes all of the decisions made in the central period, while the second only freezes the production periods and not the production quantities. The second variant yields better solutions than the first, due to a significant reduction in the number of binary variables and computational time. Even though the problem is not in a maritime setting, the choice of freezing strategies is highly relevant for the rolling horizon heuristic we develop.

Rakke et al. (2011) solves their ADP planning problem with a rolling horizon approach. In order to keep the computational time within reasonable limits, they set the length of the central period to one month, while the length of the forecast period is set to two months. The freezing strategy involves freezing all the decisions that are made in the central period, as a way of reducing the size of the problem. In the forecast period, the binary variables are relaxed to reduce computational effort, in exchange for reduced information from the forecast period. Due to the size of the problem, the authors argue that the length of the forecast period should stay minimal. They point out that the length, at the same time, should be long enough to let the decisions at the central period be affected by the forecast decisions and to let the forecast decisions be affected by the central period. Deviations are penalized on a monthly and annual basis. Since the deliveries might deviate from the monthly demands due to differences in vessel capacities in the fleet, the deviations from the previous central period are transferred to the new central period. This way the the future demands are adjusted so that they depend on previously made decisions. While our ADP planning problem penalizes deviations monthly and annually, Rakke et al. (2011) penalize monthly deviations and deviations per time window. On top of the RHH, a mixed integer programming (MIP) based improvement heuristic is used to identify improving solutions and further explore the solution space of the whole horizon. Their results show that the RHH yields high quality solutions for real-world instances.

Another approach to reduce the size of the problem is aggregation and disaggregation (AD). Rogers et al. (1991) presents a review on AD techniques used in the optimization literature and develops a general framework for AD. These concepts are used to develop a heuristic solution method for the ADP planning problem in this thesis.

Chapter 4

Problem Description

In this chapter, we present a description of the Annual Delivery Program (ADP) planning problem for a Liquefied Natural Gas (LNG) producer. The output generated by the ADP planning problem is a delivery schedule that takes demand fulfillment, and berth, inventory and routing constraints into account. First, the general specifics on creating the ADP is presented in Section 4.1. The more case specific parts of the problem are then considered in Section 4.2 and 4.3.

4.1 The ADP Planning Problem

The objective of the problem in this thesis is to create an ADP that minimizes the operational costs for an LNG producer. The ADP is an annual delivery schedule for one year with a time resolution of a day. It suggests departure days, which vessels to send, and pickup and delivery points for the whole planning horizon. The relevant costs to consider when creating the ADP are traveling costs, penalty costs for deviations from contractual demands, and revenue from selling excess LNG in the spot marked. The latter is considered as a negative cost. The traveling costs include variable costs such as crew and vessel charter costs, and fixed costs such as the Suez Canal fee and icebreaker support.

The LNG producer is committed to deliver the amount of LNG stated in the contracts with long-term customers. This is usually specified as an annual demand, which can be divided into monthly demands. Based on the contracts, the target deliveries are distributed on a monthly basis throughout the planning horizon, and thus deliveries are planned for each month.

There is some flexibility in the delivery volumes for each time interval, but the flexibility comes at a cost. When the LNG producer deviates from the contractual demand on a monthly or annual basis, the producer is subject to pay a penalty fee.

Annual deviations are penalized differently from monthly deviations, where the latter is penalized with a constant unit cost. If the producer deviates less than a shipload for the whole planning horizon, a small unit penalty cost is imposed upon the annual deviation volume. However, if the annual deviation volume surpasses a shipload, the unit penalty fee increases tremendously. This is shown in Figure 4.1. It is more undesirable for long-term customers to receive an under-delivery rather than an over-delivery, and consequently the unit penalty fee for an under-delivery is higher than an over-delivery.

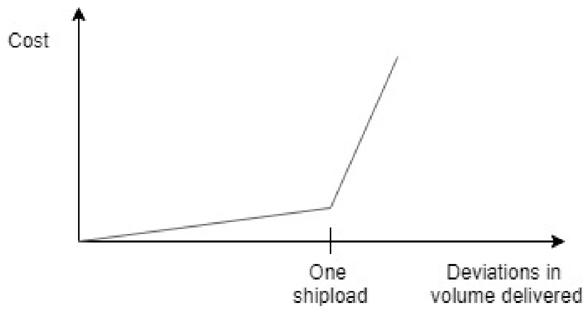

Figure 4.1: Penalty costs as a function of deviations in volume.

There is an estimated production rate at the liquefaction plant, which is given as a daily rate. For the whole planning horizon, the annual production might be larger than the sum of annual demands the producer has committed to fulfill. This results in excess LNG that can be sold in the spot markets. We assume that the unit price for LNG sold in spot markets is known when creating the ADP.

Close by the producer's port, there are several storage tanks with capacity limits that store the produced LNG. LNG is loaded onto vessels from these tanks, and then transported from the producer's port to a set of customers located in Europe and Asia. Every long-term customer is connected to a port, where the delivery of cargo takes place. The loading and unloading processes between vessel and port are estimated to one day. The producer has the opportunity to transship the cargo at a transshipment port. In order to transfer the cargo onto another vessel, a storage tank is used. The capacity of this storage tank is also limited. In addition to transshipment, the port also functions as a delivery point for customers. Thus, when cargo is unloaded at the transshipment port, it is either stored in the tank or delivered directly to a customer.

Every customer port has one or multiple storage tanks. The capacity limits of these tanks are not considered in this problem and are assumed to be non-limiting for the ADP scheduling. At the producer's port and the transshipment port, there is only one berth available for use, and therefore only one vessel may dock at a time. The berth availability at the customers' ports are assumed to be non-limiting as well.

4.2 Seasonal Routes and Vessels

The producer operates with a heterogeneous fleet of vessels. The vessels differ when it comes to the following characteristics: capacity, sailing speed and operational costs. There are three main types of vessels, which are referred to as type A, type B and type C. Vessels of type A and B are ice-going vessels and vessels within either category are homogeneous. Vessels of type A and B are sent from the production port and travel either to the transshipment port or directly to customers. Vessels of type B can only be used when the Northern Sea Route (NSR) is open. During the toughest conditions when NSR is open, vessels of type B are required to use icebreaker support, which imposes a fixed icebreaker support fee per transit. Vessel availability is shown in Figure 4.2 below. Considering that ice-going vessels are equipped to travel in sea ice, only these can use the NSR when it is open. They are consequently also more expensive to operate. Vessels of type C are conventional vessels and are chartered to pick up cargo from the storage tank at the transshipment port and transport the volumes to the customer ports. A vessel of type C is always available when needed. The fleet of conventional vessels is heterogeneous and can be used the whole year.

There may be different routes to use from the producer to a customer. It is possible to travel using a direct route from the production port to a customer, but this depends on the location of the customer and time of the year. Customers located in Europe can be reached directly any time of the year. For customers located in Asia, this is not the case. The direct route used to reach them is called the Northern Sea Route (NSR). Due to the ice conditions along the route that vary seasonally, the NSR can only be used at certain times of the year. When the NSR is closed, the producer has no other option but to send the vessels via Europe and use the conventional Suez route. A voyage along the NSR must be finished before the route closes.

Due to sea ice along the first part of the conventional route from the production port, ice-going vessels have to be used. But when the vessels reach the ice-free parts of the route, they are no longer needed. Consequently, the producer prefers not to use these vessels the whole distance, and uses transshipment at the transshipment port located in Europe. Here, a less expensive vessel picks up the cargo from the storage tank and continues the voyage to the customer port. It is also possible to use transshipment for voyages to customers in Europe. The routes are summarized below in Figure 4.2.

We assume that traveling times between the ports are known. The traveling times vary depending on departure month and vessel type. Traveling time is determined on the day of departure.

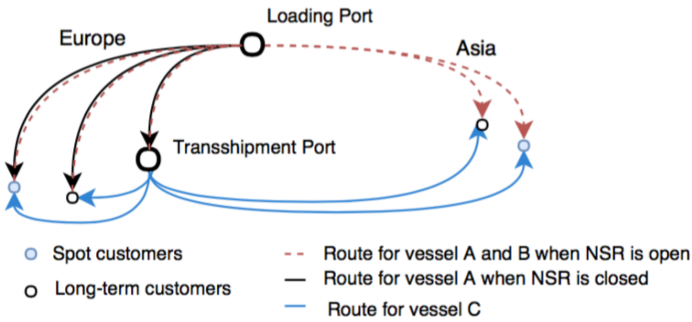

Figure 4.2: The figure shows the different routes from the producer's port, and which vessels that may use which route.

4.3 LNG Cargo and Partial Loading

4.3.1 Boil-off

When an LNG vessel has embarked on a voyage, the cargo is reduced daily with a fixed natural boil-off rate. This means that the amount of cargo picked up differs from the amount of cargo unloaded at a port. For vessels of type A and B, both natural and forced boil-off occur. The latter is a fixed amount of LNG from the tanks that is purposely "forced" to use as fuel. Since the vessels are in dock during loading and unloading processes, the forced boil-off amount is lower than during sailing. Cargo transported by vessels of type C are only subject to a fixed daily natural boil-off rate.

4.3.2 Partial Loading

The LNG volume loaded onto a vessel at the production port depends on whether the vessel is headed to the transshipment port or directly to a customer.

The common industry practice is to operate with full ship loads. However, due to quite limited storage space in the tank at the transshipment port, some residual might be left after loading and unloading operations. The residual amount might become big enough to prevent a vessel from unloading a full ship load and creates a bottleneck. Instead of unloading the ship load partially at the transshipment port and travel back to the production port with partial loads, an alternative approach could be to load the vessels partially at the production port. In this case, the producer may load the vessel with a volume that is just enough to fully unload the cargo at the transshipment port. This is called partial loading. Partial loading would operate with the same amount of LNG as for partial deliveries. Since the storage tank at the transshipment port is only operated by the LNG producer, we assume that the producer is aware of the inventory level during the whole planning horizon. In order to prevent sloshing, the loading volume should be at least γ percent of the vessel's total tank volume.

Partial loading only applies to the voyages between the production and transshipment ports. Voyages directly to customers or spot markets deal with full shiploads only.

Chapter 5

Mathematical Model

In this chapter, we formulate the ADP planning problem as a mixed integer programming (MIP) model. The mathematical model presented here is based on the model in Bugge and Thavarajan (2017), but some changes are made. A major change is the implementation of partial loading.

5.1 Assumptions

The following assumptions and simplifications are made in order to reduce the complexity of the problem. Some of these assumptions and simplifications are also presented in Bugge and Thavarajan (2017).

- The duration of a one-way trip, T_{ijvt} is assumed to be integer. T_{ijvt} includes the day when cargo is loaded onto the vessel at the loading port and $2T_{ijvt}$ includes both the loading day and the day when the cargo is unloaded at the transshipment port or at a customer.

- There are four types of conventional vessels, with a given number of each type. However, the total amount of all the conventional vessels are assumed to be non-limiting, and there is at least one conventional vessel available to pick up cargo at the transshipment port.

- During a day, only one operation is possible. This implies that on a given day, a vessel is either sailing, loading cargo, unloading cargo or idle.

5.2 Notation

Indices

i, j	Origin and destination point.
m	Time interval.
v	Vessel.
t	Time period.

Sets

$\mathcal{C}$	Set of customers.
$\mathcal{C}^A$	Set of customers, both long-term and spot, that cannot be visited directly, when the NSR is closed, $\mathcal{C}^A \subset \mathcal{C}$.
$\mathcal{C}^D$	Set of customers, both long-term and spot, that can be visited directly or via transshipment, $\mathcal{C}^D \subset \mathcal{C}$.
$\mathcal{C}^{LT}$	Set of customers with long-term contracts. It is mandatory to serve these customers, $\mathcal{C}^{LT} \subset \mathcal{C}$.
$\mathcal{C}^S$	Set of spot markets. $\mathcal{C}^S \subset \mathcal{C}$.
$\mathcal{M}$	Set of time intervals.
$\mathcal{P}$	Set of ports.
$\mathcal{P}^O$	Set of producer ports, $\mathcal{P}^O \subset \mathcal{P}$.
$\mathcal{P}^T$	Set of transshipment ports, $\mathcal{P}^T \subset \mathcal{P}$.
$\mathcal{V}$	Set of vessels.
$\mathcal{V}^A$	Set of vessels of type A, $\mathcal{V}^A \subseteq \mathcal{V}$.
$\mathcal{V}^B$	Set of vessels of type B, $\mathcal{V}^B \subseteq \mathcal{V}$.
$\mathcal{V}^C$	Set of conventional vessels, $\mathcal{V}^C \subseteq \mathcal{V}$.
$\mathcal{T}$	Set of time periods.
$\hat{\mathcal{T}}$	Set of time periods used for the parameter describing when the Northern Sea Route is open.
$\overline{\mathcal{T}}_{ijvt}$	Set of departure times where the arrival time is outside the planning horizon, that is $t \in \overline{\mathcal{T}}_{ijvt}$ if $t + T_{ijvt} >\mid \mathcal{T} \mid$ and $t \in \mathcal{T}$, $\overline{\mathcal{T}}_{ijvt} \subset \mathcal{T}$.
$\mathcal{T}_m$	Set of time periods in time interval m, $\mathcal{T}_m \subset \mathcal{T}$.

Note that the set of customers, $\mathcal{C}$, can be divided into two subsets based on customer type, $\mathcal{C}^{LT}$, $\mathcal{C}^S$. The set of ports $\mathcal{P}$, can be divided into the subsets $\mathcal{P}^O$ and $\mathcal{P}^T$.

Parameters

B_i	Number of berths available at port i.
C_{ijvt}	Shipping costs for vessel v embarking on a round trip from i to j at time t.
$\underline{C}_j^+$	Annual penalty cost for over-delivery below one shipload at customer j.
$\underline{C}_j^-$	Annual penalty cost for under-delivery below one shipload at customer j.
$\overline{C}_j^+$	Annual penalty cost for over-delivery above one shipload at customer j.
$\overline{C}_j^-$	Annual penalty cost for under-delivery above one shipload at customer j.
C_{jm}^+	Penalty cost for over-delivery at customer j in time interval m.
C_{jm}^-	Penalty cost for under-delivery at customer j in time interval m.
D_{jm}	Total demand at customer j during the time interval m.
F^L	Forced boil-off when loading or unloading.
F^S	Forced boil-off when sailing.
N_{vt}	An indicator parameter. Is equal to 1 if the Northern Sea Route is open at time t for vessel type v, 0 otherwise. $t \in \hat{\mathcal{T}}$.
O	Remaining percentage of cargo in vessel v due to natural boil-off. $O = 1-$ daily boil-off rate .
P_t	LNG production rate at the producer during time t.
R_{jt}^S	Revenue from selling a unit of LNG in the spot market located at customer j at time t.
$\overline{S_i}$	Upper storage limit at port i.
$\underline{S_i}$	Lower storage limit at port i.
s_{i0}	Initial storage level at port i.
T_{ijvt}	Travel time from i to j using vessel v. The travel time includes loading time t at port i and depends on t. Unloading at port j is not included in T_{ijvt}. $2T_{ijvt}$ describes the total travel time for the round trip.
$\underline{Q_j}$	Lowest possible cargo delivered to customer j.
Q_v	Amount of cargo collected by vessel v.
Q_{ijvt}	Cargo transported from port i and delivered at customer j, by vessel v. The cargo is picked up by vessel v at time t.
α_{ijvt}	Parameter used for calculating cargo delivered to port $\mathcal{P}^T$ from $\mathcal{P}^O$.

β_{ijvt} Parameter used for calculating cargo delivered to port $\mathcal{P}^T$ from $\mathcal{P}^O$.

γ Parameter used for calculating lower bound on cargo picked up when sailing from port $\mathcal{P}^O$ to $\mathcal{P}^T$. In order to avoid sloshing, γ is set equal to 0.7

Decision Variables

a_j^+ Total over-delivery to customer $j \in \mathcal{C}^{LT}$ above one ship load, for the whole planning horizon.

a_j^- Total under-delivery to customer $j \in \mathcal{C}^{LT}$ above one shipload, for the whole planning horizon.

l_{ijvt} Cargo picked up when sailing from $i \in \mathcal{P}^O$ to $j \in \mathcal{P}^T$ at time $t \in \mathcal{T}$ for vessel $v \in \mathcal{V}^A \cup \mathcal{V}^B$.

s_{it} Storage level at port $i \in \mathcal{P}$ at the end of time period t.

x_{ijvt} Is 1 if vessel v picks up cargo at port $i \in \mathcal{P}^O \cup \mathcal{P}^T$ the following day, at time $t \in \mathcal{T}$ and travels to $j \in \mathcal{P}^T \cup \mathcal{C}$, 0 otherwise. Note that $i \neq j$.

y_j^+ Total over-delivery to customer $j \in \mathcal{C}^{LT}$ below one shipload, for the whole planning horizon.

y_j^- Total under-delivery to customer $j \in \mathcal{C}^{LT}$ below one shipload, for the whole planning horizon.

y_{jm}^+ Over-delivery to customer $j \in \mathcal{C}^{LT}$ in time interval $m \in \mathcal{M}$.

y_{jm}^- Under-delivery to customer $j \in \mathcal{C}^{LT}$ in time interval $m \in \mathcal{M}$.

z_{ijvt} Cargo unloaded at port $j \in \mathcal{P}^T$ at time $t \in \mathcal{T}$, when traveling from $i \in \mathcal{P}^O$ with vessel $v \in \mathcal{V}^A \cup \mathcal{V}^B$.

5.3 Model Description

Objective

$$
\begin{aligned}
\min \sum_{i \in \mathcal{P}^O \cup \mathcal{P}^T} \sum_{j \in \{\mathcal{C} \cup \mathcal{P}^T | j \neq i\}} \sum_{v \in \mathcal{V}} \sum_{t \in \mathcal{T}} C_{ijvt} x_{ijvt} + \sum_{j \in \mathcal{C}^{LT}} (\overline{C}_j^+ a_j^+ + \overline{C}_j^- a_j^-) \\
+ \sum_{j \in \mathcal{C}^{LT}} (\underline{C}_j^+ y_j^+ + \underline{C}_j^- y_j^-) + \sum_{j \in \mathcal{C}^{LT}} \sum_{m \in \mathcal{M}} (C_{jm}^+ y_{jm}^+ + C_{jm}^- y_{jm}^-) \\
- \sum_{i \in \mathcal{P}^O \cup \mathcal{P}^T} \sum_{j \in \mathcal{C}^S} \sum_{v \in \mathcal{V}} \sum_{t=1}^{|\mathcal{T}| - T_{ijvt}} R_{jt}^S Q_{ijvt} x_{ijvt}
\end{aligned}
\tag{5.1}
$$

The objective function (5.1), aims to minimize the costs related to fulfilling the long term contracts. It consist of costs related to transportation, penalty due to over- and under-delivery, and sales in spot markets. Over- and under-delivery exist both on monthly and annual basis, while sales in the spot market are considered as negative costs. Operative costs related to sailing are considered in the first term in the objective. The second and the third term describes the cost related to over- and under-delivery on an annual basis. The second terms provides a positive contribution to the objective value if total over- or under-delivery exceeds one ship load, while the third term provides costs if they are lower. Monthly over- and under-delivery is included in the fourth term, while revenue from sales in spot markets are considered in the fifth term.

Routing Constraints

$$\sum_{i \in \mathcal{P}^O \cup \mathcal{P}^T} \sum_{j \in \{\mathcal{C} \cup \mathcal{P}^T | j \neq i\}} \sum_{\{\tau \in \mathcal{T} | \max(1,\ t - 2T_{ijv\tau} + 1) \leq \tau \leq t\}} x_{ijv\tau} \leq 1 \qquad v \in \mathcal{V},\ t \in \mathcal{T} \tag{5.2}$$

Constraints (5.2) make sure that each vessel returns before making a new trip. Note that the traveling time for one vessel to a given customer is dependent on loading day, and vary throughout the planning horizon.

$$\sum_{j \in \mathcal{C} \cup \mathcal{P}^T} \sum_{v \in \mathcal{V}} x_{ijvt} \leq B_i, \qquad i \in \mathcal{P}^O,\ t \in \mathcal{T} \tag{5.3}$$

$$\sum_{i \in \mathcal{P}^O} \sum_{v \in \mathcal{V}^A \cup \mathcal{V}^B} \sum_{\{\tau \in \mathcal{T} | \tau + T_{ijv\tau} = t\}} x_{ijv\tau} + \sum_{i \in \mathcal{C}} \sum_{v \in \mathcal{V}^C} x_{jivt} \leq B_j, \qquad j \in \mathcal{P}^T,\ t \in \mathcal{T} \tag{5.4}$$

Constraints (5.3) and (5.4) ensure that the number of vessels loading or unloading at the origin and transshipment port not exceeds the berth capacity at the port. At origin, the berth capacity concerns vessels loading cargo, while the berth capacity at the transshipment port deals with both loading and unloading.

$$2T_{ijvt} x_{ijvt} \leq \sum_{t \leq \tau < t + 2T_{ijvt}} N_{v\tau}, \qquad i \in \mathcal{P}^O,\ j \in \mathcal{C}^A,\ v \in \mathcal{V}^A,\ t \in \mathcal{T} \tag{5.5}$$

When the Northern Sea Route is open, vessels of type A may travel directly to customers located in Asia, if the route is open during the whole voyage. This is handled in constraints (5.5). Note that the summation of τ may exceed the planning horizon.

$$2T_{ijvt}x_{ijvt} \leq \sum_{t \leq \tau < t+2T_{ijvt}} N_{v\tau}, \qquad i \in P^O,\, j \in \mathcal{C} \cup \mathcal{P}^{\mathcal{T}},\, v \in \mathcal{V}^B,\, t \in \mathcal{T} \tag{5.6}$$

Vessel B cannot be used at all when the Northern Sea Route is closed. Thus, constraints (5.6) make sure that vessels of type B can only be used when the route is open. Note that the summation of τ may exceed the planning horizon.

Demand Fulfillment Constraints

$$\sum_{i \in \mathcal{P}^O \cup \mathcal{P}^{\mathcal{T}}} \sum_{v \in \mathcal{V}} \sum_{\{t \in \mathcal{T} | t+T_{ijvt} \in \mathcal{T}_m\}} Q_{ijvt}x_{ijvt} + y_{jm}^- - y_{jm}^+ = D_{jm}, \qquad j \in \mathcal{C}^{LT},\, m \in \mathcal{M} \tag{5.7}$$

$$\sum_{i \in \mathcal{P}^O \cup \mathcal{P}^{\mathcal{T}}} \sum_{v \in \mathcal{V}} \sum_{t \in \mathcal{T}} Q_{ijvt}x_{ijvt} + y_j^- + a_j^- - y_j^+ - a_j^+ = \sum_{m \in \mathcal{M}} D_{jm}, \qquad j \in \mathcal{C}^{LT} \tag{5.8}$$

Demand fulfillment is handled in constraints (5.7) and (5.8). The periodical demand is handled for each time interval in constraints (5.7) while the total demand is handled in (5.8). The constraints are formulated as soft constraints, which allows over- and under-deliveries.

$$y_j^- \leq \underline{Q_j}, \qquad j \in \mathcal{C}^{LT} \tag{5.9}$$

$$y_j^+ \leq \underline{Q_j}, \qquad j \in \mathcal{C}^{LT} \tag{5.10}$$

Constraints (5.9) and (5.10) ensure that the y_j^- and y_j^- are below one shipload, and that a_j^+ and a_j^- are above.

Inventory Constraints

$$s_{it} - s_{i(t-1)} + \sum_{j \in \mathcal{C}} \sum_{v \in \mathcal{V}^A \cup \mathcal{V}^B} Q_v x_{ijvt} + \sum_{j \in \mathcal{P}^T} \sum_{v \in \mathcal{V}^A \cup \mathcal{V}^B} l_{ijvt} - P_t = 0, \qquad i \in \mathcal{P}^O,\, t \in \mathcal{T} \tag{5.11}$$

$$s_{jt} - s_{j(t-1)} - \sum_{i \in \mathcal{P}^O} \sum_{v \in \mathcal{V}^A \cup \mathcal{V}^B} z_{ijvt} + \sum_{i \in \mathcal{C}^A \cup \mathcal{C}^D} \sum_{v \in \mathcal{V}^C} Q_v x_{jivt} = 0, \qquad j \in \mathcal{P}^T,\, t \in \mathcal{T} \tag{5.12}$$

$$\underline{S_i} \leq s_{it} \leq \overline{S_i}, \qquad i \in \mathcal{P}^O \cup \mathcal{P}^T,\, t \in \mathcal{T} \tag{5.13}$$

Constraints (5.11)-(5.13) handle the inventory level at the origin and transshipment port. Constraints (5.11) describes the inventory level at the origin port as a result of production rate, cargo picked up and the storage level from the previous time period. The constraints consist of two parts describing cargo picked up, $Q_v x_{ijvt}$ and l_{ijvt}. The first part is cargo picked up for delivery to customers or to the spot market. The second, describes cargo picked up for delivery to the transshipment port. The cargo delivered to the transshipment port is not necessarily a full ship load. Constraints (5.12) handle the inventory level of the storage tank at the transshipment port. This inventory level is formulated as result of cargo delivered from origin, cargo picked up and the inventory level from the previous time period.

Partial Loading Constraints

$$z_{ijv(t+T_{ijvt})} = \alpha_{ijvt} l_{ijvt} - \beta_{ijvt} x_{ijvt}, \qquad i \in \mathcal{P}^O,\, j \in \mathcal{P}^T, v \in \mathcal{V}^A \cup \mathcal{V}^B,\, t \in \mathcal{T} \backslash \overline{\mathcal{T}}_{ijvt} \tag{5.14}$$

Constraints (5.14) describe the z-variable as the amount of cargo unloaded at the transshipment port. $t + T_{ijvt}$ is the day the unloading process occurs, and the day the vessel occupies the berth at the port. As a result of boil-off, the z-variable is smaller than the l-variable. The cargo delivered to the transshipment port, is equal to cargo picked up at the origin multiplied with a rate α_{ijvt}, minus β_{ijvt}. α_{ijvt} and β_{ijvt} are results of both forced and natural boil-off. The derivation of α_{ijvt} and β_{ijvt} is presented in Appendix A, and the expressions are: $\alpha_{ijvt} = O^{T_{ijvt}}$ and $\beta_{ijvt} = F^L O^{T_{ijvt}} + F^S(\frac{O^{T_{ijvt}-1}}{O-1} - 1) + F^L + \frac{F^S}{O}(\frac{(\frac{1}{O})^{T_{ijvt}-1}-1}{\frac{1}{O}-1})$, where O is the remaining percentage of cargo in vessel v due to natural boil-off. $O = 1-$ daily boil-off rate.

$$l_{ijvt} - Q_v x_{ijvt} \leq 0, \qquad i \in \mathcal{P}^O,\, j \in \mathcal{P}^T, v \in \mathcal{V}^A \cup \mathcal{V}^B,\, t \in \mathcal{T} \tag{5.15}$$

$$l_{ijvt} - \gamma Q_v x_{ijvt} \geq 0, \qquad i \in \mathcal{P}^O,\, j \in \mathcal{P}^T, v \in \mathcal{V}^A \cup \mathcal{V}^B,\, t \in \mathcal{T} \tag{5.16}$$

Constraints (5.15)-(5.16) are big-m and small-m formulations used to connect the continuous l-variables with the binary x-variables. (5.15) ensure that if $x_{ijvt} = 1$, l_{ijvt} gets a value smaller or equal to Q_v. However, constraint (5.16) prevent l_{ijvt} from being smaller than γQ_v.

5.4 Model Formulation

$$
\begin{aligned}
\min & \sum_{i\in\mathcal{P}^O\cup\mathcal{P}^T}\ \sum_{j\in\{\mathcal{C}\cup\mathcal{P}^T|j\neq i\}}\ \sum_{v\in\mathcal{V}}\sum_{t\in\mathcal{T}} C_{ijvt}x_{ijvt} + \sum_{j\in\mathcal{C}^{LT}} (\overline{C}_j^+ a_j^+ + \overline{C}_j^- a_j^-) \\
& + \sum_{j\in\mathcal{C}^{LT}} (\underline{C}_j^+ y_j^+ + \underline{C}_j^- y_j^-) + \sum_{j\in\mathcal{C}^{LT}}\sum_{m\in\mathcal{M}} (C_{jm}^+ y_{jm}^+ + C_{jm}^- y_{jm}^-) \\
& - \sum_{i\in\mathcal{P}^O\cup\mathcal{P}^T}\ \sum_{j\in\mathcal{C}^S}\sum_{v\in\mathcal{V}}\ \sum_{t=1}^{|\mathcal{T}|-T_{ijvt}} R_{jt}^S Q_{ijvt}x_{ijvt}
\end{aligned}
\tag{5.1}
$$

s.t

$$
\sum_{i\in\mathcal{P}^O\cup\mathcal{P}^T}\ \sum_{j\in\{\mathcal{C}\cup\mathcal{P}^T|j\neq i\}}\ \sum_{\{\tau\in\mathcal{T}|\max(1,\ t-2T_{ijv\tau}+1)\leq\tau\leq t\}} x_{ijv\tau} \leq 1 \qquad v\in\mathcal{V},\, t\in\mathcal{T} \tag{5.2}
$$

$$
\sum_{j\in\mathcal{C}\cup\mathcal{P}^T}\sum_{v\in\mathcal{V}} x_{ijvt} \leq B_i, \qquad i\in\mathcal{P}^O,\, t\in\mathcal{T} \tag{5.3}
$$

$$
\sum_{i\in\mathcal{P}^O}\ \sum_{v\in\mathcal{V}^A\cup\mathcal{V}^B}\ \sum_{\{\tau\in\mathcal{T}|\tau+T_{ijv\tau}=t\}} x_{ijv\tau} + \sum_{i\in\mathcal{C}}\sum_{v\in\mathcal{V}^C} x_{jivt} \leq B_j, \qquad j\in\mathcal{P}^T,\, t\in\mathcal{T} \tag{5.4}
$$

$$
2T_{ijvt}x_{ijvt} \leq \sum_{t\leq\tau<t+2T_{ijvt}} N_{v\tau}, \qquad i\in\mathcal{P}^O,\, j\in\mathcal{C}^A,\, v\in\mathcal{V}^A,\, t\in\mathcal{T} \tag{5.5}
$$

$$
2T_{ijvt}x_{ijvt} \leq \sum_{t\leq\tau<t+2T_{ijvt}} N_{v\tau}, \qquad i\in P^O,\, j\in\mathcal{C}\cup\mathcal{P}^{\mathcal{T}},\, v\in\mathcal{V}^B,\, t\in\mathcal{T} \tag{5.6}
$$

$$
\sum_{i\in\mathcal{P}^O\cup\mathcal{P}^T}\ \sum_{v\in\mathcal{V}}\ \sum_{\{t\in\mathcal{T}|t+T_{ijvt}\in\mathcal{T}_m\}} Q_{ijvt}x_{ijvt} + y_{jm}^- - y_{jm}^+ = D_{jm}, \qquad j\in\mathcal{C}^{LT},\, m\in\mathcal{M} \tag{5.7}
$$

$$
\sum_{i\in\mathcal{P}^O\cup\mathcal{P}^{\mathcal{T}}}\ \sum_{v\in\mathcal{V}}\sum_{t\in\mathcal{T}} Q_{ijvt}x_{ijvt} + y_j^- + a_j^- - y_j^+ - a_j^+ = \sum_{m\in\mathcal{M}} D_{jm}, \qquad j\in\mathcal{C}^{LT} \tag{5.8}
$$

$$
y_j^- \leq \underline{Q_j}, \qquad j\in\mathcal{C}^{LT} \tag{5.9}
$$

$$y_j^+ \leq \underline{Q_j}, \qquad j \in \mathcal{C}^{LT} \tag{5.10}$$

$$s_{it} - s_{i(t-1)} + \sum_{j \in \mathcal{C}} \sum_{v \in \mathcal{V}^A \cup \mathcal{V}^B} Q_v x_{ijvt} + \sum_{j \in \mathcal{P}^T} \sum_{v \in \mathcal{V}^A \cup \mathcal{V}^B} l_{ijvt} - P_t = 0, \qquad i \in \mathcal{P}^O,\, t \in \mathcal{T} \tag{5.11}$$

$$s_{jt} - s_{j(t-1)} - \sum_{i \in \mathcal{P}^O} \sum_{v \in \mathcal{V}^A \cup \mathcal{V}^B} z_{ijvt} + \sum_{i \in \mathcal{C}^A \cup \mathcal{C}^D} \sum_{v \in \mathcal{V}^C} Q_v x_{jivt} = 0, \qquad j \in \mathcal{P}^T,\, t \in \mathcal{T} \tag{5.12}$$

$$\underline{S_i} \leq s_{it} \leq \overline{S_i}, \qquad i \in \mathcal{P}^O \cup \mathcal{P}^T,\, t \in \mathcal{T} \tag{5.13}$$

$$z_{ijv(t+T_{ijvt})} = \alpha_{ijvt} l_{ijvt} - \beta_{ijvt} x_{ijvt}, \qquad i \in \mathcal{P}^O,\, j \in \mathcal{P}^T, v \in \mathcal{V}^A \cup \mathcal{V}^B,\, t \in \mathcal{T} \backslash \overline{\mathcal{T}}_{ijvt} \tag{5.14}$$

$$l_{ijvt} - Q_v x_{ijvt} \leq 0, \qquad i \in \mathcal{P}^O,\, j \in \mathcal{P}^T, v \in \mathcal{V}^A \cup \mathcal{V}^B,\, t \in \mathcal{T} \tag{5.15}$$

$$l_{ijvt} - \gamma Q_v x_{ijvt} \geq 0, \qquad i \in \mathcal{P}^O,\, j \in \mathcal{P}^T, v \in \mathcal{V}^A \cup \mathcal{V}^B,\, t \in \mathcal{T} \tag{5.16}$$

$$x_{ijvt} \in \{0, 1\}, \qquad i \in \mathcal{P}^O,\, j \in \mathcal{C} \cup \mathcal{P}^T,\, v \in \mathcal{V},\, t \in \mathcal{T} \tag{5.17}$$

$$y_j^+,\, y_j^-,\, a_j^+,\, a_j^- \geq 0, \qquad j \in \mathcal{C}^{LT} \tag{5.18}$$

$$y_{jm}^+,\, y_{jm}^- \geq 0, \qquad j \in \mathcal{C}^{LT},\, m \in \mathcal{M} \tag{5.19}$$

$$l_{ijvt}, z_{ijvt} \geq 0, \qquad i \in \mathcal{P}^O,\, j \in \mathcal{P}^T, v \in \mathcal{V}^A \cup \mathcal{V}^B,\, t \in \mathcal{T} \tag{5.20}$$

Chapter 6

Solution Methods

In this chapter, we present two solution methods to solve the ADP planning problem. A rolling horizon heuristic (RHH) is described Section 6.1, while an aggregation and disaggregation heuristic (ADH) that solves a reduced instance of the full problem is discussed in Section 6.2.

6.1 Rolling Horizon Heuristic

The goal of the planning problem in this thesis is to create a cost effective ADP for the LNG-producer over a long time horizon. The length of the time horizon itself is a challenge when it comes to computational efficiency. As discussed in Chapter 3, rolling horizon methods can be applied to scheduling problems in order to produce good solutions within reasonable time. The heuristic solves the ADP planning problem in sub-horizons, which means that we solve smaller problems iteratively. RHH as a solution method provided good solutions for the ADP planning problem studied by Rakke et al. (2011), which motivates us to use the same approach.

Description

The idea behind RHH is to divide the planning horizon into shorter sub-horizons and solve the ADP planning problem through a series of iterations. In each iteration, the MIP is solved for one sub-horizon. Since the complexity of solving the problem is reduced by considering one sub-horizon at a time, the overall computational time may be improved. When the heuristic terminates, a feasible solution to the ADP planning problem for the whole planning horizon is returned, which consists of the solutions from solving each sub-horizon.

When solving the ADP planning problem, we divide the planning horizon into sub-horizons and solve the problem in every sub-horizon. Let TS denote a time section, which corresponds to a sub-horizon of the planning problem. A time section TS_k is solved in iteration *k*. The time section TS_k is further divided into two periods, one central period TP_k^C and one forecast period TP_k^{FO}. Each period has a constant length of duration. The length of a central period does not necessarily need be the same as the length of a forecast period. During an iteration *k*, the planning problem is solved for the time section TS_k with branch-and-bound, and a simplification strategy is added to the problem in the forecast period. In the next iteration *k+1*, we shift the time section TS_k forwards so that the former forecast period, TP_k^{FO}, becomes the new central period TP_{k+1}^C. The former forecast period is rescheduled in the new central period. There are two possible ways to shift the time section: the whole forecast period TP_k^{FO} becomes the new central period TP_{k+1}^C, or only the first part of the forecast period TP_k^{FO} becomes the new central period TP_{k+1}^C. If the lengths of central period and forecast period are equal, the whole forecast period TP_k^{FO} becomes the new central period TP_{k+1}^C.

When we shift the time section from TS_k to TS_{k+1}, we fix or "freeze" the decision variables in the central period TP_k^C. TP_k^C now becomes a part of the frozen period. In the frozen period, the decisions from former iterations have been fixed according to a freezing strategy. It is possible to freeze the decision variables in the whole central period or just the first part of the central period. The part of the central period that is frozen in iteration k and becomes a part of the frozen period in $k+1$, is called freezing length or TF_k. The length of TF_k could be equal to the length of the central period TP_k^C, or shorter.

Figure 6.1 shows how the heuristic iterates over the planning horizon. In the figure, the central period is longer than the forecast period. In addition, two-thirds of the central period is frozen in each iteration.

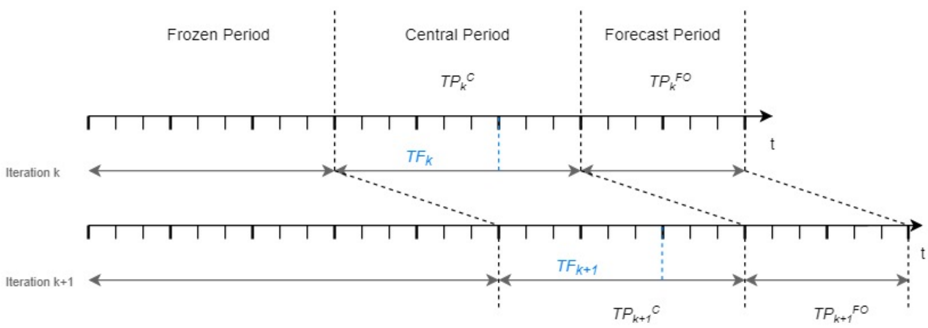

Figure 6.1: The rolling horizon heuristic

The Central Period

For each central period, we update the accumulated deviation in deliveries. The accumulated deviation in deliveries describe the total over- or under-delivery delivered to a customer during a period of time. In each central period, the accumulated deviation is equal to the sum of monthly deviations from the previous iterations and deviations in the current central period. At the end of the planning horizon, the accumulated deviation for a customer will be equal to the annual demand less the amount of cargo delivered in the whole planning horizon.

We update the accumulated deviations by calculating the difference in demand and cargo delivered, for all previous and the current central period. If we let $\mathcal{T}^{CP}$ denote the set of time periods in the central period, $\mathcal{M}^{CP}$ the set of time intervals in the central period, $\mathcal{T}^{F}$ the set of time intervals in the frozen period, and let $\mathcal{M}^{F}$ be the set of time intervals in the frozen period, the annual demand-constraints (5.8) can be reformulated as:

$$\sum_{i \in \mathcal{P}^O \cup \mathcal{P}^T} \sum_{v \in \mathcal{V}} \sum_{\{t \in \mathcal{T} | t + T_{ijvt} \in \mathcal{T}^{CP}\}} Q_{ijvt} x_{ijvt} + y_j^- + a_j^- - y_j^+ - a_j^+ =$$
$$\sum_{m \in \mathcal{M}^F \cup \mathcal{M}^{CP}} D_{jm} - \sum_{i \in \mathcal{P}^O \cup \mathcal{P}^T} \sum_{v \in \mathcal{V}} \sum_{\{t \in \mathcal{T}^F | t + T_{ijvt} \in \mathcal{T}^F\}} Q_{ijvt} x_{ijvt}, \qquad j \in \mathcal{C}^{LT}$$

Where y_j^-, a_j^-, y_j^+, a_j^+ is used to describe the accumulated deviation in deliveries for one customer.

The Frozen Period

The decision variables from the central period are frozen according to a freezing strategy before proceeding to the next iteration. There are two relevant freezing strategies to consider: we either freeze all of the decision variables or only the binary decision variables from the central period. The first option reduces the solution space for the next iteration considerably, since vessels are fixed to a voyage and cannot be used again before return time. This also prevents the model from changing the loading volumes for transshipment and storage values in later iterations.

The Forecast Period

In the forecast period, a simplification strategy is applied to the problem. There are two things to consider when designing the forecasting period. The first is the simplification strategy, while the second concerns the length.

When we select a simplification strategy, we determine whether to relax the binary restrictions on the decision variables in the forecast period or not. According to Rakke et al. (2011), when the decision variables take on continuous values, we risk less accurate forecasting information for the next periods. But in return, we might reduce some computational effort during the solution process. When it comes to the length of the forecast period, Rakke et al. (2011) argue that the forecast length should be long enough to be affected by and affect decisions made in the central period. It is worth mentioning that the length of the forecast period also affects the size of the problem we solve in each iteration. Therefore, in order to reduce the computational time, the forecast period should be rather short. At the same time, if a voyage has a departure day during the central period and a return day after the end of the central period, the forecast period should be long enough to include the return day.

Transfer of Information

At the end of each iteration, some information is transferred to the next iteration. When the accumulated deviations are updated in each iteration, the departures in the frozen period must be known.

In addition to accumulated deviations, other information should be transferred between the iterations. The storage level on the last day in TF_k becomes the the initial storage level in the central period TP^C_{k+1} and should therefore be transferred. In iteration $k+1$ the model should also be aware of departed vessels that have not returned by the end of the previous central period TP^C_k. These decisions affect the vessel availability in iteration $k+1$ and should thus be included in the iteration.

6.2 Aggregation and Disaggregation Heuristic

In the previous section, RHH is proposed as an approach to solve the ADP planning problem by solving a reduced version of the problem iteratively. Another approach to reduce the size of the problem is to aggregate the nodes in a problem and solve the reduced case. The solution to the reduced problem is then disaggregated. We develop an Aggregation and Disaggregation Heuristic (ADH) for this purpose.

The ADH consists of two components: the aggregation of nodes in a problem instance and disaggregation of a solution to the reduced problem instance. The procedure is shown below in Figure 6.2. Customers, or nodes, are clustered together and becomes an aggregated customer. The aggregation of nodes is based on the geographic area of the customers. The aggregated problem instance is then solved with branch-and-bound to get a set of feasible solutions. The solutions are then given as input to a Disaggregation Heuristic (DH), which disaggregates the solution by rerouting the voyages to aggregated nodes to individual customers. With exact methods, the computational time increase exponentially when the number of nodes increase. A reduction of the number of nodes in the network can lead to a reduction in the computational time, and consequently produce a delivery schedule in a shorter amount of time (Rogers et al., 1991). The ADH may be used to give the producer an idea of a potential ADP when the number of buyers increase or decrease, or when demands are adjusted.

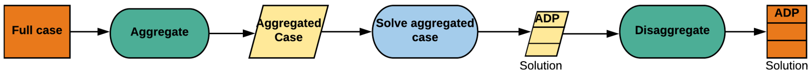

Figure 6.2: Overview of the Aggregation Disaggregation Heuristic

According to Rogers et al. (1991), the nodes should be grouped according to a clustering strategy. The clustering strategies are based on similarities, so that error or data loss is minimized during the aggregation and disaggregation process. We choose to cluster the long-term customers located in the same geographic areas: Europe and Asia. If we were to cluster the nodes without having geographic areas in mind, the disaggregated solution would consist of substantial spread in travel times. The two aggregated, long-term, customers are denoted as LT-EU and LT-Asia.

Besides the long-term customers, there is one spot customer in each geographic area. The producer may send a ship load to spot customers when there is excess LNG left in the production tanks, while for the long-term customers, the producer is obligated to send ship loads every month to fulfill the demand stated in the contracts. Hence, due to differences in delivery purposes, the spot-customers are not clustered together with the long-term customers.

The next step is to decide how the parameter values of each individual node is handled during aggregation. The demand of one aggregated customer is equal to the sum of the demands of each individual customer that is "included" in the aggregated customer. The aggregated customers are assigned the longest travel times among their individual customers to prevent routing infeasibility when the vessels are rerouted. This way, the vessels are rerouted so that they arrive before or at the same time as the solution of the aggregated case. After aggregation, the reduced problem instance is solved with branch-and-bound.

Since we cluster the nodes according to geographic areas, the disaggregation is a straightforward procedure. Voyages scheduled to an aggregated customer are rerouted to the individual customers in the same geographic area. Algorithm 1 below shows the disaggregation procedure. When the heuristic disaggregates the voyages in the initial solution, it needs to take berth, inventory and routing feasibility into consideration. For the voyages where partial loading applies, the heuristic does not change the value of the cargo picked up.

Algorithm 1: Disaggregation of Voyages

Initialization:
Let $\mathcal{S}_a$ be the set of voyages from the initial solution of the aggregated case
$\mathcal{S} = \emptyset$
Let $\mathcal{M}$ be the set of months in the planning horizon
Let $\mathcal{C}$ be the set of customers in the larger case
for $m \in \mathcal{M}$ **do**
    if *m = 0 or m = NSR open or m = NSR closed* **then**
        Sort $\mathcal{C}$ based on travel times
    end
    for $s \in \mathcal{S}_a$ **do**
        if *s goes to spot customer or transshipment port* **then**
            $\mathcal{S} \leftarrow \mathcal{S} \cup s$
        end
        else
            for $c \in \mathcal{C}$ **do**
                if *customer c has unfulfilled demand in month m* **then**
                    $s_r \leftarrow$ reroute the voyage to customer c
                    $\mathcal{S} \leftarrow S \cup s_r$
                    Update remaining demand in month m for customer c
                end
                if *initial voyage s is not assigned to any customers* **then**
                    $s_r \leftarrow$ reroute the voyage to a spot customer in the same geographic area
                    $\mathcal{S} \leftarrow S \cup s_r$
                end
            end
        end
    end
    Calculate the deviation in month m for all customers
end
Calculate annual deviation for all customers
Calculate objective
return $\mathcal{S}$

6.2.1 Description of Disaggregation Procedure

The heuristic starts with reading the initial solution $\mathcal{S}_a$ from the aggregated case. The solution contains planned voyages and departure times to the aggregated customers, and the heuristic reroutes the voyages and determines the new destination and new arrival time. $\mathcal{S}_a$ is sorted chronologically by departure times. Since each aggregated customer is assigned the longest travel time from the producer's or transshipment port, we avoid the issue of new arrival dates ending up in the next month after rerouting, thus missing the demand for the current month.

The algorithm is initiated with an empty set of distributed voyages S. There is also a set of customers C for each aggregated customer, where these customers are in the same geographical area as the aggregated customer. The customers are prioritized by travel times in decreasing order, so that customers with the longest travel times are prioritized first. In combination with $\mathcal{S}_a$ sorted chronologically, this should prevent the new arrival dates from being set the previous month *m-1*, if the initial voyage s has departure time in month *m-1* and arrival time in month m.

The algorithm then begins iterating through the list of voyages with arrival times in month m. If the voyage is headed to an aggregated customer, the heuristic uses the set of customers that are in the same geographic area as the aggregated customer and proceeds to rerouting. If the voyage on the other hand, heads to the transshipment port or to a spot customer, the voyage is added to the result set S and the heuristic proceeds to the next voyage.

At the rerouting stage, the heuristic first chooses a customer c from the set of customers $\mathcal{C}$. If the customer has been assigned enough voyages to satisfy the monthly demand, the heuristic proceeds to the next customer in the list. Otherwise, the customer is assigned the voyage. If a voyage cannot be rerouted to any of the customers, the voyage is rerouted to a spot customer in the same geographic area as the corresponding aggregated customer. This is the case if a customer is located at the transshipment port and cannot be assigned a voyage departing from the transshipment port, and the other customers have been assigned their voyages. The following attributes of the rerouted voyage s_r need to be updated: destination, travel time, boil-off adjusted amount of cargo delivered, and vessel availability. The modified voyage s_r is then added to the result set S.

When the heuristic finishes the rerouting stage, the customer is assigned the new voyage with arrival in month m, and the remaining demand for customer c in month m is updated. After assigning all the initial voyages with arrival times in month m, the heuristic calculates the monthly deviations for each customer.

When all voyages from the initial solutions are rerouted, the objective value of the result set is calculated.

6.2.2 Discussion

The aggregated customers are assigned pessimistic travel times. After disaggregation, the idle time for the vessels may increase due to the spread between the pessimistic travel time and the travel times of the individual customers. Among the Asian customers, the differences in travel times are 1 or 2 days. For the European customers, the spread is bigger, and depends on whether the voyages are mostly via transshipment or direct. Since one of the European customers has their delivery destination at the transshipment port, transshipment is not needed, and consequently the travel time is shorter. A bigger difference between the travel times of the customers in an aggregated node can lead to increased idle time for the vessels in the ADP. Therefore, the travel times should affect the choice of aggregation strategy. Due to the choice of pessimistic travel times, the ADH produces a conservative and feasible ADP.

The pessimistic travel times may also lead to over-deliveries to the individual customers, as a result of smaller loss in cargo due to boil-off when the travel times become shorter during rerouting.

Post Processing

Another consequence of the pessimistic travel times are the rerouted arrival dates. If the solution of the aggregated problem instance contains voyages with arrival times in the beginning of a month m, the voyage might be rerouted so that the new arrival time ends up in the previous month *m-1* because of shorter travel time. This leads to an under delivery in month m and an over delivery the previous month *m-1*. Therefore, a possibility could be to postpone the departure of the voyage at least t days, while ensuring that the new departure day is inventory, berth and routing feasible (the vessel has to finish the new round trip before embarking on a later voyage).

In addition to shorter traveling times, the choice of vessels can lead to a great amount of under- and over-deliveries to the customers. After all the voyages are rerouted, the deliveries to each customer are evaluated. If customers are suffering from huge over-or under-deliveries, it may be possible to change the destination for some of the voyages in order to adjust the amount of cargo delivered. Two vessels that arrive two different customers in the same month are allowed to switch destinations. We call this a swap. The customers must be a part of the same aggregated customer, to guarantee that the swap is feasible. In addition, as we want to improve the solution, the new arrival dates should be within the original arrival month.

Chapter 7

Input Data

This chapter presents an overview of the input data used in the model. Parts of the data in this chapter are similar to the data described in (Bugge and Thavarajan, 2017). For the sake of completeness, a summary of the data is also presented here. Problem specific information is not included in this chapter due to non-disclosure agreements. Storage capacities at the producer and transshipment port and characteristics for vessel A and B are therefore not specified in this chapter. Most of the data related to the commodity can be given in m^3, tonnes or MMBtu. A table with the conversion rates is shown below in Table 7.1. The data listed in the table are based on a conversion table in GIIGNL (2018).

Table 7.1: Conversion between units

	m^3 LNG (liquid)	tonnes LNG	MMBtu
m^3 LNG (liquid)	-	0.45	23.12
tonnes LNG	2.21	-	51.02
MMBtu	0.0433	0.0196	-

7.1 Ports

Table 7.2 shows an overview of the ports considered in the problem. The locations of the customers are chosen based on descriptions in Section 2.1.2, and do not necessarily reflect the real-life situation. Three types of ports are listed in the table: *Production*, *Transshipment* and *Customer*. The customers are further divided into long-term and spot customers.

Table 7.2: Overview of ports and customers considered in the problem. LT denotes the long-term customer, and S is the spot customers.

Name	Customer Type	Area
Production	-	-
Transshipment	-	Europe
Customer 1	LT	Europe
Customer 2	LT	Europe
Customer 3	LT	Asia
Customer 4	LT	Asia
Customer 5	LT	Asia
Customer 6	LT	Asia
Spot Customer 1	S	Europe
Spot Customer 2	S	Asia

Production and Transshipment Port

The producer located at the production port yields an annual production of LNG. This annual production is divided into a fixed daily production. There is only one berth at the production port and the transshipment port.

Long Term Customers

Each of the long-term customers listed in Table 7.2 have a monthly demand that must be fulfilled. The customers are located in different parts of the world. Each customer should be visited every month, but the cargo delivered differs from customer to customer, due to different travel times and boil-off. The sum of the monthly demand for all customers during a year is approximately 90% of the annual production.

Spot Customers

Table 7.2 includes two spot customers; one in Europe and one in Asia. Sales to the spot customers are included as revenue in the planning of the ADP. In 2016, the average spot price in Asia was \$5.52/MMBtu (International Gas Union, 2017). The revenue from spot sales to the Asian spot customer is based on average spot price in Asia and set to be equal to \$128 per m^3.

Recall from Section 2.1, that the amount of LNG imported to Europe are significantly lower than the Asian imports. Based on this, we assume that the revenue from spot sales in Europe is smaller compared to the same amount sold in the Asian market. It should therefore be preferable to sell the spot cargo in the Asian market instead of the European. However, if some of the spot cargoes depart near the end of the planning horizon, it may not be possible to reach the Asian market within the planning horizon. In these cases, the LNG should be sold in the European market. In 2016, the UK spot price hit a low of $ 3.67/MMBtu (International Gas Union, 2017). Based on this, the revenue from spot sales in Europe is set equal to 50 % of the Asian spot price.

7.2 Vessels

The fleet in this problem consists of 41 LNG carriers. The vessels within classification A and within classification B share the same characteristics, while the vessels of type C are heterogeneous. Four set of different characteristics are created for vessel C.

LNG carriers do usually have a maximum speed of 21 knots in open water (GIIGNL, 2009), and therefore the selected speed range for vessels of type C lies between 15 and 20 knots. The selected capacities for the vessels of type C attempt to reflect the variations in the world LNG tanker fleet, and varies between 135,000 to 161,000 m^3. The selected capacities are similar to capacities listed in the comprehensive overview of the total LNG carrier fleet of 2017, by GIIGNL (2018).

7.2.1 Traveling Time

The traveling time between the ports is calculated for each type of the vessels. When the traveling time is calculated, vessel speed, sea ice level, and distance are taken into consideration.

The distance between the ports is generated using a tool provided by Marine Traffic (2018). The tool suggests different routes between two ports, where the path with the shortest distance is chosen. For the voyages between the transshipment port and the Asian customers, the vessels travel through the Suez Canal.

One of the vessel characteristics affecting the traveling time is the vessels' ability to travel in harsh sea conditions. Recall from Chapter 4, that only vessels of type A and B can travel from the producer and that type B is only usable when NSR is open. Due to the distinctive vessel characteristics for the types, the opening months for NSR are different for vessels A and B. Vessels of type A can use the route eastwards from July to November, while type B can use the route from July to October. The opening periods are determined based on the Admittance Criteria for Navigation stated at the websites of Centre for High North Logistics (CHNL) (CHNL, 2018c).

To evaluate the travel conditions along NSR the Sea Ice Index Animation Tool at the websites of the National Snow and Ice Data Center is used. The tool shows a graphical image of the median ice edge on a monthly basis from 1978 to 2017, as well as the median ice edge calculated from 1981 to 2010 (National Snow & Ice Data Center, 2018). The graphical image indicates the extent of the ice cover. These areas may require lower speed which influences the traveling time.

7.2.2 Operative Costs

The operative costs differ between the types of vessels. The operative costs we are interested in can be divided into crew costs, charter cost, canal cost and the cost of icebreaker support. The costs are summarized in Table 7.3.

Table 7.3: Operative Costs

Vessel Type	Cost Type	Cost($)
A & B	Crew costs	9,222 per day
B	Icebreaker support	229,561 or 459,140 per round trip
C	Charter costs	55,000-60,000 per day
C	Canal costs	350,000 per round trip

For vessels of type A and B crew cost are considered. The crew cost is based on an example given in Lopac (2008). In addition to crew cost, the cost of icebreaker support is included in the operative costs for vessel B.

When NRS is open, vessel B can use the route. The ice-conditions may vary during the opening season, and when the ice-conditions are at the toughest, the vessels need icebreaker support. The cost for one transit through the NSR is determined by the number of navigation zones a vessel pass through, the vessel's ice class and gross tonnage (CHNL, 2018a). Gross tonnage is a measure of a ships total interior volume (Dinsmore, 2011). The cost of icebreaker support is chosen based on a cost estimation at the websites of the Centre for High North Logistics (CHNL, 2018b). When the vessels are traveling westwards in July, the fee is estimated to \$229,140 per round trip, while the cost is estimated to \$459,140 per round trip eastwards in July and both ways in October.

For the vessels of type C, we only consider a daily charter cost and canal costs. We assume that the charter cost includes all the operative costs except canal cost. The charter cost for vessels of type C is based on an example given in Lopac (2008), and vary in the range between \$55,000-\$60,000. The canal costs are estimated based on the vessel type, cargo transported and loading condition (Suez Canal Authority, 2017a). A toll calculator is available on the web pages of Suez Canal Authority. Using this calculator, the canal fee is estimated to be \$350,000 for a round trip for all the vessels of type C (Suez Canal Authority, 2017b).

Fuel costs are not considered for any of the types of vessels, as we assume vessel A and B use forced boil-off as fuel. For vessel C, we assume that fuel costs are included in the charter costs.

7.2.3 Boil-off

The cargo delivered to the customers must be adjusted for boil-off. Here, we distinguish between natural boil-off and forced boil-off. Natural boil-off is the LNG that vaporizes due to the heat exchange from the soundings, while forced boil-off implies that some additional LNG are forced into vaporization and used as fuel.

When the conventional vessels depart from the transshipment port, they are fully loaded. Recall from the previous section that charter costs are assumed to include fuel costs, and we assume that the conventional vessels do not use LNG as fuel. Thus, the reduction of cargo on board these vessels is reduced daily by a fixed rate caused by natural boil-off. The daily boil-off rate is set to be 0.11%. As mentioned in Chapter 2.2, some LNG should be left in the vessel after delivery, to preserve the temperature in the tank. We assume that the difference in cargo picked up and cargo delivered, is equal to the total amount of natural boil-off for the whole round trip. Cargo delivered to the customers has been pre-processed beforehand using the boil-off function shown below.

For the conventional vessels, the boil-off function is given as:

$$f_t = Of_{(t-1)}$$

Where f_t describes the amount of LNG in the vessels on day t, and $O = 1 - 0.0011$.

We assume that vessels of type A and B are using forced boil-off as the only type of fuel. In addition to forced boil-off, the cargo is reduced due to natural boil-off. The daily fuel consumption must be known in order to calculate the amount of cargo removed as forced boil-off.

To determine the fuel consumption for the vessels, we evaluate the daily fuel consumption for a conventional LNG vessel with a capacity of 138 000 m^3. With a travel speed of 19 knots, the daily fuel consumption is 160 tonnes, and when loading or unloading the daily use is 3 tonnes (Lopac, 2008). Vessels A and B are more heavily equipped and can travel in harsher sea conditions than the conventional vessels referred to by Lopac (2008). We thus choose to use a fuel consumption rate for travel speed that is higher than the one used in (Lopac, 2008). The fuel consumption for type A and B is assumed to be 250 tonnes when traveling and 3 tonnes when loading or unloading.

Dodds (2014) presents a factor called Fuel Oil Equivalent Factor. This factor is the conversion ratio between m^3 of LNG and the equivalent mass of fuel oil in tones (Dodds, 2014). In (Dodds, 2014), the factor is used for conventional vessels, but we assume it to be similar for vessels of type A and B. Based on this factor, the amount of cargo removed each day, due to forced boil-off is 520 m^3 when the vessels are sailing, and 6.25 m^3 when the vessels are loading or unloading.

The cargo on board vessels of type A and B is reduced daily due to both natural and forced boil-off. The natural boil-off reduces the amount of cargo each day by a given rate. Hence, the cargo on board the vessel can be given as a recursive function of time, when the vessel is sailing:

$$f_t = O(f_{(t-1)} - F^S)$$

where f_t is the current amount of cargo in a vessel on day t, $O = 1 - 0.0011$, and F^S is the reduction of cargo due to forced boil-off when sailing, $F^S = 520\ \text{m}^3$. When the vessels are traveling between the supplier and customers, it is possible to pre-process the amount of cargo delivered to the customers. The expression is given below, and the derivation can be found in Appendix A.

$$Q_{ijv(t+T_{ijvt})} = Q_v O^{T_{ijvt}} - F^L O^{T_{ijvt}} - F^S(\frac{O^{T_{ijvt}} - 1}{O - 1} - 1) - F^L - \frac{F^S}{O}(\frac{(\frac{1}{O})^{T_{ijvt}-1} - 1}{\frac{1}{O} - 1})$$

$Q_{ijv(t+T_{ijvt})}$ is the cargo delivered to customer j on day $t + T_{ijvt}$, t is the loading day, T_{ijvt} the traveling time and F^L is the reduction of cargo due to forced boil-off when the vessel is loading or unloading. $F^L = 6.25\text{m}^3$. When the vessels are sailing between the supplier and the transshipment port, it is not possible to pre-process the amount of cargo delivered, as it depends on cargo picked up. Constraints (5.14) are used instead when the vessels are traveling between origin and the transshipment port.

7.3 Penalty Costs

In the problem described in this thesis, two kinds of penalty costs exist. Over- and under-deliveries in each month are penalized, in addition to over- and under-deliveries for the entire time horizon. Recall from Chapter 4 that the producer is obligated to deliver the stated contractual amount to the customer each month. There is some flexibility related to the delivered volumes, but this flexibility comes at a cost. Over-deliveries are more desired than under-deliveries for the long-term customers. Therefore, under-deliveries are penalized with a higher cost than over-deliveries both monthly and annual.

The costs of over-delivery are USD 25 per m^3 for deviations from monthly demands. The monthly penalty costs for under-delivery is USD 190 per m^3. This cost should be high enough to avoid spot sales instead of satisfying the demand. The cost of under-delivery is thus estimated to be approximately $1.5 * revenue$ when selling the LNG in the Asian spot market.

As mentioned, the purpose of the costs is to avoid over- and under-deliveries. However, it is difficult to deliver the specific demand to the customers in each month, as the demand may differ from cargo delivered. Therefore, an annual penalty is used to meet the total demand for the whole planning horizon. The yearly penalty should be significantly higher than the monthly. In our formulation of annual demand, the over- and under-deliveries below one shipload, are not penalized as strictly as the volumes above. As cargo delivered to the customer varies with vessel type and time of the year, one ship-load is set to the lowest possible delivery. The annual penalty costs are summarized in Table 7.4 below, where the costs are given in USD per m^3.

Table 7.4: Costs used for annual over- and under-deliveries

	Over-delivery	Under-delivery
Below one ship-load	5	7
Above one ship-load	300	400

7.4 Planning Horizon and Initial Values

The initial planning horizon begins in April. We add a start-up month to the initial 12 months ADP as a consequence of the traveling times. Recall that the duration of some of the traveling times to customers is just above one month. In these cases, the departure day should be in *m-1*, so that the deliveries for month m arrive in m. Thus, the purpose of the start-up month is to send vessels ahead of time to prevent delays in deliveries due to long traveling times. Naturally, there is no demand, and the spot unit price is zero in the start-up month. With the addition of one start-up month before the start of the planning horizon, the planning horizon begins in March.

The initial storage level in the start-up month is set to 50% of the storage capacity at the producer, and equal to 0 at the transshipment port.

Chapter 8

Computational Study

In this chapter, we present the results obtained with the different solutions methods. First, the settings used for the rolling horizon heuristic is determined in Section 8.1. Four versions of the heuristic is tested in this section. In Section 8.2 the results from solving the full case are presented. We solve the full case with an exact solution method in Section 8.2.1 and with the rolling horizon heuristic in Section 8.2.2. In order to create a solution for the full case with the aggregation disaggregation heuristic (ADH), the aggregated case must be solved. Different aggregation strategies are discussed and evaluated in Section 8.3.1, before Section 8.3.2 presents the results obtained from the heuristic. In Section 8.4 the solution methods are compared and evaluated.

For both the exact solution method and RHH, Fico Xpress with Xpress Mosel Version 4.6.0 and Xpress Optimizer Version 31.01.09 is used. The instances are run on a Elite Desk 800 G2 SFF, with 64-bit Windows 10 Operating System, processor Inter(R) Core(TM) i7-6700 CPU 3.40 GHz and 32.0 GB RAM. The ADH is implemented in Java version 8.0, with Eclipse Neon as integrated development environment, and run on a Mac OSx environment with 2.6GHz Intel Core i5 processor and 8GB RAM.

8.1 Rolling Horizon Heuristic Settings

In this section, we discuss the different settings for the RHH presented in Chapter 6.1. Based on the discussion and results obtained during testing, one strategy is chosen for the heuristic.

When testing the settings, the following stop criteria are set in each iteration:

- Optimality Gap: In each iteration, a limit on the gap between the best solution and lower bound is set. If the gap becomes less than 1%, the best solution is returned.

- Max Time: For each iteration, a maximum time limit is set. This limit is set to 3,600 seconds. If the desired optimization gap is reached within this time limit, the best-known solution is returned.

Table 8.1: Tested strategies for RHH

Case	Freezing Length	Central Period	Forecast Period
1	Two months	Two months	Two months
2	Two months	Two months	Three months
3	Three months	Three months	Two months
4	Two months	Three months	Two months

Central and Forecast Strategies

For the problem in this thesis, the demand is given on a monthly basis as well as on an annual basis. It is therefore natural to use whole months to define the lengths of the different periods used in the heuristic. Recall from Section 6.1 that a short forecast period is desirable in order to keep the heuristic efficient. Due to the length of the travel times, it takes more than one month for the vessels to travel to some customers. We therefore choose to set the minimum length for the forecast and central period to two months.

In order to keep an efficient solution time in each iteration, we choose to keep the length of a time section TS at most 5 months.

We want to reduce the computational effort by relaxing the binary constraints in the forecast period. The simplification strategy used, is thus to let the binary decision variables take continuous values.

Choosing a Length for the Freezing Period

Recall from Section 6.1, when the heuristic rolls over to the next iteration, the decisions made in the current iteration are fixed or "frozen". The freezing strategy chosen is to freeze all the decision variables in the freezing length or TF. This length affects the decision space in the next iteration and for this purpose; we test two different freezing lengths. The first length implies freezing all decision variables in the central period. The whole central period thus becomes a part of the frozen period in the next iteration. This strategy is tested on instances 1-3 listed in Table 8.1. Although this strategy would, in theory, reduce the size of the decision space for the next iteration, problems arise regarding the inventory level at the transshipment storage tank.

Voyages to the transshipment port with departure times near the end of the central period may cause inconveniences to the inventory level at the port. With a freezing length equal to the central period, these departures are frozen in the next iteration while the corresponding arrival times become parts of the central period. The storage capacity is limited at the transshipment port, and since the cargo delivered to the port may differ from cargo picked up, some departures can become infeasible when the heuristic rolls over the time horizon. Let the following example illustrate one of the problems that may occur at the transshipment port:

Consider iteration k where a vessel departs from the producer at the end of the central period, and arrives at the transshipment port on day t in the forecast period. We let the storage level at the transshipment port be at maximum at the start of the forecast period. Note that the problem may arise with other storage levels as well.

If the cargo delivered to the transshipment port on day t is more than the capacity of the vessels picking up cargo at the port, two vessels must depart before the cargo can be delivered on day t. One vessel can depart fully loaded on day $t-2$, and the remaining amount of LNG can be removed by another vessel using partial loading on day $t-1$. Recall from the previous section that partial loading is allowed in the forecast period due to the simplification strategy.

When the time horizon shifts in iteration $k+1$, partial loading is no longer allowed on day $t-1$, as the day is within the central period. The vessels must be fully loaded to depart from the transshipment port, and thus the residual amount of LNG in the tank cannot be removed. Neither is it possible to change the amount of cargo delivered to the port on day t, as the departure corresponding to the arrival time on day t is in the frozen period. As a result, the solution obtained in iteration k will become infeasible in iteration $k+1$. Figure 8.1 shows the problem, and how it leads to an infeasible problem in iteration $k+1$ when the storage level exceeds maximum capacity. This is marked with a red line in the figure on the right-hand side.

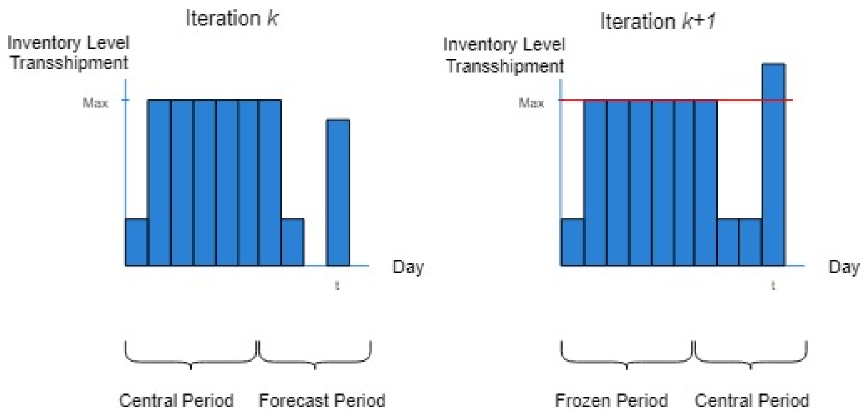

Figure 8.1: End of central period-problem at the transshipment port. The left figure shows the inventory level at the transshipment port in iteration k, while the right shows the inventory level in iteration $k+1$.

A possible way to get around this issue is to allow the heuristic to modify the amount of cargo loaded onto vessels traveling between the producer and transshipment port in the last month of the frozen period. When we test the combinations 1-3 listed in Table 8.1, we freeze all the decision variables except for the l-variables for the last month in central period. In the next iteration, it is therefore possible to change the amount of cargo loaded onto the vessels traveling between the producer and transshipment port.

Even though it is possible to modify the cargo picked up at the producer, this may not be enough to avoid infeasible solutions. We still have strict limits on the l-variables, and the allowed reduction of the variables may not be enough to prevent the infeasible storage level at the transshipment port. Another drawback with the proposed changing of cargo picked up is that a reduction of the l-variable leads to an increased storage level at the producer. The required modification of cargo picked up may not be possible, as the storage level at the producer can exceed maximum capacity.

In addition to the infeasibility issues described above, the results obtained from this strategy show a tendency towards selecting vessels of type C that are less suitable than other available vessels on a long-term basis. When the heuristic is planning the departures satisfying the demand in the forecast period, some of these departures are set to central period. In the forecast period, the binary constraints for x-values are relaxed. Over- and under-deliveries are thus easily avoided in this period. In addition, if a vessel is partially used, the operating costs of using the vessel are multiplied with the partial x-value. These circumstances make the prioritizing of vessel of type C different, and vessels that are less suitable on a long-term basis may be chosen.

The second freezing length tested implies only freezing the first part of the central period in each iteration. The last part of the central period is solved two times without the simplification strategy. This freezing length is tested as case 4 in Table 8.1. When the last month in the central period in iteration k becomes the first month in the central period in iteration $k+1$, we avoid the infeasibility issues described above. It is therefore not necessary to allow changes in the frozen period. This freezing length also avoids the problem related to unsuitable vessels of type C, as the last month in the central period is rescheduled in the next iteration.

When choosing a strategy, the performance of the tests listed in Table 8.1 are evaluated. Based on the performance we choose to set the forecast period to 2 months, and the central period to 3 months. However, in order to avoid end of central period-problems, the freezing length is two months. This strategy provides the best objective value and lowest deviations from the contractual demands.

With a freezing length of two months, the produced ADP consists of an even number of months. Due to the required start-up month described in Section 7.4, we are interested in an ADP consisting of at least 13 months. We thus use seven iterations to create an ADP with a 14-months planning horizon.

8.2 Full Case

In this section, we present the results from solving the full case. The full case consist of the customers listed in Table 7.2 in Section 7.1. The exact solution method is presented first, before proceeding to the RHH. We consider a 13-months and 14-months planning horizon to create a 12-months ADP as a result of a required start-up month and the choice of RHH-strategies respectively. For the exact method, the case is run until it reaches optimality or a maximum time limit. The maximum time limit is set to 36,000 seconds.

To evaluate the performance of the RHH, we use the best objective value of the exact method as a lower bound. We therefore present the results of solving the ADP planning problem with a 14-months planning horizon by exact method here as well.

8.2.1 Exact Method

Presolve is a function in Xpress that generates cuts to reduce the number of variables and constraints before the solution process begins. Since the size of the ADP planning problem affects the computational efficiency, enabling Presolve would reduce the size of the problem in Xpress by eliminating redundant variables and constraints early. The size of the problem before and after Presolve is applied, is shown below in Table 8.2 for both planning horizons.

Table 8.2: Number of variables and constraints for the full case before and after applying Presolve.

Planning Horizon		Before Presolve	After Presolve
13	Constraints	75,923	27,248
	Variables	92,030	84,713
14	Constraints	80,909	29,324
	Variables	98,030	90,713

Presolve manages to reduce the size of the problem significantly before the solution process begins. Therefore, we decide to enable Presolve when we solve the problem with Xpress.

Table 8.3 depicts the results from the 13-months and 14-month instances. The computational time (CPU), given in seconds, indicates when the case is solved to optimality, or if the maximum time limit is reached. The objective value is given in 1000 USD, and considers the costs and revenues for the whole planning horizon. The ADP-objective denotes the objective value of a 12-month ADP, where we exclude the costs in the start-up period and costs and revenues for departures in month 14. The deviations from contractual demand in month 14, both annually and monthly, are also left out since they occur past the ADP-planning horizon. These costs are taken into account when creating an ADP for the following year. The gap is calculated as $(UB - LB)/LB$, where we use the best objective value as upper bound (UB), and the best bound as lower bound (LB).

Table 8.3: Results from solving the full case by exact methods.

Instance	Objective Value	ADP-objective	CPU (s)	Gap (%)
13 months	65,448.40	51,071.05	36,000	12.6
14 months	82,659.20	89,630.67	36,000	11.8

As we can see, none of the instances are solved to optimality within the time limit. Note that the ADP-objective from the 13-months instance is smaller than the 14-months ADP-objective. This is mainly due to spot sales that take place during the last month in the 13-months instance. In the 14-months instance, the spot sales take place during the 14th month, but these are not included in the ADP-objective. This also explains why the ADP-objective is larger than the objective value for the 14-months instance. The ADP-objective of the 13-months instance is naturally smaller than the objective in the same instance, due to the exclusion of operational costs from the start-up month.

The annual deviations are shown in Figure 8.2 below, where the deviations are less than 25% of a ship load in both case instances. Customer 4 receives more in annual over-delivery in the 13-months instance than in the 14-months instance, which leads to higher penalty costs in the former. However, it should be mentioned that the operational costs contribute the most in the objective values. Due to voyages in the 14-months instance with departure times during the 14th month, the operational costs are much higher in the 14-months solution compared to the 13-months solution, which explains the difference between the objective values of 13- and 14-months solutions.

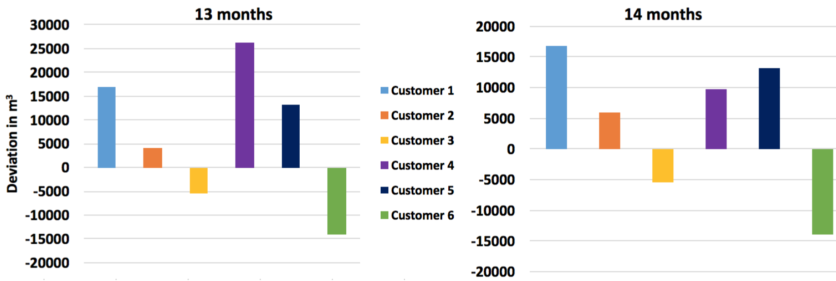

Figure 8.2: Annual deviations in m^3 from the 13-months instance on the left side, and 14-months instance on the right side

Considering that the annual deviations are low and the optimality gaps are less than 13%, the exact method produces a good ADP for the LNG producer in both case instances. However, this solution method is time consuming and we strive to produce an ADP in a shorter amount of time.

8.2.2 Rolling Horizon Heuristic

In this section, we solve the full case using the RHH. Recall from Chapter 3, that this solution method is able to find good solutions within a reasonable time for other scheduling problems. By using this heuristic to solve the full case we attempt to improve both the solution time and the solution quality. As discussed in Chapter 6, the heuristic creates a solution for the whole time horizon by repeatedly solving a MIP for every sub-horizon. For each iteration, the maximum time limit is 3,600 seconds. However, if the gap between the best bound and the best solution becomes less than 1% during an iteration, the heuristic proceeds to the next iteration.

The RHH-strategy chosen in Section 8.1, creates an ADP for 14 months. These 14 months include the start-up month. As described in Section 8.2, we are only interested in a 12-months ADP, and remove the associated costs and revenues from voyages with departure time during the start-up month or departure times during the 14th month. Table 8.4 gives an overview over the costs for a 12 months

ADP created with the heuristic, as well as the computational time. The total computational time is the sum of the computational time of each iteration.

Table 8.4: Results from RHH for the full case. The ADP-objective is given in 1000 USD, while the total computaional time is given in seconds.

Instance	ADP-objective	Total CPU (s)
14 months	88,468.69	20,400

To evaluate the quality of the ADP, the over- and under-deliveries are presented. The total amount of LNG delivered to customer 6 is below the annual demand. For the other customers, the producer over-delivers. All of the annual over- and under-deliveries are below 30% of a shipload. The deviations from the annual demand are larger for Customer 4 and 6, compared to the other customers, as shown in Figure 8.3.

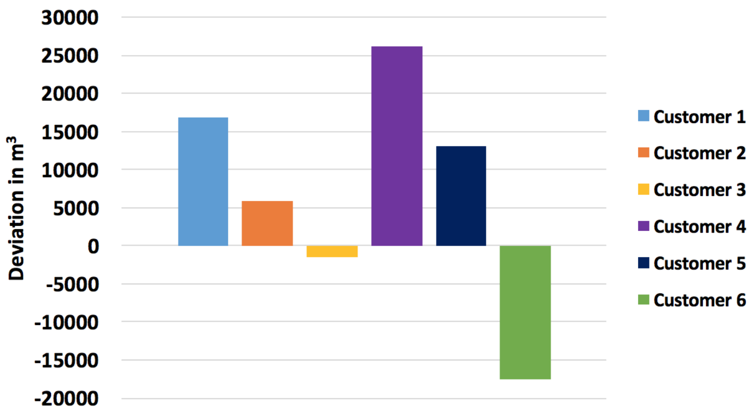

Figure 8.3: Annual deviation obtained for the full case with the rolling horizon heuristic

The Northern Sea Route opens in month 5 and closes in month 9 for vessels of type A. The opening months for vessels B are not considered relevant, as the vessel type is not used in the solution. During the opening and closing months, the under-deliveries to Customer 6 are significantly higher compared with the other months. For all the long term customers, except Customer 2 and 6, the opening of NSR leads to a greater amount of cargo delivered. In addition to the deliveries shown in the figure, two vessels deliver cargo to Spot Customer 2 in month 7. The figure showing monthly over and under-delivery is given in Appendix B.4.

An interesting aspect of the solution generated by the heuristic is the delivery pattern to long-term Customer 2. The customer is located in Europe and can be reached both directly from the producer and from the transshipment port. Approximately 83% of the voyages to the customer depart from the transshipment port. The remaining voyages travel directly from the producer, and arrives in the 2^{nd} and 11^{th} month. These months have a greater amount of over-deliveries to the customer.

Keep in mind that the rolling horizon heuristic constructs a solution by solving the problem in sub-horizons. In order to evaluate the solution for the total planning horizon, we should be aware of the behavior of the solutions found in the sub-problems. The computational time and gap found in each iteration, is summarized below in Table 8.5. In iteration 2 and 3, the gap is less than 1%, and the computational time is therefore below the maximum limit. Note that in iteration 4, the gap is significantly higher than the gap in the other iterations. In this iteration, the problem is solved for a time horizon from month 7 to month 11, where month 7, month 8, and month 9 are within the central period. As seen from the figure in Appendix B.4, all of the customers are facing over-deliveries in month 7 and 8.

Table 8.5: Gap and time used in each iteration for the RHH

Instance	Iteration	Gap (%)	Time in Iteration (s)
Full Case	1	4.50	3,600
	2	0.55	$<$ 100
	3	1.00	2,300
	4	77.32	3,600
	5	7.95	3,600
	6	5.85	3,600
	7	10.62	3,600

Figure 8.4 displays the improving solutions found in each iteration. Despite that five of the iterations use the maximum time-limit, improving solutions after 500 seconds was only found in iteration 5 and 6. In iteration 3, the best solution is found after 230 seconds. During the next 2,000 seconds, the lower bound increases and the iteration stops after approximately 2,300 seconds due to the value of the gap.

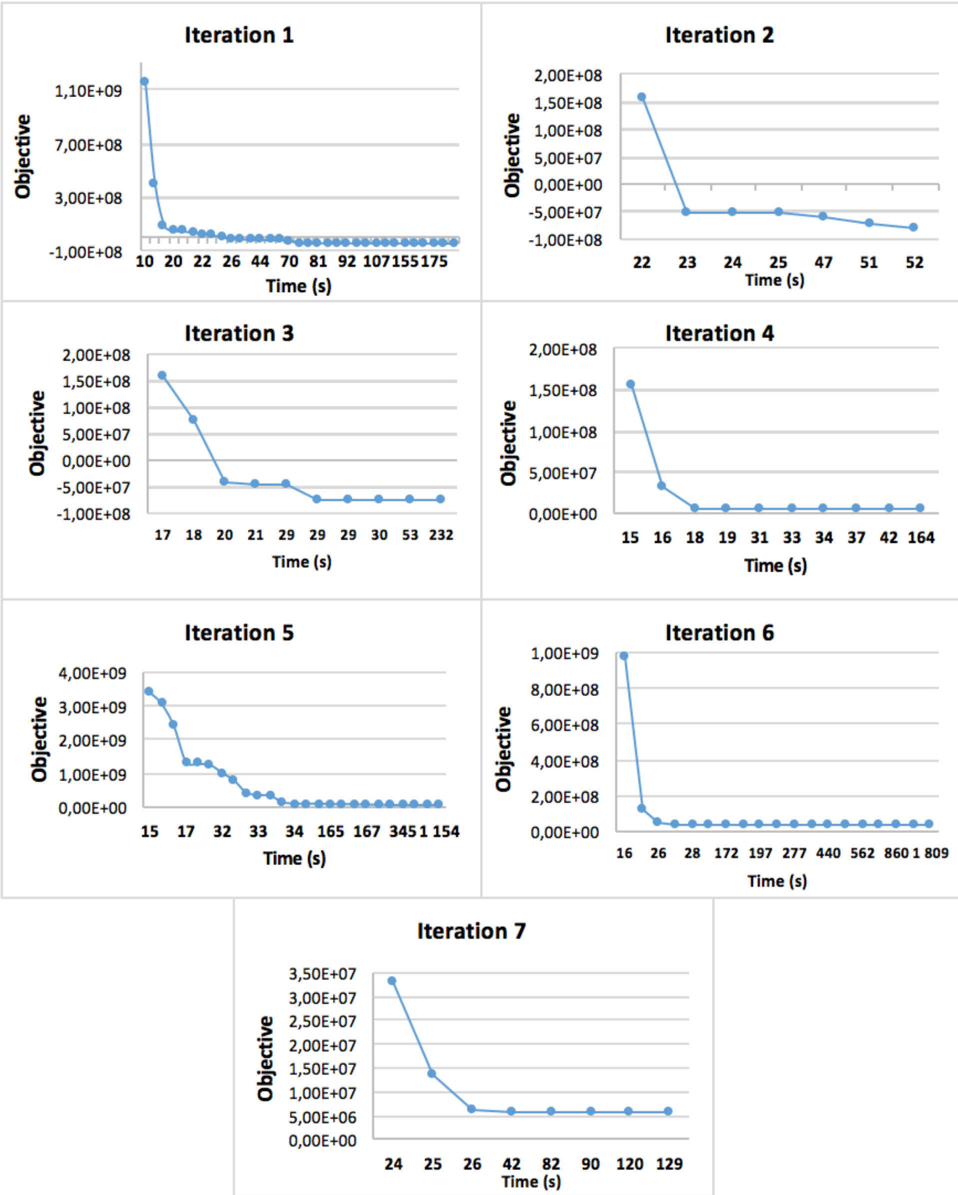

Figure 8.4: Solutions obtained in the iterations in RHH. The x-axis displays the computation time for the solution, while the y-axis shows the objective-value for each solution.

The figure shows that for each iteration, the best solutions are remarkably different in the objective value and in solution time. The objective value is a measure of the total costs for the time horizon within the iteration. The objective for an iteration also includes the cost of the total accumulated deviations in demands for the frozen and central period. When the heuristic rolls over the sub-horizons from one iteration to another, the frozen period increases. This implies that the total accumulated deviations in one iteration depends on accumulated deviations in the previous iterations. However, in the last iteration, this cost is below 10% of the objective for the best solution within the iteration.

As the sub-problems solve the problem for different months, seasonality is an important aspect of the solutions. When the NSR is open, the travel times from the producer to the customers are shorter, and in addition, it is possible to reach all customers within a month. With a lower travel time, more cargo is delivered to each destination, and the sum of the daily costs decreases. When the cargo delivered to each destination decreases, the total revenue per ship load delivered to the spot market also increases, due to the constant spot price.

Another important contribution to the objective value in the iterations is the in-going storage level. Recall from Section 6.1, that some information should be transferred from one iteration to another. The storage level at the producer and the transshipment port are depended on the inventory level the previous day. The storage level the last day in the frozen period should therefore be known. This value is used to calculate the storage level the first day of the central period. If the in-going storage level is low, the amount of excess cargo available is small, and less cargo can be delivered to the spot market during the central and forecast period.

Figure 8.4 can be used to evaluate the best solution found in iteration 4. As the NRS is open the first part of iteration, the best solution should be better than the one in iteration 5. In iteration 3 two spot sales occur in the central period and the NSR is open during the whole sub-horizon. These two spot sales are the only spot sales included in the solution for the whole planning horizon. The solution in iteration 4 should therefore be worse than best solution in iteration 3. Based on the plots in Figure 8.4, we can conclude that the best objective in iteration 4 seems reasonable if it is compared with the best solutions in the other iterations.The large gap in iteration 4 may be caused by the change of structure in the problem, when the NSR closes the first day of the forecast period.

8.3 Aggregated Case

In this section, we use the aggregation disaggregation heuristic (ADH) presented in Chapter 6 to create an ADP. The ADH consists of two main components: solving the aggregated version of the full case and disaggregating the solution to produce an ADP for the full case. As discussed in Chapter 6, several aggregation strategies exist for this ADP planning problem. We test three different strategies for the input in the ADH, and based on the results, we select the strategy that yields the ADP with the lowest penalty costs.

8.3.1 Aggregation Strategies

Each aggregation strategy is solved by the exact method. The aggregation strategies are mainly based on geographic areas, but vary with respect to transshipment for customers located in Europe. As mentioned in Chapter 6, we choose two geographic areas: Europe and Asia. Long-term customers located in Europe are clustered together, while long-term customers in Asia are clustered together. The aggregated customers are denoted as LT-EU and LT-Asia respectively. Additionally, a spot customer is located in each geographic area. We test the following strategies:

- Strategy 1: 2 aggregated customers: LT-EU and LT-Asia. Only direct voyages to LT-EU are permitted.
- Strategy 2: 2 aggregated customers: LT-EU and LT-Asia. Transshipment and direct voyages to LT-EU are permitted.
- Strategy 3: 1 aggregated customer: LT-Asia. The customers in Europe remain individual customers, and voyages to Customer 1 can only be direct.

The strategies are visualized in Figure 8.5.

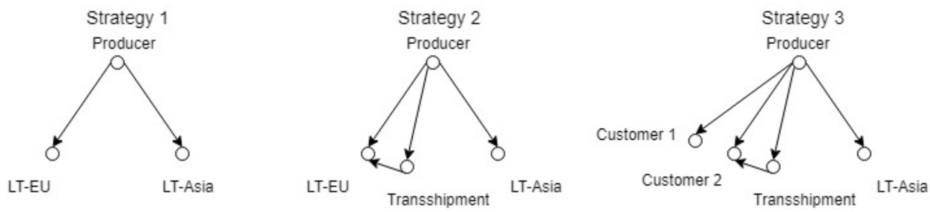

Figure 8.5: Aggregation Strategies

Table 8.6 shows the results from the aggregation strategies, where the computational time (CPU) and optimality gap are from the exact method. The maximum time limit is 36,000 seconds. The penalty costs are from the resulting ADP after disaggregation. None of the strategies where solved to optimality within the maximum time limit. All of the strategies consider a 13-months planning horizon.

Table 8.6: Results from testing the aggregation strategies.

Aggregation strategy	Penalty Costs	CPU Exact (s)	Optimality Gap Exact (%)
Strategy 1	21,754.56	36,000	9.15
Strategy 2	21,611.59	36,000	9.14
Strategy 3	13,071.06	36,000	16.7

In order to evaluate and select the best strategy, we use the penalty costs and deviations. After the disaggregation procedure, the operational costs are most likely to decrease as a result of the pessimistic travel times. However, the penalty costs may increase due to changes in cargo delivered. We denote the resulting solution after ADH as ADH-solution, while a solution from the aggregated case is denoted as input solution.

Aggregation Strategy 1

The ADH with Strategy 1 produces an ADP with the highest penalty costs. After disaggregation, the penalty costs increase as a result of over-deliveries to the customers with travel times shorter than the aggregated travel times. Recall that the aggregated customers are assigned the most pessimistic travel times among the customers that constitute an aggregated customer. If the travel time of a rerouted voyage is shorter than the pessimistic travel time, the amount of cargo delivered is larger due to decreased boil-off loss. This is problematic for the European customer with the shorter travel times.

For the long-term customers in Asia, the differences in travel times are not as large as for the case in Europe. In fact, the difference between the one-way pessimistic travel time and the shortest travel time among the Asian customers is 2 days. Among the European customers on the other hand, the difference is 4 days.

In Chapter 6, we discuss the possibility of premature arrival dates after disaggregation, as a result of the conservative travel times in the aggregated case. One of the rerouted voyages in the ADH solution is affected by the large spread in travel times among the customers in Europe. Here, the original voyage to LT-EU has an arrival time during month m. When the voyage is rerouted to Customer 1, the new arrival time ends up in month *m-1*, because of the large difference in travel times. Customer 1 has already been assigned a delivery from a voyage with arrival in month *m-1*, so the heuristic reroutes the voyage to Spot Customer 1 instead, resulting in under-delivery for Customer 1 in month m. We carry out a post-processing step to rectify this. We postpone the departure day of the voyage with at least the difference between the pessimistic travel time and the travel time to Customer 1, $T_{LTEU} - T_{Customer1}$ days, as long as the postponed voyage is inventory, routing and berth feasible.

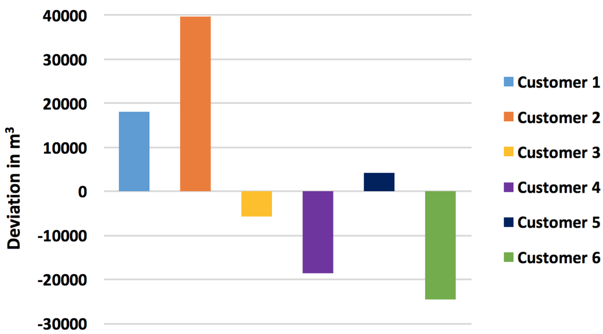

Figure 8.6: Annual deviation after ADH, given aggregation with Strategy 1

In Figure 8.6, the annual deviations after disaggregation are presented. The substantial amount of over-delivery to Customer 2 is a result of the occurrences of over-deliveries every month. Since Customer 2 and LT-EU have the same travel times, one would therefore assume that the change in deviation between the aggregated case and Customer 2 would be smaller. However, the monthly demand of Customer 2 is smaller than the cargo delivered in a given month, leading to over-deliveries. Customer 1, on the other hand, has a larger monthly demand and shorter travel time. The amount of cargo delivered each month is not far from the demand, which leads to small over-deliveries.

Customer 4 experiences quite a big amount of under-deliveries in months 6, 7 and 10 due to the vessel choice in the input solution (see Appendix B.2). Vessels of type B, which have lower tank capacities, are used in month 6 and 7, and are rerouted to Customer 4. In the input solution, the voyages carried out with vessels of type B have the departure day in the previous month and arrival day in the next. The departure day determines the travel time and consequently the amount of cargo delivered. Since the travel time in the departure month is longer than in the arrival month, the amount of cargo delivered is smaller. The cargo delivered from this voyage in combination with the other deliveries that are made with vessels of type A in the arrival month, is close to the aggregated demand. But when the voyages are disaggregated, the deliveries made by vessels of type B deviate from the demand of the individual customers in Asia. As a result of this, Customer 4 experiences large under-deliveries in months 6 and 7.

In month 10, a conventional vessel with the smallest capacity in the fleet is sent to LT-Asia. The conventional vessels with both larger capacity and best cost-to-capacity ratio are at this time occupied, so the smallest conventional, which has the second best in cost-to-capacity ratio, is therefore sent instead. Here, a similar problem, where differences between the cargo delivered and individual demand after disaggregation as a result of vessel choice, occurs. The small conventional vessel is rerouted to Customer 4, which explains the substantial under-delivery in month 10.

The monthly demand of Customer 6 is the largest among the customers in Asia. After the disaggregation, Customer 6 experiences large monthly under-deliveries more frequently due to difference in cargo delivered and vessel capacity. If we compare the deviation with the full case 13-months instance solved by exact method (see Figure 8.2) and by the RHH (see Figure 8.3), Customer 6 faces a large annual under-delivery in these solutions as well. This shows that it is challenging to satisfy the monthly demand of Customer 6 due to differences in demand and vessel capacity.

Besides the large spread in travel times for the European customers, another shortcoming with this strategy is that transshipment to customers in Europe is not permitted. The purpose of using transshipment as a way of transferring cargo onto conventional vessels is ignored. For this reason, we do not proceed further with Strategy 1.

Aggregation Strategy 2

In this aggregation strategy, transshipment is added as a possibility for the aggregated customer in Europe. There are some similarities in the ADH-solution produced with Strategy 2 as in the ADH-solution produced from Strategy 1.

The direct voyages to LT-EU remains the dominating routing choice from the aggregated solution, where 87.5% of the voyages to LT-EU are direct. The reason behind is the aggregated demand. Here, the sum of the direct deliveries in a given month to LT-EU is closer to the monthly aggregated demand than the deliveries via transshipment. Recall that the conventional vessels have smaller capacities than the ice-going vessels and deliver less in every voyage. So, when a direct voyage is rerouted to Customer 2, the delivery volume is larger than the monthly demand, which in turn leads to over-deliveries. The few transshipment voyages to the LT-EU occurring in the solution are rerouted to Customer 2, since voyages to Customer 1 can only be direct.

Unlike the ADH-solution from the aggregated case with Strategy 1, all of the individual customers in Asia receive under-deliveries on an annual basis. In this case, the main reason behind is the input solution, where Customer LT-Asia experience under-deliveries more frequently compared to the input solution from Strategy 1. This leads to increased under-deliveries to Customer 3, 5 and 6. Customer 4 does not suffer from the choice of vessels as much as in the previous input solution with Strategy 1, and hence the amount of under-deliveries has decreased substantially. If we compare the vessel choice for the month where one of the deliveries to LT-Asia are made with a vessel of type B in Strategy 1, we see that only vessels of type A are used, and departure and arrival times are in the same month. Therefore, the vessel choice is better in the input solution of Strategy 2.

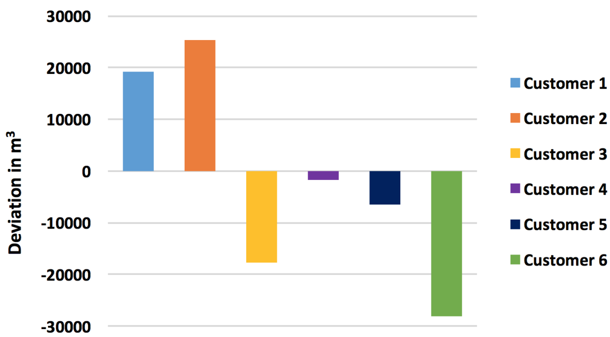

Figure 8.7: Annual deviation after ADH, given aggregation with Strategy 2

A drawback with this strategy is when voyages to LT-EU only use transshipment in a given month. These voyages cannot be rerouted to Customer 1 without modifying the other decision variables. A potential rerouting to Customer 1 implies that the cargo picked up and cargo delivered values need to be changed to prevent inventory infeasibility at the production and transshipment storage tanks. The disaggregation procedure would therefore reroute voyages to a spot customer instead Customer 1, which leads to an under-delivery.

Aggregation Strategy 3

We see that the aggregation of the two long-term customers in Europe in accordance with strategies 1 and 2 lead to substantial over-deliveries for the individual customers after disaggregation. The ADH-solutions of both strategies contain considerable over-deliveries for the individual customers in Europe. Additionally, Strategy 1 overlooks the transshipment aspect of the planning problem for the European customers. As a consequence of these factors, Strategy 3 only aggregates the long-term customers in Asia.

As Table 8.6 shows, the total penalty costs are much lower with Strategy 3, since the travel times and demands of the individual customers in Europe are now taken into account when solving the aggregated case by exact method. Around 83% of the voyages go to Customer 2 go via the Transshipment port, where the cargo is transferred onto a conventional vessel with smaller capacity than the ice-going vessel. The cargo delivered by the conventional vessel is closer to the monthly demand of Customer 2, compared to the direct voyages from previous strategies. As shown in Figure 8.8, the monthly deviations for the customers in Europe are much smaller compared to the results from the aggregated cases with Strategy 1 and 2.

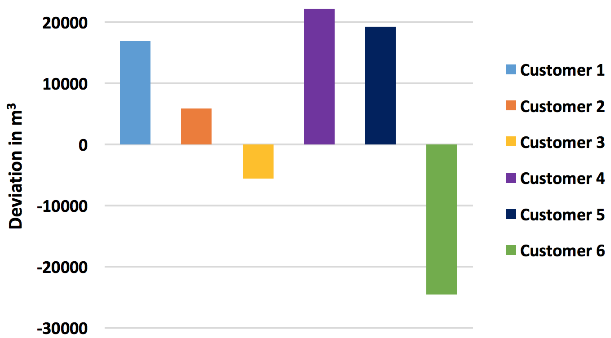

Figure 8.8: Annual deviation after ADH, given aggregation with Strategy 3

The annual deviations for customers 1, 2 and 3 are reduced when Strategy 3 is used, compared to Strategy 1 and 2. Because of frequent over-deliveries to LT-Asia in the input solution, Customer 4 and 5 receive frequent over-deliveries as well, leading to an over-delivery on an annual basis. On the other hand, Customer 6, who has the largest demand among the customers in Asia, experiences frequent under-deliveries in all of the strategies.

Note that the gap from solving the aggregated case with Strategy 3 is slightly worse compared to the gaps of the other aggregation strategies. Since the customers in Europe are not aggregated, the complexity increases due to the increased number of nodes in the problem, thus increasing the computational effort. However, the penalty costs are lower than the penalty costs from the other strategies, which makes the solution a good input for the disaggregation procedure.

Since Strategy 3 discerns between the European long-term customers by taking transshipment explicitly into account and has lower penalty costs, we choose to proceed with this aggregation strategy.

8.3.2 ADH

So far, the aggregated case has been solved by exact method. The result is used as input to the disaggregation procedure to create a solution for the full case. The computational time of the disaggregation procedure is minimal, which implies that the solution method used to solve the aggregated case is the sole contributor to the computational time of the ADH. Based on the results in Table 8.6, we see that the exact method is time consuming. Considering that the RHH is able to solve the ADP planning problem quicker than the exact method, we use the RHH to solve the aggregated case before disaggregation.

The combination of RHH and ADH is denoted as RHH-ADH, while the combination of exact method and ADH is denoted as E-ADH. In order to compare these two solution method combinations, the E-ADH is solved for a 14-month planning horizon like the RHH-ADH. Since we are only interested in a 12-month ADP, we remove the start-up month and the last month from the results to get an ADP-objective. The results from both solution method combinations are presented below in Table 8.7.

Table 8.7: Solutions from the ADH without post-processing. The ADP-objective is given in 1000 USD and the CPU in seconds.

Solution Method	ADP-objective	CPU (s)
E-ADH	91,724.041	36,000
RHH-ADH	102,047.131	18,150

The objective value of RHH-ADH is worse compared to the objective value of E-ADH. The input solution from the RHH has more frequent under-deliveries to LT-Asia than the input solution from the exact method. Monthly over- and under-deliveres are displayed in Figure 8.10. In the RHH-ADH solution, the difficulties arise in months 6, 7 and 12. In month 7, Customer 3 and 6 suffer from substantial under-deliveries, while Customer 5 experiences quite a big under-delivery in month 12. The big under-delivery in month 12 is a result of the input solution, where the monthly deviation to LT-Asia is about 18,000m^3 in under-delivery. Customer 4, on the other hand, receives almost twice the amount of over-delivery in the RHH-ADH solution as in the E-ADH solution, which is illustrated in Figure 8.9.

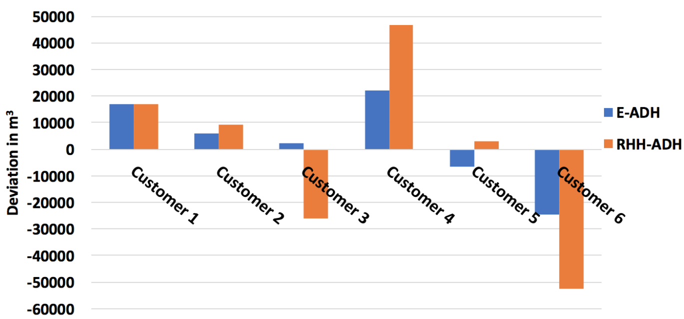

Figure 8.9: Annual deviation from E-ADH and RHH-ADH

Destination Swap

To reduce the over- and under-deliveries, we consider the possibilities for modifying the destinations of some of the voyages in the ADH-solution. The fleet of vessels is heterogeneous and by swapping the rerouted destination for vessels heading to the same geographic area, we may reduce some of the over- or under-deliveries. A swap implies a switch of the destination between two voyages. When two destinations are swapped, we must ensure that the new arrival days are in the same month as in the ADH-solution before the swap.

In the solution obtained from E-ADH, we see that Customer 4 receives substantial over-deliveries, while Customer 6 faces substantial under-deliveries. Therefore, we swap some of the voyages between Customer 4 and 6, in an attempt to improve the solution. Figure 8.10 depicts the monthly over- and under-deliveries. We see that it is beneficial to swap the voyages with arrival days in month 9, 10 and 12 for these customers due to the difference in the vessels' capacities. These rearrangements of the departures decreases the costs of under- and over-delivery with 14.0%.

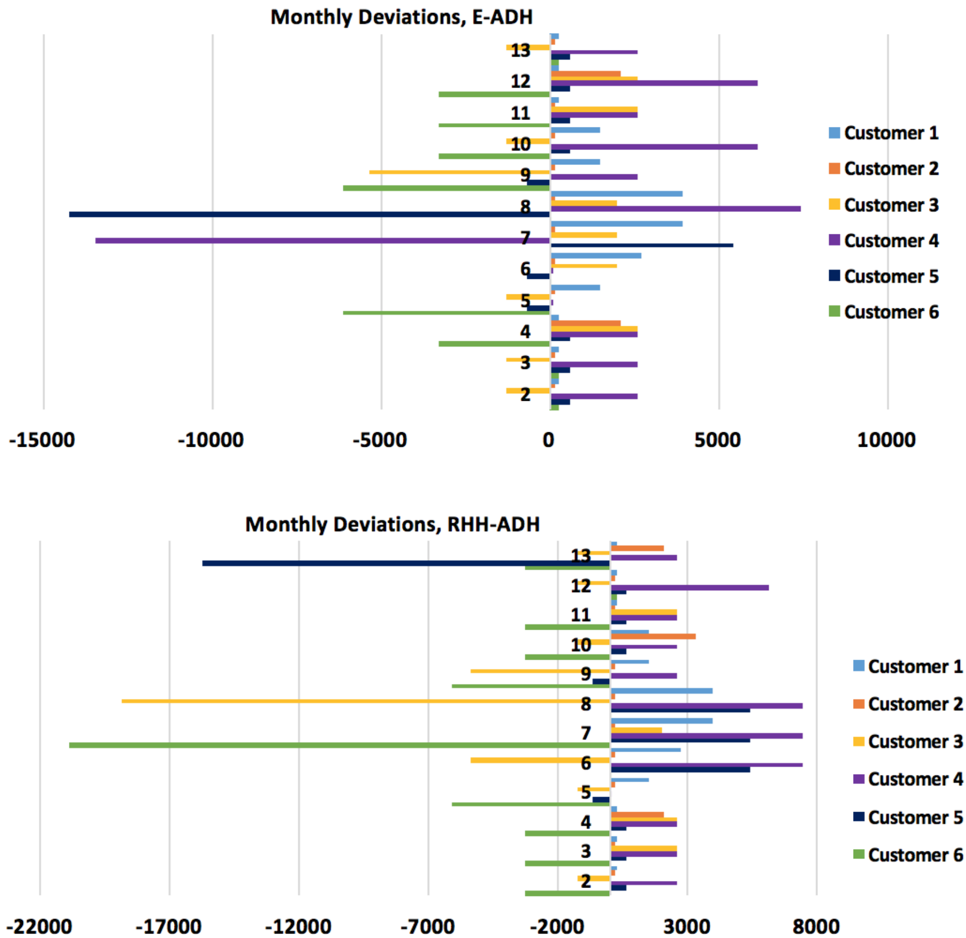

Figure 8.10: Monthly deviations from E-ADH and RHH-ADH before destination swap

In the solution given by RHH-ADH, we evaluate the departures to Customer 3, 4 and 6, as these customers are suffering from the highest deviations. Three of the departures to Customer 4 can be switched with two departures to Customer 6, and one to Customer 3. This post-processing step decreases the cost of under- and over-delivery by 11.8%.

Table 8.8 below shows how the post-processing of the solutions decreases the ADP-objective. The new annual deviations are illustrated in Figure 8.11. Note that the post-processing of the solutions has decreased the over-delivery to Customer 4 and the under-delivery to Customer 6 significantly for both the E-ADH and RHH-ADH.

Table 8.8: Solutions from the ADH before and after destination swaps

Solution Method	ADP-objective before swaps	ADP-objective after swaps
E-ADH	91,724.041	89,475.70
RHH-ADH	102,047.131	99,014.31

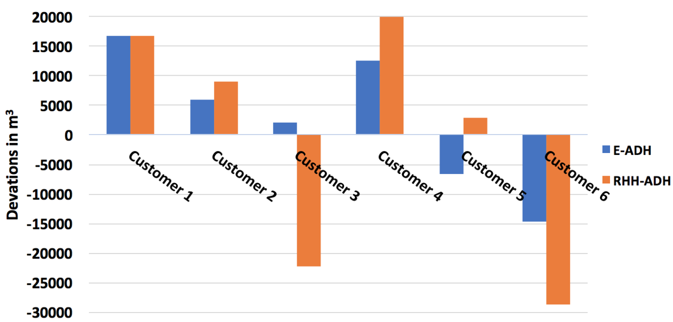

Figure 8.11: Annual deviations after post-processing the ADH solutions

The resulting ADP from RHH-ADH is not as cost-efficient as the ADP created with E-ADH. However, as Table 8.7 and 8.8 depict, RHH-ADH only uses half of the computational time of E-ADH to produce a solution, whereas E-ADH stops when the maximum time limit is reached.

The RHH has a maximum time limit for each iteration and produces an ADP in a shorter amount of time compared to exact method. An advantage with the RHH is that we can adjust the time limit on the iterations, which makes it flexible to use. A longer iteration time length may lead to an ADP of higher quality, while short iteration time lengths may reduce the quality. The RHH is also more predictable than the exact method, in the sense that we have an upper bound on how long it takes to create an ADP since we operate with a time limit for each iteration.

8.4 Comparison of Solution Methods

In this Section, we compare the solution methods studied separately so far. The RHH creates a 14-months ADP, and in order to compare the solution methods, we use the 14-months planning horizon for the other methods as well. In Table 8.9, the different solution methods are listed. When we calculate the gap, the ADP-objective from the exact solution method is used as a lower bound. The upper bound is given by the best solution of a solution method.

Table 8.9: Comparison of solution methods. The ADP-objective is given in 1000 USD and the gap is calculated using the exact solution as lower bound.

Solution Method	ADP-objective	CPU (s)	Gap (%)
Exact	89,630.67	36,000	-
RHH	88,468.69	20,400	1.3
E-ADH	89,475.70	36,000	0.2
RHH-ADH	99,014.31	18,150	10.5

Starting with the over-all performance of the solution methods, we observe that the best solution is given by the RHH. This heuristic produces an ADP with a better ADP-objective value than the exact solution method and the ADH. None of the solutions from the ADH gives an ADP with a better ADP-objective value compared with the RHH. However, the E-ADH obtains a better solution than the exact method after the post-processing step. The differences in the ADP-objectives for the three best solutions are not large. As Table 8.9 indicates, the solutions from RHH and E-ADH have gaps less than 2% of the exact solution method. The solution from RHH-ADH, on the other hand, is 10.5% worse than the solution obtained with the exact solution method.

In the solutions from each method, there are two voyages heading to Spot Customer 2 when the NSR is open. The differences in the objective values come from the vessel choices, since the operational and penalty costs depend on the vessel choices. We observe that vessels of type B are not used in the solution given by the exact method or in RHH. In E-ADH, vessels of type B are used twice, while in RHH-ADH the type is used once. There are differences in the use of the vessels of type C in the solutions. In the solutions from RHH, RHH-ADH and E-ADH, only two types of vessel C are used. These two types have the best cost-to-capacity ratio. The solution from exact method is using a vessel from a third type of C in addition. The third type has a lower charter cost per day, but has a lower tank capacity than the other types. This vessel is sent from the transshipment port to Customer 4, and arrives in the 12th month. If we compare the figures showing annual over- and under-delivery for the different solution methods, we can observe that the exact solution method has a lower amount of over-delivery to Customer 4.

In general, the solutions obtained with the RHH have a higher amount of over- and under-deliveries compared to the solutions obtained with the exact solution method. For the RHH and the exact solution method there are small differences in total under-deliveries, but the RHH solution delivers approximately 15,000m^3 more to the customers than the solution of the exact method. Recall from Section 8.3.2 that this is also the case for the ADH. After the disaggregation procedure, the over- and under-deliveries increase. Despite the increase in deviations, it is worth mentioning that none of the customers in all of the solutions suffer from a deviation of more than half a ship load.

The delivery pattern to long-term Customer 2 differs in each solution. Customer 2 can be reached directly from the producer and from the transshipment port. In the solutions from the exact method, RHH, and E-ADH, the same delivery pattern to the customer is created, where 83.5% of the arrivals departs from the transshipment port. These voyages use the same type of vessel C. In the RHH-ADH solution, the number of voyages departing from the transshipment port to the customer is 75%. Figure 8.9 and 8.11 show that a reduction in voyages departing from the transshipment port leads to increased over-deliveries to the customer. This is due to the transfer of cargo onto a smaller conventional vessel with a capacity closer to the monthly demand of the customer.

Table 8.9 also shows the computational time for the solutions. The RHH-ADH use the shortest computational time to create an ADP. Recall that the computational time for the disaggregation procedure is reckoned to be minimal, so the computational time of solving for the aggregated case is the main contributor. Because the number of nodes are reduced in the aggregated case, the computational time of solving the aggregated case with RHH is shorter than solving the full case with RHH. In both cases, two of the iterations reached the optimality gap limit, but for the aggregated case this occurs faster than for the full case. Both the exact solution method and E-ADH have a computational time of 36,000 seconds.

The RHH provides a better solution within a shorter amount of time, than the exact method. A drawback with the heuristic is that in each iteration, only a part of the total planning horizon is evaluated. Deliveries to the customers are adjusted for over and under-deliveries in earlier iterations, but deliveries in the consecutive iterations are not considered. As we can see from Figure 8.4, the quality of the solutions found in each iteration depend on seasonality. Recall from Section 8.2.2, that when the NSR closed between the central and the forecast period, the gap was significant higher compared to the other iterations. The somewhat myopic exploration of the planning horizon in combination with seasonal effects in routing choice, may be the reason behind the higher amount of over and under-deliveries. In spite of the RHH creating what we consider good solutions for the ADP-problem, these solutions may not be suitable as input in the ADH due to the higher amount of over and under-deliveries.

The ADH improves the operational costs from the input solution due to the pessimistic travel times, but the deviations from annual demand are not improved. When the RHH-ADH reroutes the vessels, the deviations increase compared to the aggregated input solution. For E-ADH, the total difference in over and- under-deliveries are small compared with the exact method. The amount of over-deliveries are 8000m^3 less than the exact method, while the under-deliveries are 2000m^3 more. Despite the deviations, the E-ADH provides a better objective than the exact solution within the same computational time.

The biggest advantage with the ADH, is that the computational time depends only on the computational time of the aggregated solution. The aggregated case is smaller and hence the complexity is significantly lower compared to the full case. As the RHH obtains a solution faster for the aggregated case than for the full case, this improves the solution time for the RHH-ADH. However, the reduction of computation time comes at the expense of the solution quality. The ADH provides better results after the post-processing of the departures, but the solution is worse compared to the solutions from other methods.

In order to evaluate the total performance of the solution methods, the intended use of the ADP can be considered. The ADP can either be a draft used for negotiations with the customers, or a suggested plan made after the negotiations. If the ADP is used as a draft, the ADH can be useful due to the computational time. RHH-ADH have the shortest computational time and can produce an ADP faster than the other solution methods. RHH is the best option if the ADP is should be optimized after the negotiations. Even though the RHH does not solve the ADP planning problem with the shortest computational time, it produces the most cost-efficient ADP.

Chapter 9

Concluding Remarks

The problem in this thesis is to solve an annual delivery program (ADP) planning problem for an LNG producer with a heterogeneous fleet of vessels. The goal is to create an ADP that fulfills the contractual demands at a minimum cost. Operative costs for the vessels and penalty costs related to over- and under-deliveries are included in the objective. Revenue from selling excess LNG in the spot markets is considered as a negative cost.

The producer is located north of the Arctic Circle, while the customers can be found in different areas of the world. Specialized ice-going vessels travel from the producer either directly to the customers or to a transshipment port. The Northern Sea Route is used to reach customers located in Asia directly. When the route is closed, the ice-going vessels must travel to Europe and unload the cargo at the transshipment port. From this port, conventional LNG-vessels are used for delivery to the customers in Asia. The problem is formulated as a mixed integer programming (MIP) model that allow partial loading when the vessels are traveling from the producer to the transshipment port. The purpose of this thesis is to use heuristic approaches to minimize the costs of the ADP. Solution time is also an important consideration for the producer, and should be evaluated along with the objective value. Three different solution methods are tested and compared to find the best solution for the problem. The exact solution method using branch-and-bound did not obtain a gap below 10% within a computational time of 36,000 seconds. Two heuristics are used to create better solutions and reduce the computational time. The first one tested, is a rolling horizon heuristic (RHH), similar to the one presented in Rakke et al. (2011). The RHH reduces both the computational time and the objective value compared to the exact solution method.

An aggregation disaggregation heuristic (ADH) is developed to reduce the computational time even further. In the ADH, the customers are aggregated according to an aggregation strategy. The aggregated case is then solved with the exact solution method (E-ADH) and RHH (RHH-ADH). Afterwards, the solutions are disaggregated.

The performance of the ADH depends on several factors:

- Aggregation strategy: after testing different aggregation strategies, the strategy leading to best results includes an aggregation of customers based on geography and routing choice.

- Solution method used for the aggregated case: as the computational time in the disaggregation procedure is minimal, the total computational time for the heuristic depends on the time used to solve the aggregated case.

- Over- and under-deliveries in the solution for the aggregated case: the computational study in Chapter 8 shows that the amount of over- and under-deliveries increases after the disaggreation procedure. For the ADH to be able to produce high quality solutions, the amount of over- and under-deliveries in the input solution from the aggregated case should be limited.

The results obtained from the ADH differ. The E-ADH obtained better solutions within the same computational time as the exact method. For RHH-ADH the computational time is further decreased, but the objective value is worse. Neither E-ADH or RHH-ADH yields a better objective value than RHH. RHH-ADH, on the other hand, solves the problem with shorter computational time than RHH due to the aggregation.

The aggregated case has a reduced complexity compared to the full case, and as described in Chapter 8, the RHH produces a solution faster for the aggregated case. The RHH-ADH can thus be a suitable decision tool when quick feedback is important. In addition, if the decision maker is familiar with an estimated distribution of the demand, and want to obtain solutions for alternative demand scenarios, the ADH is well suited. Once a solution for the aggregated case is found, solutions for different distributions of the demand within the aggregated customers are quickly obtained.

Chapter 10

Future Research

There are several areas of improvement when it comes to solving the ADP planning problem.

Two heuristic solutions methods have been developed to create an Annual Delivery Program effectively. The quality of the solution from the Aggregation Disaggregation Heuristic (ADH) highly depends the input solution from the aggregated case. The penalty costs increase after disaggregation, so if the input solution has large deviations, the solution after disaggregation becomes worse. The vessel choice in the input solution is not optimal for the disaggregated solution due to different individual customer demands. A vessel combination may be close to the demand of an aggregated customer, but during disaggregation, the vessels are assigned to customers to avoid premature deliveries. A vessel with smaller capacity that is often rerouted to a customer with higher demand leads to substantial under-deliveries annually. Therefore, departure times should be modified to avoid considerable penalty costs. Therefore, the ADH can be improved with a re-optimization procedure after disaggregation, such as a neighborhood search heuristic or a MIP-based improvement heuristic, to modify vessel choice and departure times.

Matheuristics is a more recent solution methodology within the field of heuristic solution approaches. Here, mathematical programming concepts are combined with heuristics used to create or improve solutions. A neighborhood search in combination with a matheuristic could have been added on top the ADH and RHH to improve the solutions.

An interesting extension to the ADP planning problem is disrupting management. The Northern Sea Route is characterized by varying sea ice levels and uncertainty in weather conditions, which introduces the potential for creating robust ADPs. By including uncertainty in travel times, the producer needs to re-schedule an ADP to minimize the costs of disruption. The ADP planning problem can be reformulated as a two-stage stochastic model, where the first stage generates an initial ADP, while the second stage is a recourse problem that re-optimizes the ADP based on the realization of stochastic parameters.

The rolling horizon heuristic (RHH) can be adapted to a scenario based approach that solves a two-stage stochastic ADP planning problem. As the heuristic rolls over, a scenario is realized with a probability distribution. Based on new information that arrives in every central period, the recourse problem is solved, and predictions are made for the rest of the horizon. Considering the length of the planning horizon, a RHH approach for a two-stage stochastic ADP planning problem sems ideal.

Another solution method to a two-stage stochastic ADP planning problem is to combine optimization with simulation. In this case, the simulation procedure is used to evaluate the solution from the optimization procedure. The simulation procedure should then re-optimize the proposed schedule as a consequence of scenario realizations.

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Appendices

Appendix A

Derivation of Boil-Off Constraints

In this appendix α_{ijvt} and β_{ijvt} in constraints (5.14) are derived. In order to derive the expressions, some new notation are introduced. In addition, some of the indices are reduced in order to simplify the notation during the derivation.

Let $\hat{l}_t$ describe the inventory level at a vessel when traveling between the producer and the transshipment port. Note that the definition of $\hat{l}_t$ differs from the definition of l_{ijvt} used in Section 5.4. l_{ijvt} is the cargo loaded onto the vessel, while $\hat{l}_t$ is the cargo on board the vessel when traveling. In this section, we let $\hat{l}^0$ be the amount of cargo loaded onto the vessel. The inventory level in a vessel when traveling between two ports is given by:

$$\hat{l}_{t+1} = (\hat{l}_t - F^S)O \tag{A.1}$$

Where F^S is cargo used as fuel when sailing (forced boil-off) and O is the remaining percentage of cargo in vessel due to natural boil-off.

If we let $t = \hat{t}$ denote the day the vessel picks up cargo, and $\hat{l}_{\hat{t}}$ the amount of cargo loaded into the vessel at day $\hat{t}$, the expression can be formulated as:

$$\hat{l}_{\hat{t}+1} = (\hat{l}_{\hat{t}} - F^S)O \tag{A.1}$$

Where the cargo on-board the vessel at time $\hat{t}$ is given by:

$$\hat{l}_{\hat{t}} = (\hat{l}^0 - F^L)O \tag{A.2}$$

F^L is the forced boil-off when loading or unloading.

Similarly, the inventory level at day $\hat{t}+2$:

$$\begin{aligned}\hat{l}_{\hat{t}+2} &= (\hat{l}_{\hat{t}+1} - F^S)O \\ &= (((\hat{l}^0 - F^L)O - F^S)O - F^S)O \\ &= \hat{l}^0 O^3 - F^L O^3 - F^S O^2 - F^S O\end{aligned} \tag{A.3}$$

And the inventory level at $t = n$, given that $n > \hat{t}$:

$$\begin{aligned}\hat{l}_n &= \hat{l}^0 O^{n-\hat{t}+1} - F^L O^{n-\hat{t}+1} - F^S O^{n-\hat{t}} - F^S O^{n-\hat{t}-1} - \ldots - F^S O \\ &= \hat{l}^0 O^{n-\hat{t}+1} - F^L O^{n-\hat{t}+1} - F^S R,\end{aligned} \tag{A.4}$$

Where

$$R = O^{n-\hat{t}} + O^{n-\hat{t}-1} + \ldots + O \tag{A.5}$$

$R+1$ is a geometric sequence, as each therm is multiplied by a fixed non-zero number. In this case the non-zero number is O. It is therefore possible to express R as a finite sum. Since $R+1$ is a geometric sequence it is possible to find the summation of the sequence. For a geometric sequence, the summation of all the therms up to the n-th therm is given by:

$$S_n = \frac{k^n - 1}{k - 1}, \qquad \text{given that } k \neq 1, \text{ where } k \text{ is the fixed non-zero number.}$$

$$R = \sum_{i=1}^{n-\hat{t}} O^i \implies R = S_{n-\hat{t}+1} - 1 = \frac{O^{n-\hat{t}+1} - 1}{O - 1} - 1 \tag{A.6}$$

Equation (A.1) is valid as long as the vessel is sailing. If the vessel loads at $t = \hat{t}$, it unloads at $t = \hat{t} + T$, and the last sailing day before unloading is at $t = \hat{t} + T - 1$. Where T is the traveling time between the ports. The inventory level at the last sailing day before unloading is then:

$$\begin{aligned}\hat{l}_{\hat{t}+T-1} &= \hat{l}^0 O^T - F^L O^T - F^S O^{T-1} - \ldots - F^S O \\ &= \hat{l}^0 O^T - F^L O^T - F^S (\frac{O^T - 1}{O - 1} - 1)\end{aligned} \tag{A.7}$$

At the end of the unloading day, we have the expression for the inventory level:

$$\hat{l}_{\hat{t}+T} = (\hat{l}_{\hat{t}+T-1} - F^L - z_{\hat{t}+T})O \tag{A.8}$$

where F^L is the forced boil-off when unloading, and $z_{\hat{t}+T}$ is the cargo unloaded.

In order to find an expression for $\hat{l}_{\hat{t}+T}$, we use equation (A.1) and the fact that the vessel should be empty at the end of the day when it returns to the starting port. If the vessel loads at $t = \hat{t}$, the last sailing day is $t = \hat{t} + 2T - 1$.

$$\hat{l}_{\hat{t}+2T-1} = (\hat{l}_{\hat{t}+2T-2} - F^S)O \implies \hat{l}_{\hat{t}+2T-2} = \frac{\hat{l}_{\hat{t}+2T-1}}{O} + F^S$$

$$\begin{aligned}
\hat{l}_{\hat{t}+2T-3} &= \frac{\frac{\hat{l}_{\hat{t}+2T-1}}{O} + F^S}{O} + F^S \\
&= \frac{\hat{l}_{\hat{t}+2T-1}}{O^2} + \frac{F^S}{O} + F^S \\
&\vdots \\
\hat{l}_{\hat{t}+T} &= \frac{\hat{l}_{\hat{t}+2T-1}}{O^{(\hat{t}+2T-1)-(T+\hat{t})}} + \frac{F^S}{O^{(\hat{t}+2T-1)-(T+\hat{t})-1}} + \ldots + \frac{F^S}{O^0} \\
&= \frac{\hat{l}_{\hat{t}+2T-1}}{O^{(T-1)}} + F^S K
\end{aligned} \tag{A.9}$$

$\hat{l}_{\hat{t}+2T-1} = 0$ and $K = \frac{1}{O^{T-2}} + \ldots + 1$, where K is a geometric sequence with $k = \frac{1}{O}$, and $S_{T-1} = \frac{(\frac{1}{O})^{T-1} - 1}{\frac{1}{O} - 1}$.

$$\implies \hat{l}_{\hat{t}+T} = F^S\left(\frac{(\frac{1}{O})^{T-1} - 1}{\frac{1}{O} - 1}\right) \tag{A.10}$$

Equation (A.7), (A.8) and (A.10) provides an expression for z:

$$z_{\hat{t}+T} = \hat{l}_{\hat{t}+T-1} - F^L - \frac{\hat{l}_{\hat{t}+T}}{O} = \hat{l}^0 O^T - F^L O^T - F^S\left(\frac{O^T - 1}{O - 1} - 1\right) - F^L - \frac{F^S}{O}\left(\frac{(\frac{1}{O})^{T-1} - 1}{\frac{1}{O} - 1}\right) \tag{A.11}$$

As T is dependent on start port, end port and vessel, we need to include the indices i, j and v. We let $\hat{l}^0 = l_{ijvt}$ and $z_{\hat{t}+T} = z_{ijv(T+t)}$, given that vessel v loads at port i at time t, and travels to port j. In addition, $z_{ijv(T+t)}$ should be 0 if $l_{ijvt} = 0$. Thus, the constant terms are multiplied with x_{ijvt}.

By letting $\alpha_{ijvt} = O^{T_{ijvt}}$, and $\beta_{ijvt} = F^L O^{T_{ijvt}} + F^S(\frac{O^{T_{ijvt}} - 1}{O - 1} - 1) + F^L + \frac{F^S}{O}(\frac{(\frac{1}{O})^{T_{ijvt}-1} - 1}{\frac{1}{O} - 1})$, we get the expression:

$$z_{ijv(t+T)} = \alpha_{ijvt} l_{ijvt} - \beta_{ijvt} x_{ijvt} \tag{A.12}$$

Which correspond to constraints (5.14) presented in Section 5.2.

Appendix B

Graphs Showing Monthly Over- and Under-deliveries

B.1 RHH Full Case

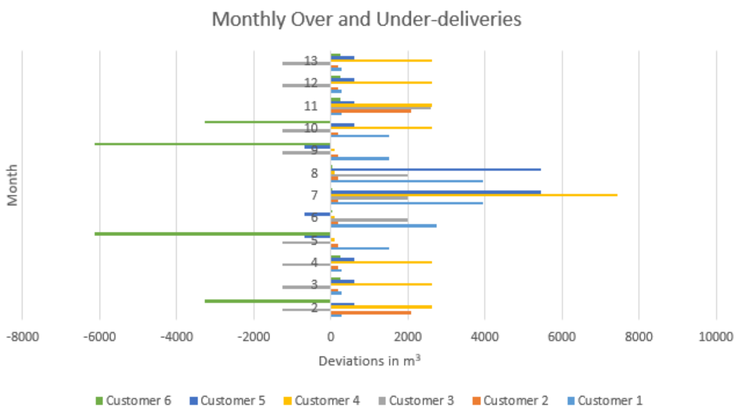

Figure B.1: Monthly deviations full case

B.2 Aggregated Case

Aggregation Strategy 1

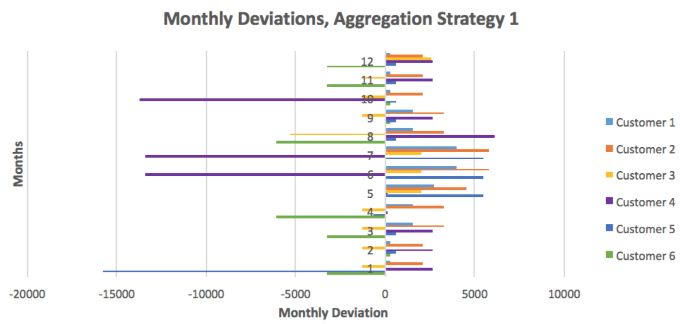

Figure B.2: Monthly deviations Strategy 1

Aggregation Strategy 2

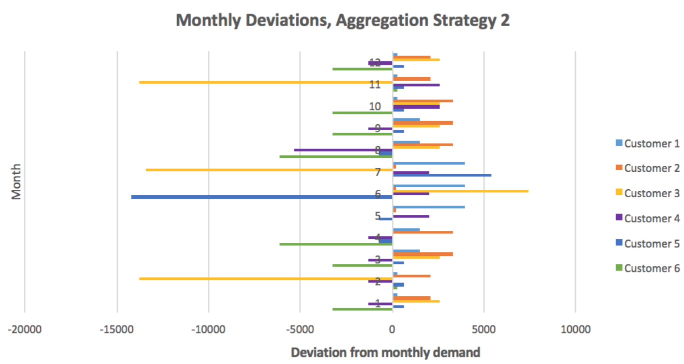

Figure B.3: Monthly deviations Strategy 2

Aggregation Strategy 3

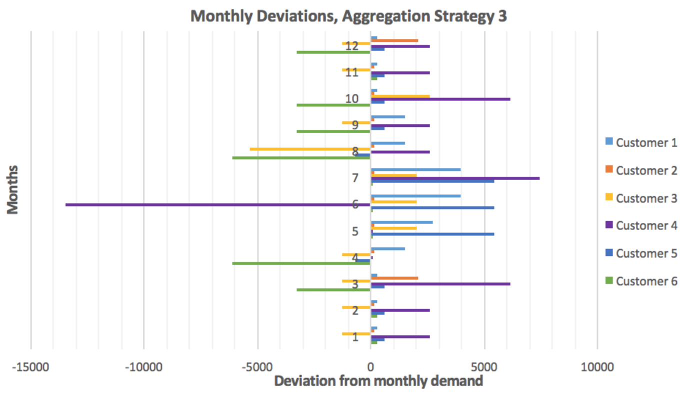

Figure B.4: Monthly deviations Strategy 3

B.3 E-ADH After Post-processing

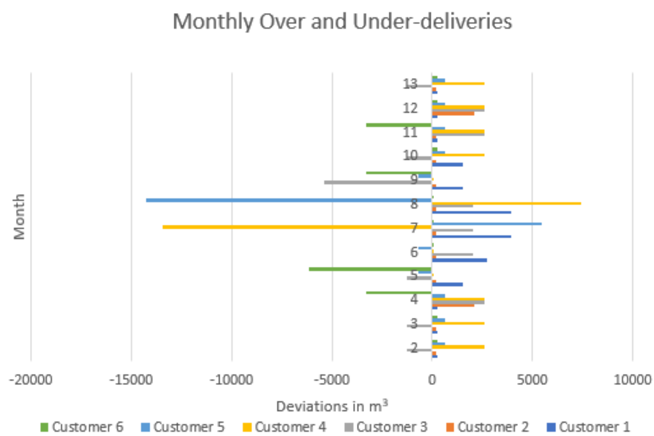

Figure B.5: Monthly deviations E-ADH after post-processing

B.4 RHH-ADH After Post-processing

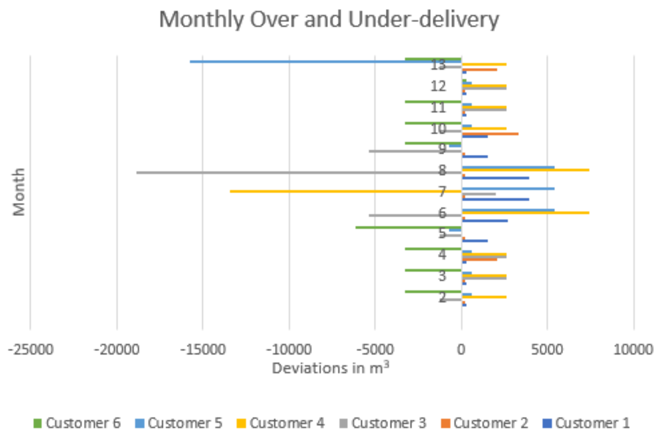

Figure B.6: Monthly deviations RHH-ADH after post-processing