Master's degree thesis

LOG950 Logistics

Supply Vessel Planing Problem with demand uncertainty

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Molde University College
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Preface

The topic of this master thesis is "Supply Vessel Planning Problem with demand uncertainty". The thesis was written at Molde University College - Specialized University in Logistics as a final step in achieving of Master of Science (MSc) in Logistics degree in Operations management specialization.

Irina Gribkovskaia, Professor at Molde University College - Specialized University in Logistics supervised the work. The Norwegian oil and gas operator Statoil provided the data used in the computation experiments. The authors carry out the development of the solution method and its implementation as a decision-support tool. They also conducted experiments and analysis of results.

We would like to take this opportunity of thanking our supervisor, Irina Gribkovskaia for outstanding guidance and support in Master thesis writing. You introduced us to the offshore upstream logistics. Yours first-hand experience inspired us for the research in the oil and gas industry and helped to formulate the research problem. We are very grateful for the ideas in the solution method development, constructive critics and precise feedback, which helped a lot with Mater thesis improvement. We would also like to thanks Yauheni Kisialiou, Ph.D. student at Molde University College - Specialized University in Logistics for collaboration, interesting discussions and yours valuable expertise in modelling and simulation. Gratitude for Halvard Arnzten for being available for discussions and questions about statistical analyses.

We would like to express special gratitude for Statoil and Ellen Karoline Norlund for collaboration and provided real data. Thank you for inviting us to Statoil headquarters in Bergen in Logistic department and introducing us to planning process of supplies to offshore installations.

Summary

Petroleum industry started its history in 19th century and became one of the richest industries in the world nowadays. In 2014, there was a petroleum price collapse, which in consequence led the industry to a tangible decay. All oil and gas operators have increased interest to find strategies and methods, which can improve their business processes in order to minimize logistic costs.

Research area of this thesis is upstream petroleum logistics. The problem involves the supply of a set of offshore installations with required materials and equipment on a regular basis from an onshore supply base by a fleet of supply vessels. In the literature, the problem is known as Periodic Supply Vessel Planning Problem (PSVPP). The supply is seriously disturbed by uncertain demand on installations, caused by specificity of technological processes on installations and by other factors. Moreover, the demand at installations has a dynamic nature, what means it is changing during a planning horizon. The aim of this master thesis is to develop a solution methodology for the PSVPP with uncertain demand.

This work presents analyses of the installations' demands and a decision-support tool for the PSVPP with demand uncertainty. The developed solution approach involves combination of optimization and simulation methodologies. The proposed methodology enables researcher to generate supply vessel schedules with minimized expected total cost. Vessels schedules are generated using two-phase solution approach based to set partitioning formulation of PSVPP. To control a level of robustness we developed a mechanism allowing to set the upper bound on the probability of a voyage's demand exceeds vessel's capacity. We constructed optimization tool to generate multiple schedules with different level of robustness. In the developed simulation model we incorporate recourse actions aim to eliminated infeasibility of a schedule under uncertain demand. Subsequent simulation is used to define expected total cost of each schedule.

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ALNS – an Adaptive Large Neighbourhood Search

ATD – Actual Time Departure

CEO – Chief Executive Officer

DES – Discrete Event Simulation

DSVRP – Dynamic Stochastic Vehicle Routing Problem

HGSADC – Hybrid Genetic Search with Adaptive Diversity Control

LNS – a Large Neighbourhood Search

NOK – Norwegian Krone

NTNU – Norwegian University of Science and Technology

PSVPP – Periodic Supply Vessel Problem

PSVPP-FC – Periodic Supply Vessel Planning Problem with Flexible departures and Coupled vessels

PVRPTW – Periodic Vehicle Routing Problem with Time Windows

SVPP – Supply Vessel Planning Problem

TW – Time Windows

VRP – Vehicle Routing Problem

VRPSD – Vehicle Routing Problem with Stochastic Demand

1.0 Introduction

The Norwegian Continental Shelf is the base of the Norwegian petroleum economy. The first offshore oil field was discovered in 1966, but unfortunately, it was dry. At the end of 1969, the oil field Ekofisk was discovered – the first major discovery on the Norwegian Continental Shelf, and one of the largest oil fields ever discovered. Now the Norwegian Continental Shelf counts 85 oil fields in the Norwegian Sea, North Sea and the Barents Sea (Norway's Petroleum History 2018). However, exploration of oil fields and petroleum production are very complex, unpredictable processes, which demand large investments and precise decisions. Notwithstanding, the Norwegian Petroleum industry has already earned around 12 trillion NOK. It has however had its ups and downs. In 2014, the world oil and gas industry met a petroleum price collapse (Biscardini , et al. 2017), which brought a tangible decay in the industry.

DNV GL's survey of 2017 shows that oil and gas operators confidence is returning, and with it new investment. Figure 1.1 shows that after the price drop, due to the new economic policies of oil and gas operators, oil price and industry confidence started to grow again.

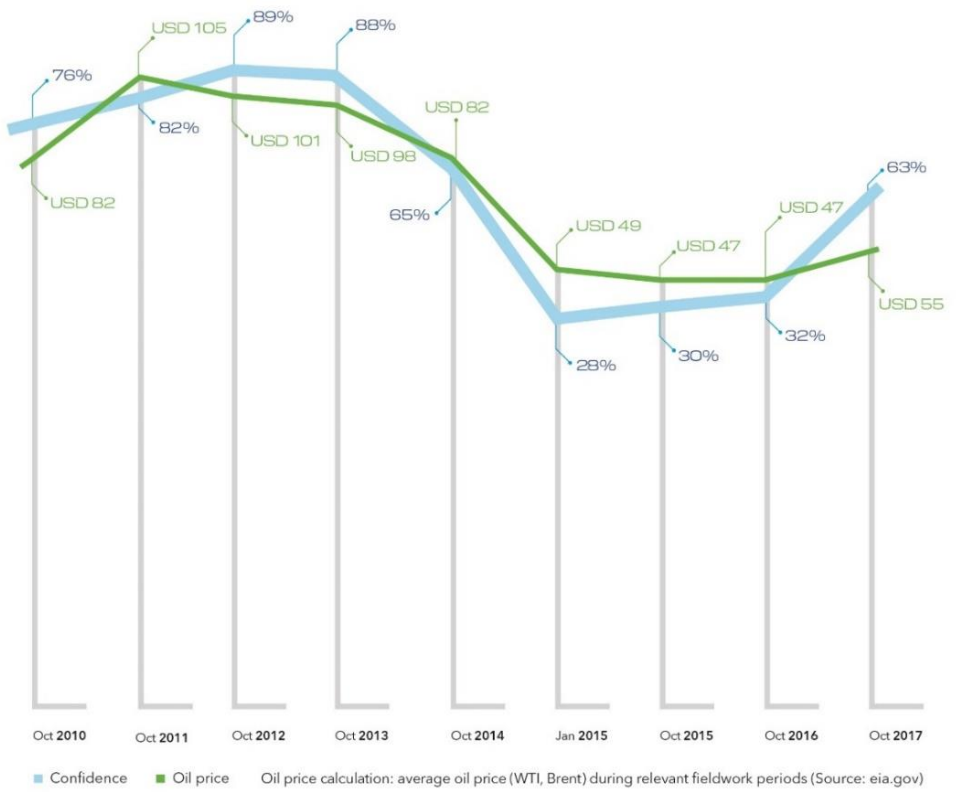


Figure 1.1 Oil price vs. industry confidence

However, "*while confidence has returned, the DNV GL survey also shows that cost control remains one of the most prominent issues for oil and gas companies. We've seen the industry make a number of tough decisions by reducing staffing numbers, reducing prices and costs – we now have to find new ways of collaborating to work more efficiently*" says Hari Vamadevan, Senior Vice President, DNV GL – Oil & Gas (Slater 2018).

At first sight, it may look like the petroleum industry is now out of the crisis of 2014, but this is not the case. The price of oil and gas are still lower than the average over last few years. In the long-term perspective, consumption of oil and gas will decrease because of the trend of implementing and using renewable energy sources. Moreover, extraction of resources from already explored fields is increasing in complexity over time, leading to higher expenses. In addition, oil and gas operators fight every day with more and more complexities.

As the result, all oil and gas operators have increased interest in finding strategies and methods, which can improve their business processes in order to minimize expenses. This is especially true in cases where it may be possible to avoid tough decisions such as firing employees in order to reduce staff-related costs.

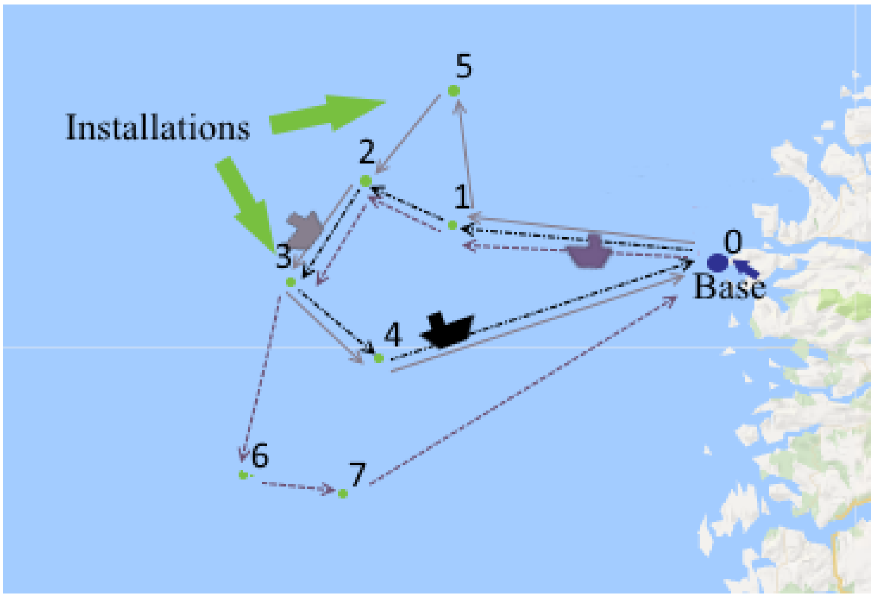
Oil and gas operators have five main sequenced business processes in the oil and gas supply chain (Petroleum Industry 2015):

- Exploration: Search by petroleum geodesists and physicists for potential oil and gas fields underground or under the sea-bed, and their exploration (drilling exploratory wells);
- Extraction (production): Transfer of crude oil and nature gas to the surface;
- Transportation: Transfer of extracted crude oil and gas from the oil field to the refineries;
- Refinement: Refinery processes where extracted crude oils and nature gas transformed into useful petroleum products, for example, petroleum naphtha, gasoline, diesel fuel, etc.;
- Distribution: This stage includes processes of transportation from refineries to the distribution centres, sales, marketing and deliveries to the end customers.

The sequence of these business processes in the supply chain also can be divided into two parts: upstream and downstream logistics. *Upstream logistics* refers to processes of searching, extracting and transporting of raw materials - crude oils and natural gas. On the other hand, *downstream logistics* refers to processing raw materials, collected in previous stages into finished goods. This includes sales, marketing and distribution of finished goods (Bass 2018). Talking about oil and gas operators, upstream logistics includes exploration, extraction and transportation, and downstream logistics includes refinement and distribution.

Decision-making in the planning process of the upstream offshore logistics of oil and gas operators has a significant impact on all business processes of the company. As explained above, the downstream logistics operate with the raw materials received by the upstream logistics. Thus, all inappropriate decisions made on the stage of upstream logistics leads to even greater consequences for the downstream logistics, and affecting the whole supply chain. Upstream logistics is an important strategic stage of the supply chain. Offshore upstream logistics implies supply of required materials and equipment to offshore installations: from suppliers by road and sea transport to the onshore supply bases and further to installations by the fleet of supply vessels. Supply vessels are the most expensive logistic resources on the upstream offshore logistics. Chartering cost of a supply vessel on long-term contracts (4 – 6 months) lie between NOK 110 000 and NOK 140 000 per day, while charter additional supply vessel on a short-term contract (days) is between NOK 150 000 and NOK 400 000 per day (Engh 2015).

In this work, we are going to focus on upstream logistics in the offshore oil and gas industry, specifically on the service of offshore installations. Picture 1.1 Picture 1.1 Supply of offshore installations from onshore baseshows how service of offshore installations takes place from the onshore supply base.



Picture 1.1 Supply of offshore installations from onshore base

Supply-vessel planning takes place in the Logistic department of the oil and gas operator. Logistic department‘s employees (*logistic planners)* manage and control supplies to the offshore installations, and make decisions about schedule reconstruction. They plan supplies to offshore installations on three levels:

1) Strategic: Supply schedule construction and fleet composition for the season (4 – 5 months);
2) Tactical: Revision of a season with updated data (2 weeks – 1 months);
3) Operational: Single vessel voyage revision (1 – 7 days).

The planning process of oil-and gas operators is described in Chapter 2.1.

Installations in this process are the most important customers. The main goal of the oil and gas operators is to increase revenues by selling petroleum products. Petroleum products are extracted on installations by complex processes, which require various materials and equipment on an ongoing basis. Delays in the supplies to the installations with required cargo at the required time leads to delays in sales of petroleum products, which leads to decreased revenues and expenses for the oil and gas operator. Consequently, the main goal of the logistic planners is to supply installations with the demanded cargo at the requested time. In other words, they must ensure the highest *service level* for the installations. Service level refers to the percentage of supplies delivered to offshore installation at the requested time with the demanded cargo from the onshore supply base.

On the other hand, installations must provide logistic planners with information about the amount of a cargo and expected delivery times in order to ensure reliable supply planning. Logistic planners require the availability of information for planning process. However, one of the challenges in this case, which highly influences planning of installations’ supply, is uncertainty in installations’ demands. It exists due to various reasons such as unstable well production, ad-hoc and emergencies, etc. Because of this, installations may not be able to provide information about the exact amount of demanded cargo even a few days before the next planned delivery.

Unavailability of information about installations’ demand is a reason why oil and gas operators experience challenges with development of reliable and accurate seasonal vessel schedules. Because of it, logistic planners have to include various slacks and buffers in the schedule, and apply expensive solutions in case of demand peaks such as hiring spot vessels and helicopters.

In this work, we analyse installations' demands and their behaviour and compare planned schedules with executed schedules using data provided by Statoil. Based on the results of the analysis, we developed a cyclic solution two-phase method, which allows logistic planners to build robust seasonal schedules for the installations' supply with demand uncertainty. The method will be implemented as a decision-support tool. The first phase is a schedule constriction, which consists of two steps: voyage generation, which is developed using the programming language C#, and a seasonal schedule construction, implemented using the programming language AMPL and CPLEX as a solver. The second phase is simulation of the constructed schedule with recourse actions, implemented in the programming language Python. The simulation provides a representation of the constructed schedule behaviour. Thereby, we can evaluate the robustness of a seasonal schedule comparing planned schedule cost with expected cost. It provides an information on how the input data should be changed to improve robustness of the seasonal schedule. Applying the method several times generates an efficient solution in respect of the costs and robustness level. We conducted experiments to evaluate the developed method. The experiments provide our model's superior efficiency.

The rest of the paper is organized in the following way. Chapter 2.0 is dedicated to the problem description and statement. Literature review is introduced in Chapter 3.0. Chapter 5.0describes the data, which were provided for this research by Statoil. Methodology, data analyses and assumptions are represented in Chapters 4.0, 6.0 and 7.0, respectively. Further, in the work there is provided solution method and decision-support tool description. Chapter **Error! Reference source not found.** contains results of the method evaluation and experimenting. Conclusion with possible further research is provided at the end of the thesis.

2.0 Problem Description

This Chapter is dedicated to the description of all aspects and challenges of the planning process at the stage of upstream offshore logistics of the oil and gas operators. The described problem is based on the Statoil company's business processes and data.

Statoil was founded in 1972 from the need of the Norwegian oil and gas industry. Nowadays, Statoil is one of the biggest oil and gas companies in the world, the leading operator on Norwegian Continental Shelf and the largest oil and gas company in Norway. Despite the fact that Statoil does occupy a strong position in the market of oil and gas industry, the company also felt the crisis of 2014. As can be seen in Figure 2.1, how total revenues and other income has decreased over time.

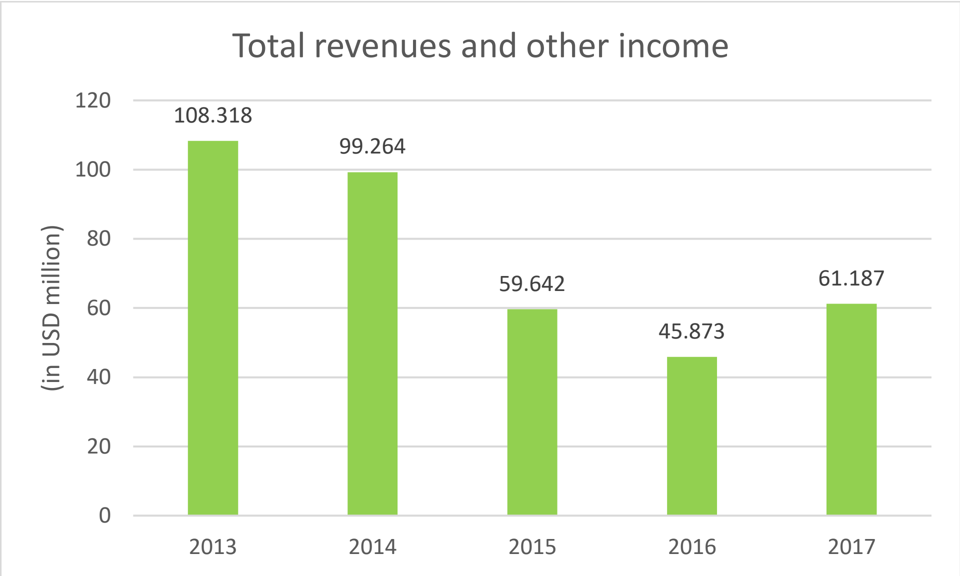


Figure 2.1. Statoil revenues from 2013 to 2017 (Statoil annual report and Form 20-F 2017 2017).

In 2018 year Statoil expect 1-2% of production growth, to drill around 40 exploration wells and, of course, to continue improvement. "*We have taken down our capital expenditure to 9.4 billion dollars from an initial guiding 11 billion dollars. This has been achieved from continued improvement efforts and strong project deliveries. In cooperation with our suppliers and partners, we are getting more for less*", says Eldar Sætre, CEO of Statoil (Fourth quarter 2017 results and capital markets update 2018 2018). Statoil has high interest in the further improvement of the company's business processes in order to cut expenses, because they still did not reach their before-crisis revenues.

Because of the reasons described above, Statoil is interested in the current research and provided access to their data, organized a meeting to introduce their work environment and planning processes at the Logistic department in headquarters in Bergen in order to make this research more appropriate and practical.

2.1 Offshore Upstream Planning Process

Offshore upstream logistics is planning and controlling supplies for offshore installation from an onshore supply base by the fleet of supply vessels on a periodic term.

Statoil operates in the North Sea, the Norwegian Sea and the Barents Sea. It is a very rough environment, especially in wintertime. The company takes into consideration differences in weather conditions between summer and winter by separating the year into two seasons accordingly, and construct schedules for each of them in respect of the weather conditions. There are no clear edges between seasons. It can vary from year to year, but usually the summer season is from the end of April or the beginning of May to the end of September or the begging of October. In this work, we are going to focus on planning for the summer season.

2.1.1 Vessel schedule construction

The seasonal supply vessel plan is a predetermined weekly schedule, which repeats during the whole season. By the *weekly schedule* is meant a sequence of voyages with set departure times from the supply base for each vessel in the fleet. The seasonal schedule is defined a month before the season starts. It sets the weekly schedule and how many vessels of which type the company should charter for the season (*fleet size*).

An example of a seasonal schedule can be seen in Table 2.1. As you can see, the company uses the fleet consisting of three vessels. On Monday vessel 1 starts its voyage at 16:00. It is going to arrive at the installation 1 on Tuesday at 05:30, installation 2 on Tuesday at 15:45 and return to the base on Wednesday at 07:45 to prepare for the next voyage on Wednesday, which starts at 16:00. Also on Wednesday vessel 3 is going to start its voyage at 17:30.

A seasonal schedule is constructed according to the drilling activity plan diagram of installations, data provided by installations and expert evaluation. The drilling activity plan diagram of installations is an annual plan of drilling operations on installations for each supply base of the oil and gas operator, of which you can see an example in Figure 2.2. *Drilling* is a process of cutting a hole into the seabed and setting there steel pipes to provide

Table 2.1 Seasonal vessel schedule (Provided by Statoil)

Chronological schedule																			
1		**Mon**	2		**Tue**	3		**Wed**	4		**Thu**	5		**Fri**	6		**Sat**	7	**Sun**
	Departure	**16:00**		Departure	**16:00**		Departure	**16:00**		Departure	**16:00**		Departure	**16:00**		Departure	**16:00**		
	Vessel 1	Visit		Vessel 2	Visit		Vessel 3	Visit		Vessel 2	Visit		Vessel 1	Visit		Vessel 2	Visit		
Inst1	Tue	05:30	Inst3	Wed	02:30	Inst5	Thu	07:00	Inst3	Fri	02:30	Inst7	Sat	05:30	Inst4	Sun	05:30		
Inst2	Tue	15:45	Inst4	Wed	15:30	Inst6	Thu	14:00	Inst4	Fri	15:30	Inst4	Sat	09:45	Inst3	Sun	11:30		
Base	Wed	07:45	Base	Thu	06:15	Inst1	Thu	17:30	Base	Sat	06:15	Inst2	Sat	15:15	Inst2	Sun	22:45		
						Base	Fri	11:00				Base	Sun	05:00	Base	Mon	14:45		
							Vessel 1						Vessel 3						
						Inst7	Thu	05:30				Inst8	Sat	07:00					
						Inst2	Thu	13:45				Inst9	Sat	15:45					
						Base	Fri	05:45				Inst1	Sat	19:45					
												Base	Sun	13:30					

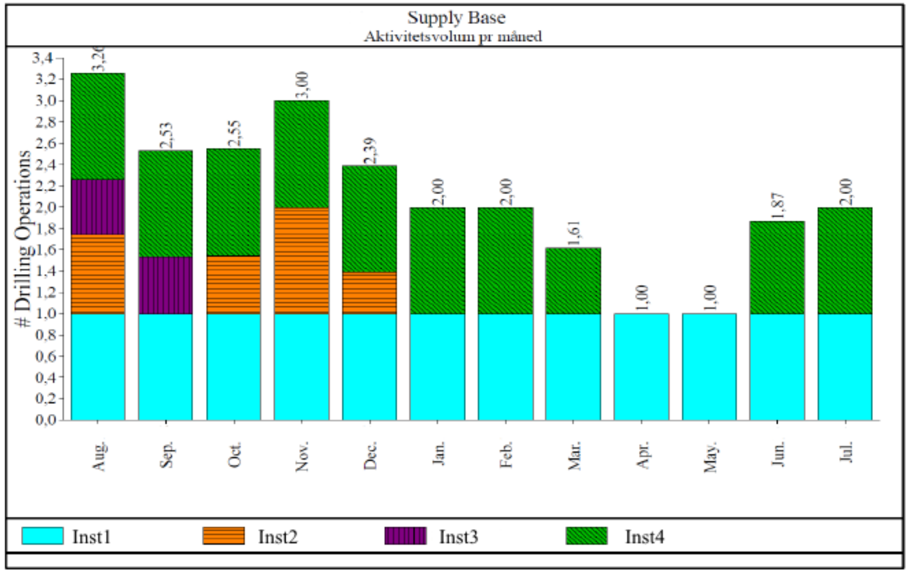


Figure 2.2 Drilling activity plan diagram (Provided by Statoil)

integrity for further oil and gas extraction. These operations count as the most unpredictable and cargo consuming. Therefore, the drilling activity plan diagram of installations is critical for seasonal schedule construction. Moreover, the annual plan of drilling operations can be changed during the year for various reasons, for example: a well requires drilling activity for a longer period than expected; the list of assigned installations to the supply base was changed, etc.

The drilling activity diagram shows in which period installation has a drilling activity. For example, in September, as you can see in Figure 2.2 that there were no drilling activities on installation 2. In October drilling activities started. The number of drilling operations for installation 2 for October is 0.5, which means that drilling activities lasted for half of the month and started in the second part of October. Installation 2 had drilling activities during November (number of drilling operations equals 1). In December, number of drilling operations was 0.4, what means in the beginning of month (0.4 of month) there were drilling activities and after they stopped. In the rest of the year installation 2 had no drilling activities.

For the seasonal schedule planning each installation provides forecast about approximate amount of cargo they need during a week and how many deliveries of a cargo (visits) they require during a week (*visit frequency*). Combinations of these two parameters called *installations demands.* In advanced, sometimes installations demands become available close to the next shipment (visit). Therefore, for the schedule constructing also used expert evaluation.

Logistic planners' experts evaluate the same parameters as installations, using their experience and historical data to make the data more reliable and appropriate. Usually installations provide reinsured data, with inflated parameters, in order to be safe in case of demands peaks. The cooperation between installations and logistic department appeared relatively recently. Several years ago, installations were very strict about their requirements and it was impossible to discuss it and to change it. Nowadays, collaboration and review of the results allow logistic planners and installations discuss and find a compromised solution for the seasonal planning.

Logistic planners plan the seasonal schedule for 5-6 months a month before it starts. The data, on which it is based, is very general and uncertain in the planning period. During the season data becoming more and more appropriate and reliable. Therefore, logistic planners change schedule accordingly to updated data on three levels: strategic planning, tactical planning and operational planning. The reason for schedule changes appears, because of variations of installation visit frequencies, increasing or decreasing of installations’ demands, assigning of new installation to the supply base, etc. during the season.

Strategic planning level implies planning and building of a seasonal schedule. This schedule is the main plan of supplies to installations. Tactical planning revises the seasonal schedule several times per season and changes schedule from period to period depend on data updates. There is no standard duration of a period. It can vary from months to weeks. Usually schedule updates every month. Tactical planning reacts on changes in processes on installations, on rig transfer, etc. Repetitive weekly schedule in this case is changed for the whole next period. However, the major goal is to make minimal changes in the schedule after revision.

Table 2.2 shows the comparison of planned schedule with executed schedule. For example, we will look on planned schedule for May and compare every Saturday. As you can see, on the strategic level it was planned only one voyage to Installation 1, 2 and 3 on Saturday. However, in the real life it shows one and two voyages with additional visits to installations 4 and 5. There are no any voyages, which correspond to the plan and which are the same. This example emphasize how often planned schedule changes and the necessity of its revision on different levels during the planning period.

Table 2.2 Comparison of planned schedule and executed voyages

Scheduled	Executed			
Saturday	6 May Saturday	13 May Saturday	20 May Saturday	26 May Saturday
Voyage Inst1	Voyage Inst4	Voyage Inst5	Voyage Inst2	Voyage Inst2
Inst2	Ints1	Inst3	Inst5	Inst5
Inst3	Voyage Inst3	Inst4	Inst1	Inst1
	Inst5	Voyage Inst2	Voyage Inst4	Inst3
	Inst2	Inst1	Inst3	Inst4

The cause of frequent changes in the seasonal schedule is that it builds on the uncertain data on demands. When data becoming exact, operational planning revises the schedule for the recent week and makes necessary changes in it in order to satisfy installations needs 100%. In changes included voyages modification and charter additional vessels, in case of impossibility to reach 100% service level by available fleet. Vessels, which charted because of necessity for a short period, are called spot vessels.

Statoil fight the demands uncertainty by continuous revision of the schedule on different levels. Figure 2.3 shows a chain of work of logistic planners in Statoil Logistic department.

Figure 2.3 Seasonal schedule construction (Provided by Statoil)

Tactical and operational planning are reaction on inaccurate seasonal schedule construction on strategic level. Obviously, if on the stage of seasonal schedule construction the data on demands would be more precise this would entail fewer changes in it, thus, fewer revisions on tactical and operational levels of planning, which require additional expenses for the company. In this work, we are going to focus on the strategic seasonal schedule construction in order to minimize demand uncertainty impact on it.

Supply service

Service of installation is the main process in petroleum upstream logistics. By the service is meant delivering all the required cargo in the defined time frames.

Supply base

Everything starts from the onshore supply base. It is a control and management centre of supplies to installations. Each supply base has a set of installations and fleet, which are assigned to it. Here vessels get prepared for the next trip, load and unload, start and finish their voyages. Supply base has opening hours and set possible departure times for the vessels during its opening time, which cannot be changed.

Fleet of supply vessels

The supply base fleet consists of vessels, which are charted for a long-term basis – charter vessels. Each vessel characterized by daily charter cost, speed of sailing, available deck capacity and fuel consumption rate. They are uniform in capacities, speeds, consumption rates and costs. Consequently, in this problem we will assume that the fleet is homogeneous – all vessels have the same parameters. In case of critical situations, when oil and gas operator cannot supply requested cargo in time by the fleet, spot vessels are hired. For example, critical situations can be special equipment needed immediately, pipe is damaged, unexpectedly huge demand occurs, bad weather condition, etc. Charter of spot vessels or helicopters leads to appearance of high additional costs for the oil and gas operator, which once again emphasizes the importance of accuracy in planning of seasonal schedule.

Voyage

When charter vessel loaded, it starts its voyage from the supply base. Voyage is a sequence of installations, which should be visited in order to deliver demanded cargo and pick-up waste. It starts and ends on the supply base. The amounts of waste and delivered cargo are equal. Delivering is a prior operation, therefore, pick up waste is an accompanying process, for which we do not reserve space on the vessel.

Supply base located onshore usually next to the ports, because of it offshore point defined. Offshore point is a point through which vessel passes to go out into the open sea on the way from/to supply base. It is used in order to calculate distances between installations and supply base in way that is more accurate. In Figure 2.4, you can see voyage structure.

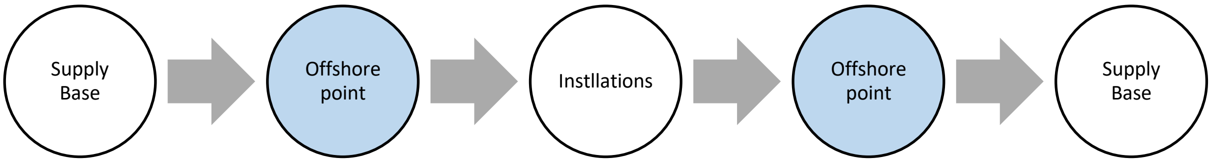


Figure 2.4 Voyage structure

Voyage duration consists of vessel sailing time, waiting time and installation service time. Sailing time calculated as multiplication of voyage distance on sailing speed. Distances between installations, offshore point and supply base calculated as a distance between two points by their geographical coordinates. See Formula 2.1.

$$D(P1, P2) = \arccos\Big(sin(P1lat * \frac{\pi}{180}) * sin(P2lat * \frac{\pi}{180}) + cos(P1lat * \frac{\pi}{180}) * cos(P2lat * \frac{\pi}{180}) * cos((P1lon - P2lon) * \frac{\pi}{180})\Big) * R, \quad (2.1)$$

where:

D – distance between two points;

P1 – point 1;

P2 – point 2;

R – Earth radius;

P1lat – latitude of point 1;

P1lon – longitude of point 1;

P2lat – latitude of point 2;

P2lon – longitude of point 2.

Respectively distance between supply base and installation is a sum of distances between supply base and offshore point and distance between offshore point and installation.

Total duration of the voyage is a sum of sailing time, service time and waiting time. Sailing time between points is calculated as a multiplication of the distance between this points and sailing speed of the vessel. Waiting time is a time spend by vessel standing next to the installation because of the queue of vessels for service, or opening hours or etc.

Service time is a time spend for unload and load of cargo from vessel on installation. Unload and load operations carried out by special crane. One uplift of the cargo from vessel to installation called lift. In average, lift takes 8 minutes. Thereby, service time directly depend on amount of cargo, which delivered. However, there is one of the biggest challenges in this problem: cargo calculated into two dimensions, tons and lifts. Tons used to check capacity constraint of the vessel before loading, where lifts used for service time estimation as on the supply base, as on the installations. Nevertheless, there is no clear transfer system from tons to lifts and back. What makes evaluation of expected service time is very complex. To evaluate it properly, logistic planners need to know all the sizes (high, width and length) and weight of every piece of cargo, which is going to uplift. For example, a lift of pipes and a lift of container are different in tonnage and value, but it is still takes around 8 minutes to lift it to installation.

Picture 2.1 Offshore installation with two lift cranes

Except duration and a sequence of installations visited, voyage is also characterized by departure time from supply base and return time and fuel cost. Moreover, voyages has natural constraints, which lead to the idea, that they cannot be too short or too long by the number of installations on the voyage, and total supplied demand to the installations should not exceed deck capacity of the vessel. Average duration of voyages in Statoil is 2-3 days due to limited lead time for delivery of cargo from supply base. Additionally, company has constraint on maximum voyage duration. Voyages, which satisfies all of these constraints: on capacity of the vessel and on the voyage duration, called feasible.

Offshore installation

Installations are unique. Construction of each installation is an independent project dependent on location, type and size of well and its needs. Installations can be static and moveable. *Rig* is an installation, which can be transported from one location to another. When rig is changing its location, all operations on it stops and, when it is moved, operations start again only. Rigs are used only for drilling operations.

On installations there are carried out various processes, which demanded different equipment and materials on a continuous basis. Supply can be proceed during opening hours on installation. Opening hours of the installation will be called installations *time windows*. Respectively, installations are divided into working round-the-clock or at certain working hours.

As described above, demand is associated with a required visit frequency, with ensured continuous service, and a certain amount of delivered cargo.

Main processes that occur on them can divide installations on production, drilling and other. The other includes installations type such as processing, accommodation, quartering, etc. Petroleum explore operations are provided on drilling installations, while on production installations – oil or gas has already been found and resource production takes place. Production installations usually are the most stable in terms of demands variation, where the drilling are the most uncertain. Moreover, installations have a limited deck capacity, what makes impossible to deliver cargo in surplus.

Weekly vessel schedule

The work of the supply base, service of installations and vessels' voyages performance executed according specified schedule. Schedule is a set of feasible voyages with assigned departure times. Each charter vessel has its own assigned schedule. Schedule is built for a week and during season repeats. An important constraint on the schedule is that the vessel cannot start new voyage until it ends the previous one, meaning overlapping of the voyages prevented. Schedule construction is on what we are going to focus in this work.

2.1.2 Demand uncertainty

Offshore upstream logistics is a complex problem with various challenges. Challenge on which this work is focused is demand uncertainty. Data on demands used through the whole supply chain of oil and gas operator. Below on

Figure 2.5 Demand influence on the supply chain, you can see how important to find a way of reliable and accurate forecast for installations demands.

Uncertainty in the data on demands causes high complexity on the stage of schedule construction, what makes it slightly reliable. During the seasonal schedule is disrupted many times. To solve occurred problems oil and gas operator have to rent additional transport. Moreover, in order to avoid disruptions, it has to revise continuously schedule on operational and tactical levels. To supply installation with required equipment and materials, cargo should be ordered from suppliers and delivered to the supply base. Clearly seen that demand uncertainty is a cause of very high expenses for the oil and gas operator.

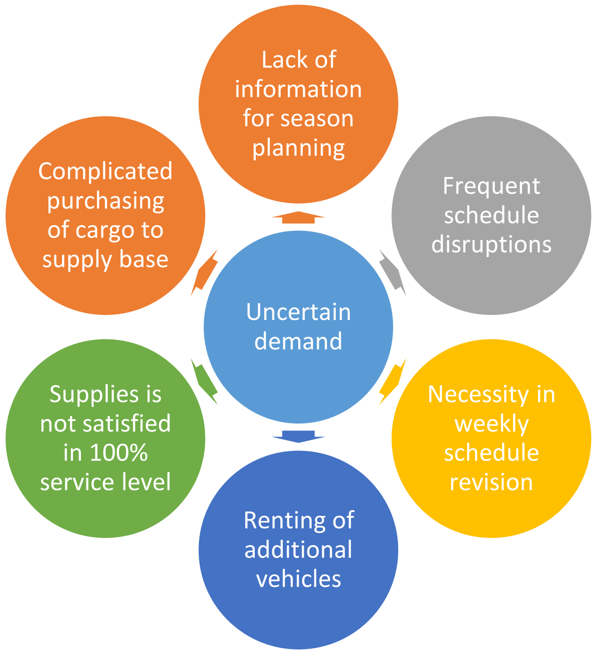


Figure 2.5 Demand influence on the supply chain

Let us look at the demand uncertainty more detailed. Before season starts, when seasonal schedule constructed, installation provide to the supply base only approximate visit frequency with insurance bias for the following season. Information about cargo for the schedule supply base get from the experts. When season starts, installations start to precise data. They provide average amount of cargo per week and more accurate visit frequency to the supply base. Usually this data précising every month, depend on changes in installations' processes. It is worth paying special attention to the fact that supplies of cargo are not evenly distributed between visits during week. The supply base get more or less exact data on amount of cargo per visit of the following week before the week starts. In addition, précising of the amount of cargo can come from 5 days to the few hours before the closest vessel's departure to the installation. It is not rare situation in oil and gas operator practice, which includes expensive solution.

The main goal of the oil and gas operators is to service installations with 100% service level. Thus, they will go for any solution, which will deliver cargo in time, no matter what. The way, how Statoil held the uncertainty described above in Chapter 2.1.

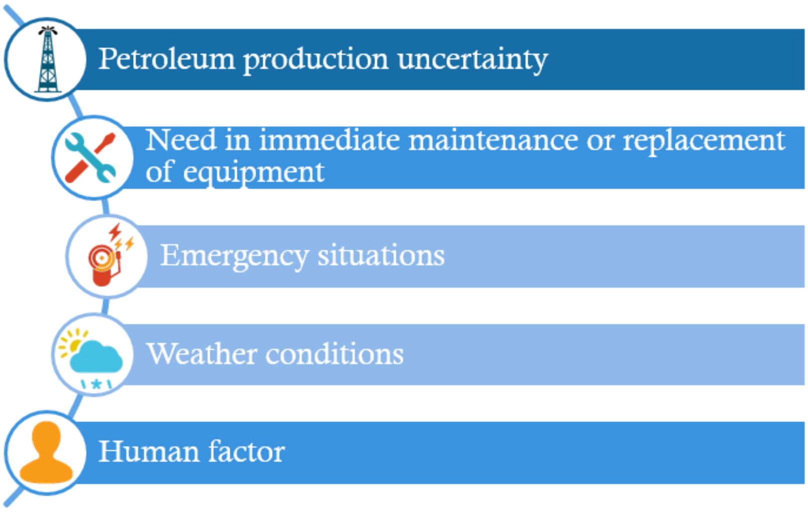


Figure 2.6 Causes of demand uncertainty

There are various cause why demand uncertainty exist in petroleum industry. The first thing, which can be given as an example of a demand uncertainty cause, is the existence of a situation, when something is damaged and needs maintenance or replacement. Other causes of demand uncertainty are emergencies and weather condition unpredictability. In addition, it is a well-known fact, that installation can find more petroleum than expected, what will entail an increasing of the demand, or, on the other side, it could happened that installation cannot reach the petroleum production level as was planned, what will lead to an unexpected decreasing of the installation demand.

Furthermore, demand unpredictability formation depends on discrepancy of information on the installation and on the supply base, of mistakes in the calculations. For instance, sometimes, supply base can get from installations one value for required cargo, but, at the time of installation's visit, it can turn out to be that different amount was actually needed. Hence, existence of human factor also should not be excluded from the causes of demand uncertainty.

2.2 Problem statement

The purpose of the research is to provide analyses of offshore installations' demands on trends and dependencies on the factors, which can have an impact on demands' behaviour. Develop a solution method, which will construct robust seasonal schedule for offshore installations supplies from onshore supply base with demand uncertainty. Implement developed method as a decision-supporting tool and conduct experiments for its evaluation.

3.0 Literature review

This Chapter reviews available literature related to the described problem and its solution methods. Additionally, we will look at the literature with theory and methods about uncertain demand implementation.

Elin E. Halvorsen-Weare defined Supply Vessel Planning Problem (SVPP) as follows "*The supply vessel planning problem consists of identifying the optimal fleet composition of supply vessels that are to service a given number of offshore installations from one common onshore depot while at the same time determining the weekly voyages and schedules for these vessels*" (Halvorsen-Weare , Fagerholt and Nonås , Optimal fleet composition and periodic routing of offshore supply vessels 2012).

The studied problem is considering the construction of a seasonal vessel schedule of supplies to an offshore installation from an onshore supply base. The seasonal vessel schedule is determined as a periodic weekly schedule. Thereby, we can conclude that the problem under consideration refers to the Periodic Supply Vessel Planning Problem (PSVPP), which is an extension of SVPP.

3.1 Supply Vessel Planning Problem

Halvorsen-Weare, Fagerholt and Nonås described a mathematical model of SVPP and the voyage-based solution method, which focused on robust solutions (Halvorsen-Weare , Fagerholt og Nonås , Optimal fleet composition and periodic routing of offshore supply vessels 2012). The solution implied fleet composition and cost minimization. The method presents itself as a cyclic two-phase approach for schedule construction for planning horizon. As you can see on the scheme of the method on the Figure 3.1, the first phase is to generate feasible voyages. The second phase is to solve a voyage-based model with generated voyages as an input. The model's solution is an optimal fleet composition and optimal vessel schedule for the planning horizon. The solution obtained can be modified by changing the input data.

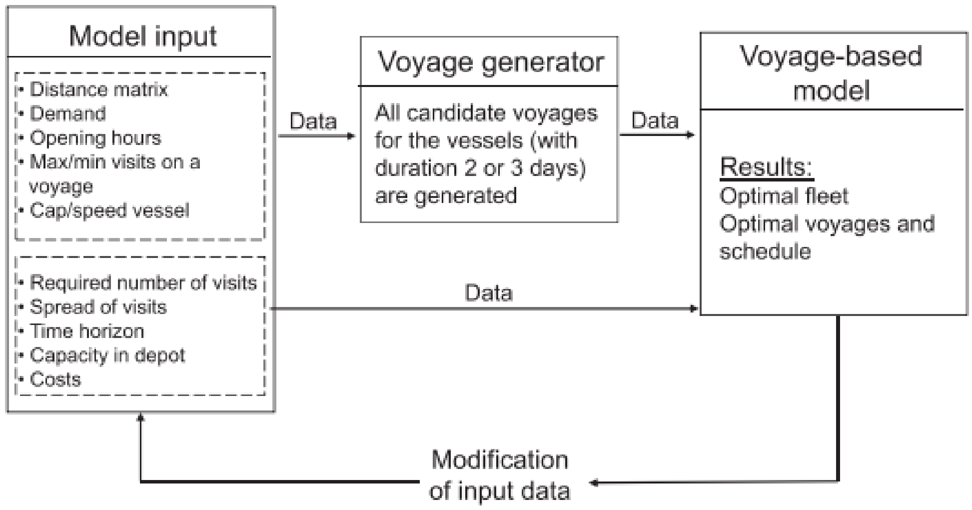


Figure 3.1 Voyage-based solution method (Halvorsen-Weare , Fagerholt and Nonås , Optimal fleet composition and periodic routing of offshore supply vessels 2012)

The input data in the approach is separated into two parts. The first part, which contains the distance matrix, opening hours, demands and characteristics of voyages and vessels, is input for the voyage generator. Please note that the demand here means a required amount of cargo from an installation. The second part consists of data on the required number of visits from each installation and characteristics of supply base and schedule (time horizon). It is used as input, with the list of generated feasible voyages to the second phase of the method. All the input data is known beforehand.

The tool was developed based on the voyage-based solution method was successfully implemented by Statoil. Thanks to this tool, Statoil has managed significantly to reduce expenses. However, for this method the installations' requirements on amounts of a cargo and visit frequencies must be predefined and deterministic, whereas in the real life they are uncertain and dynamic. This assumption for the voyage-based solution method emphasizes the relevance of the studied research, which is focused on demands uncertainty in PSVPP.

Shyshou, et la. in 2012 presented a large neighborhood search heuristic (LNS) for PSVPP (Shyshou, et al. 2012). He used the model of the problem formulated by Halvorsen-Weare in 2012 with predefined deterministic demands, but solved it, instead of the voyage-based solution method, with his developed LNS heuristic. The LNS is capable of solving the real-life size instances, in contrast to the voyage-based method.

In 2013 Norlund and Gribkovskaia studied the problem of emissions reduction in the SVPP. They suggested several strategies of speed optimization, which based on vessel's waiting and service times evaluation, in order to minimize emissions of CO_2. The solution provided significant reductions of emissions with no changes in the fleet composition (Norlund and Gribkovskaia, Reducing emissions through speed optimization in supply vessel operations. 2013).

In 2017 Borthen, et al. presented a new metaheuristic based on Hybrid Genetic Search with Adaptive Diversity Control (HGSADC) for a simplified SVPP: with a single-fixed departure times, homogeneous fleet and without time windows. However, HGSADC showed efficient and fast result on the real size instances (Borthen , et al. 2017).

Moreover, the PSVPP was expanded by flexible departures and by definition and implementation of coupled vessels (PSVPP-FC). By “flexible departure” is meant the possibility of several departure times from supply base, whereas in the classic PSVPP only one departure time was possible. Coupled vessels are vessels of the same type, which can replace each other in the schedule. Implementation of them to the PSVPP provides more efficient and cheap solution. Kisialiou, Gribkovskaia and Laporte presented a mathematical programming model of PSVPP-FC and a solution approach - an adaptive large neighbourhood search (ALNS) metaheuristic (Kisialiou , Gribkovskaia and Laporte 2018).

Another way to build a robust schedule for the PSVPP is to complement optimization with simulation. Halvorsen-Weare, Fagerholt and Ronnqvist in 2013 did research in liquefied natural gas transportation in uncertain weather condition, where she introduced and applied optimization and simulation tools (Halvorsen-Weare , Fagerholt and Ronnqvist , Routing and scheduling under uncertainty in the liquefied natural gas business 2013). She used a simulation of the problem in order to evaluate its robustness level and cost, and used optimization as a recourse action based on improved input data.

Maisiuk and Gribkovskaia studied SVPP with stochastic sailing and service times. Uncertainty of service and sailing times is caused by uncertain weather conditions (Maisiuk and Gribkovskaia 2014). They presented a discrete-event simulation model for evaluation of the vessels’ schedule. The model shows the reliability of the fleet composition of the simulated schedule and evaluates it. Analyses of simulations provide support in fleet sizing decision-making.

Norlund, Gribkovskaia and Laporte expanded the problem in their work “Reducing emissions through speed optimization in supply vessel operations”, adding consideration of the robustness of the schedule by trade-off analyses. This was done in order to find efficient solution with regard to emission reduction and robustness level (Norlund, Gribkovskaia and Laporte, Supply vessel planning under cost, environment and robustness considerations 2015). The authors improved the voyage-based solution method by implementing the third step to it. The third step is to assign a probability of voyage feasibility with respect to its duration by weather conditions simulation. If probability is lower than the determined upper bound probability, the voyage is not feasible and not going to the second phase of the voyage-based solution method.

Currently, the SVPP and its variations are studied with deterministic demand, which is predefined and is equally distributed from visit to visit during the planning time horizon. Deterministic demand is far from real life and does not reflect possible variations and uncertainty of demands during schedule construction. In real life cases, installation demand is defined as uncertain and dynamic.

SVPP was studied with uncertainties, but these were uncertainties of sailing and waiting times because of the rough weather conditions. Solution approaches for their solution were reviewed above.

As you can see, none of the available articles were dealing with demand uncertainty in SVPP. However, the PSVPP with demand uncertainty is one of the most relevant problem now for studies. In the master thesis from NTNU "Optimization of Upstream Supply Chain", Engh studied the PSVPP with demand uncertainty (Engh 2015). She introduced a two-stage recourse model with logistics strategies for planned and unplanned demands. The method is built on stochastic optimization - by developing scenarios of demand variations. Her method was tested on small, not realistic instances of four offshore installations for five days planning horizon. The drawback of the method is that you need a huge amount of scenarios, because of complexity of the problem, to make it work effectively, but in that case it will work very slowly and be capable of solving only small instances.

The PSVPP is complex problem, the solution of which implies several sub problems:

1. Vehicle Routing problem (VRP). Building all possible voyages that could be assigned to the vessels.
2. Assignment problem. This part decides which voyages should be assigned to the vessels' schedules and at what departure time;
3. Packing problem. Defining the fleet size. The fleet size here defined as the minimal number of vessels needed to ensure 100% of supplies to the installation and schedule work. In other words – how to "pack" needed voyages in the minimal fleet of the supply vessels;
4. Scheduling problem. The final step of the problem. It unites all solutions to the final form – the schedule.

Current research is focused on demand uncertainty. If we will look at constituent sub problems of PSVPP demands are used as an input data only for the VRP. In order to generate possible routes, it is necessary to know the amount of cargo the vessel is going to deliver to each of the installations on the voyage, otherwise there is no way to check the constraint on the capacity of the vessel. Thus, we are going to review the VRP with demand uncertainty and methods to solve it.

3.2 Vehicle Routing Problem

Demand, as described in the Chapter 2.1.2, defined by two uncertain parameters: the visit frequency and the amount of cargo, and it changes dynamically during the season. This data is required at the first stage of the problem as input data. As mentioned by Victor Pillac, et la. "*Dynamic and stochastic problems have part or all of their input unknown and revealed dynamically during the execution of the voyages*" (Pillac , et al. 2011), the problem can be defined as dynamic and stochastic, as you can see in the Table 3.1.

Table 3.1 Taxonomy of VRP by information evolution and quality (Pillac , et al. 2011).

		Information quality	
		Deterministic input	Stochastic input
Information evolution	Input known beforehand	Static and deterministic	Static and stochastic
	Input changes over time	Dynamic and deterministic	Dynamic and stochastic

The described problem specifies as dynamic and stochastic vehicle routing problem on the first stage according to the table above. Interest to this category of problems is rising on the last years, because it allows solving real-life cases. There are two groups of Dynamic Stochastic Vehicle Routing Problem (DSVRP), which were classified by Ritzinger, Punchinger and Hartl, and which are divided by decision making, depending on how updated information occurs (Ritzinger , Puchinger and Richard 2014):

- "*Preprocessed decisions, consists of approaches where policies or solutions are computed before the execution of the plan;*
- *Online decisions, consists of approaches where solutions are computes as soon as a dynamic event occurs*".

For each of these groups there are determined approaches, which can be used for solving DSVRPs. The problem, which is observed in this paper, is not suited for the online decisions type, because reaction time for the changes can take from several hours to several days, because of the supply chain. To implement the required changes of demand in the planned schedule, the following must be done: order the required demanded materials from suppliers, transport them to the base, find a vehicle for delivery and update schedule of the fleet of supply vessels. Obviously, this process will take time to execute. The task should be solved accurately in order to be less expensive, but the primary goal of the oil and gas operator is to supply installations with 100% service level. Changes in demands, which can be taken into consideration, can come at any time even in the day of departure to the installation with updated demand. The approach for pre-processed decisions is to find a way to estimate the relevant data of the state of the object and its decisions, and after, use the obtained values for the planning process. The problem is specified as pre-processed decisions.

Ritzinger, Punchinger and Hartl made a literature research of SVRP problems (Ritzinger , Puchinger og Richard 2014). They found out that VRP class of problems is one of the most commonly studied classes in Logistics. There are variety of problems with additional constraints, which are studied already, such as VRP with Time Windows, Capacitated VRP with Pick-up and Delivery, etc.

One of these problems is Periodic VRP with Time Windows (PVRPTW), which was formulated and studied by Dror in “Savings by Split Delivery Routing” (Dror and Trudeau , Savings by Split Delivery Routing 1989) and in “Vehicle Routing with Split Deliveries” (Dror , Laporte and Trudeau , Vehicle Routing with Split Deliveries 1994). PVRPTW is the closest to the described problem. It takes into account every constraint for the voyage generation, except demand uncertainty. Adding the missing condition on demand uncertainty changes the PVRPTW totally and requires different formulation and solution approaches.

Berhan, Beshah, et la. have found 49 articles of SVRP and classified them by domains and attributes (Berhan, Beshah , et al. 2014). From this list of literature, there are ten articles, which could be useful for this research. There are no articles, which have all described constraints in the problem, however, all the articles combine them. Research of these articles should help to understand and formulate model of the problem.

Gianpaolo, et la. (Ghiani , et al. 2008) developed waiting policies for Dynamic and Stochastic Traveling Salesman Problem. The author used a probabilistic characterization for customers’ updates, which was assumed to be known. There are also several assumptions: the order of services is provided; customers’ orders are known for a single point in time. In this article, they introduced and used exact and heuristic methods. Authors used a Markov decision process as an exact method and Wait First, Drive First policies as heuristics. In the described problem, this is only a part of the PSVPP solution. It can be used in the situations when vessels must wait before servicing an installation because of its opening hours or delays.

An interesting idea was proposed by Smith, et la., who used priority classes of stochastic demands in Dynamic VRP (Smith , et al. 2010). The idea is to provide the best service for high-priority installations class, and possible, stable service for low-priority installations class, in order to stabilize and reduce delays and waiting time in the schedule. The feature of this article is that the problem was studied from the side of how demand are formed instead of the demand’s size. Authors assumed that demand arrives according to the Poisson process with rates. They also introduced the Tube heuristic and Queue merging as approaches. Unfortunately, the problem description of this article does not include constraints on time windows, departures from base, or requested visit frequencies of installations. Similarly, in the described problem it is important to know both how demand arrives to the system and the size of the demand. The ideas of the article can be used as the basis, with several changes to be implemented for the described problem.

Aykagan and Alan solved the VRPSD with a paired-vehicle recourse strategy, where distribution of demand is known (Aykagan and Alan 2007). Most VRPSD are solved under the condition of independent vehicles, but Aykagan and Alan decided to use paired vehicles, which can replace each other or catch up voyages of each other. It would be very useful if cargo on vessels were similar, but it is possible in very few cases in this work case. Cargo requested by installations is usually a combination of standard items, like pipes, and special items, like equipment. The authors used a Tabu Search Heuristic to solve their problem. Unfortunately, it is not applicable for the PSVPP in this case.

In the problem vessels do pick-up and delivery while servicing installations. A solution to the SVRP with simultaneous pick-up and delivery, by differential evolution, was proposed by Berhan (Berhan , Krömer , et al. 2013). His work was oriented around two purposes: developing an optimal set of voyages and minimizing the fleet size. The article is very close to the problem we are going to solve, but without time windows and service time. In addition, there is an assumption in the problem statement, which does not match with this work case: “*each customer is visited exactly once by exactly one vehicle”* Berhan, Krömer, et la.

(Berhan , Krömer , et al. 2013). Demand is defined randomly following the Poisson probability distribution in the article, and solution approach is the Differential Evolution algorithm. The algorithm provided by Berhan, Krömer, et la. could be updated and used for the described problem.

Bertsimas has two relevant articles. One of them is "A Vehicle Routing Problem with Stochastic Demand" (Bertsimas, A Vehicle Routing Problem with Stochastic Demand 1991), where demand is uniformly distributed, and arrivals follow a known probability distribution. In this article, the author proposed two strategies for updating the voyages when demand changes, with heuristics for their solution. The second article is "Stochastic and Dynamic Vehicle Routing with General Demand and Inter-arrival Time Distributions" with Ryzin. This article is about analyses of dynamic VRP in Euclidean regions where demand has an arbitrary continuous distribution and arrivals follow a general renewal process, which is closer to the real-life cases than the DVRP with uniform distribution and arrival by Poisson process. Authors made detailed analyses and concluded, "*static vehicle routing methods when properly adapted can yield near optimal or perhaps even optimal policies for dynamic routing problems*" (Bertsimas and Ryzin , Stochastic and Dynamic Vehicle Routing with General Demand and Interarrival Time Distributions 1993). This research provides for our work more opportunities in the problem formulation and solution development approach. Unfortunately, in the described problem there is a very small probability that uncertain demand will have a known distribution at all.

Moghaddam, Ruiz and Sadjadi solves the problem with uncertain demands with unknown distributions (Moghaddam, Ruiz and Sadjadi 2012). The authors proposed an advanced particle swarm algorithm with decoding algorithm M1 for it to transform results for classic VRP solution view. Unfortunately, Moghaddam, Ruiz and Sadjadi solved the classic VRP without TW, visit frequency, etc. Thereby, this algorithm can be used as approach for solution of the described problem only after adaptation.

The classification of SVRPs was offered by Gengreau, Laporte and Seguin (Gendreau , Laporte and Seguin 1995). In the paper they also said "*The Vehicle Routing Problem with Stochastic Demand (VRPSD) is without any doubt the most studied of all SVRPs*" mentioning the number of authors who offered algorithms for the solution of this type of problems.

The Periodic Supply Vessel Planning problem with demand uncertainty is not well studied and that is why this problem is of special interest for our research. Moreover, it has applied characteristics.

4.0 Methodology

The purpose of this research is to analyse installation demands on the real life data and develop a method to solve PSVPP with demand uncertainty. Literature review showed that PSVPP with demand uncertainty is poor studied yet. However, uncertainty in the sailing and service times was studied by several researches with several approaches. Thus, we can emphasize three main solution approaches for PSVPP with uncertainty.

Halvorsen-Weare introduced a voyage-based method for SVPP (Halvorsen-Weare , Fagerholt and Nonås , Optimal fleet composition and periodic routing of offshore supply vessels 2012). It is a two-phase exact method, which include feasible voyages generation and schedule construction. Kisialiou, Gribkovskaia and Laporte developed PSVPP-FC mathematical programming model, which is expanded SVPP model. It can be solved by using exact method (Kisialiou , Gribkovskaia and Laporte 2018). The voyaged-based method provides an exact solution, however, it assumes than installations' demands are deterministic and are known parameters for the problem. In this method uncertainty is not implemented at all. Norlund, Gribkovskaia and Laporte suggested strategies of speed optimization on the waiting and service periods in the SVPP in order to minimize emissions (Norlund, Gribkovskaia and Laporte, Supply vessel planning under cost, environment and robustness considerations 2015). This is one of the ways how to manage the uncertainty. However, it is extremely hard to develop and implement all possible strategies for the solution method in case of demand uncertainty. Exact method provide optimal solution for the problem, but this approach has low performance speed. Because of this reason, it usually is not appplied on the real size problem instances. To find an optimal solution by this methods can take very long time.

Heuristics and metaheuristics are the most popular approaches for SVPP solutions. Shyshou, et la. a LNS heuristic for PSVPP with predefined deterministic deands (Shyshou, et al. 2012). Borthen, et la. presented HGSADC metaheuristic for a simplified SVPP, which showed greate results on the big size instances (Borthen , et al. 2017). Kisialiou, Grobkovskaia and Laporte developed ALNS metaheuristic for PSVPP-FC without any uncertainty (Kisialiou , Gribkovskaia og Laporte 2018).Heuristics and metaheuristics are used for the problems with detereministic parametres. Moreover, they provides near-optimal solution of the problem, but performs faster than exact method, thus can be applied to the real size problems.

In 2013 was introduced method of optimization with simulation for SVPP with uncertainty by Halvorsen-Weare, Fagerholt and Ronnqvist (Halvorsen-Weare , Fagerholt and Ronnqvist , Routing and scheduling under uncertainty in the liquefied natural gas business 2013). She added a simulation phase for the voyge-based method in order to evaluate and analysed constructed solution and based on these results improve input data and repeate process. Norlund, Gribkovskaia and Laporte used optimization with simulation method for SVPP with emissins reduction by speed optimization. They introcuced a trade-off analyses as a addition to this method in order to find efficient solution from the sides of robustness level and emission reduction (Norlund, Gribkovskaia and Laporte, Supply vessel planning under cost, environment and robustness considerations 2015). This method allows implement uncertainty on the second phase of simulation to the solution and improve exact solution in the respect of needed requirements. It was tested on big instances and showed efficient results and good time of performing.

Demand uncertainty in SVPP was studied in the Master thesis of Engh. She used stochastic optimization to solve the problem. Stochastic optimization includes developing possible scenariouses of demands behavior and assigning a probability of each scenarious. Her solution approach was tested on very small unrealistic instance of 4 installations and showed efficient result. In this thesis we are going to solve real life instance of the problem, which includes at least 11 installations and infinite amount of demand's behaviour scenarios (Engh 2015).

In the literature review, we also look on VRP with uncertainties. You can see from the previous Chapter 3.0, that to solve it researches were using exact method, without implementing uncertainty, strategies or algorithms combined with exact method in order to implement uncertainty to the problem, and heuristics. Smith, et la. researched Dynamic VRP with stochastic demands, introduced tube heuristic, and Queue merging as approach (Smith , et al. 2010). He assume that, it is known according to which distribution demand arrives. Review showed that this assumption is a frequent allowance in the heuristics for the VRP with uncertainty.

Analysing the above, we are going to use optimization with simulation approach to solve described SVPP with uncertainty. The problem has two dynamic stochastic parameters and will be tested on the real size instance in order to get efficient solution from the sides of schedule cost and its robustness level. That is why optimization with simulation approach suits best of all for this problem. The decision-support tool is based on the developed solution method, which consists of two phases: schedule construction and simulation modelling of planned schedule. Schedule construction consists of two steps: feasible voyages generation and schedule construction, which provided using mathematical model of PSVPP-FC with exact solution method. Simulation of planned schedule is developed using descrete-event simulation modelling in order to evaluate solutions. More detailed description of the tool you can find in the Chapter 8.0.

5.0 Data

The installations' demand is a key parameter, which has a critical role in offshore upstream planning process. The main challenge, on which this research is focused, is demand uncertainty. The very first step of the work is to analyse demands in order to find any dependencies, which we can use for the solution method development.

Statoil is interested in the current research and demonstrated cooperation with us. They provided all necessary data for analyses and experiments in this research in order to make it closer to the real life cases and to make it more effective. Moreover, Statoil organized interviews and a visit to Bergen office in Logistic department.

The data Statoil provided is a schedules planned by logistic planners for one year period on the tactical level of planning. It implies information about the fleet of supply vessels, planned voyages with departure time from supply base for each supply vessel from the fleet, day and arriving time of a supply vessel to offshore installation for each visit of the voyage, planned visit frequency of each installation and the date, from which this schedule is valid. Statoil also provided the list of executed voyages for the same period. It implies voyage numbers, installation names, departure dates from supple base to installations and the amount of delivered cargo in tons and lifts.

To build PSVPP problem solution it is necessary to know parameters, which you can see in the Figure 5.1. From the files, which Statoil provided for this research, we took everything. All missing information was taken from online sources, articles, presentations and meetings with Statoil's logistic planner, which played role of an expert in the problem.

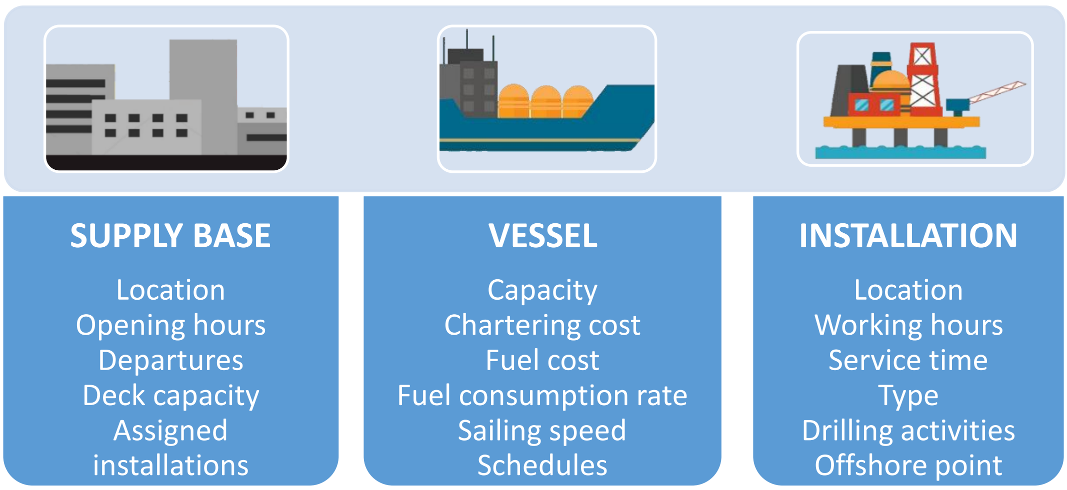


Figure 5.1 Requested data for the analyses

6.0 Data analyses

In our approach, there is a need to provide data analyses, with the goal to discover useful information for our solution method and to be able to model demands with uncertainty for providing evaluation of the solution method. Data modelling should be provided in the manner, which will allow us to perform uncertain demands in the closest to reality way.

It is undeniably important to provide an observation of executed voyages from the perspective of all actors of problem's supply chain: supply base, installations and supply vessels. After observing the data of the available executed voyages, with regard to supply base, we can notice patterns of planned schedule execution from week to week or for each weekday. Hence, we can take into consideration these patterns while developing our solution method. Observation of the data with regard to installations is important for understanding both cargo and visit demand statistics, their distributions or uncertainty for further demand generation. Consideration of the supply vessels' perspective is important, because we could understand uncertainty in the number of spot vessels usage and occurrences of ad-hoc situations. Since we can only extract information for the supply base and installations from our data, we will provide analyses only regarding these two actors of the supply chain.

From the company's logistic planner, we got historical information about executed voyages for a supply base for one year. When providing data analyses, we will consider the summer season, which lasts from May to October, because it is less dependent on weather conditions compared to the winter season. Only for defining a correlation between the amount of delivered cargo in tons, and respectively the subsequent number of lifts, we will use all year data. This is because the correlation of these two parameters is not influenced by the weather.

The data which is used for analyses of installations' demand fluctuations over a year is taken from historical data of executed voyages, showing for each visit to an installation (Installation) a voyage number (Voyage number), a departure date from supply base to the installation (ATD), delivered cargo in tons (DECK OUT (TON)) and number of lifts (# LIFTS). A presentation of available data is given Table 2.1.

Table 6.1 A presentation of available data on voyages# execution

Installation	Voyage number	ATD	DECK OUT (TON)	# LIFTS
Installation name	99999	dd.mm.yyyy	**100.0**	**40**

To analyse demand of each installation in dynamic, we additionally specify the month number, week number and a day of week for each departure from supply base to an installation. For analysis of each installation we also added information about their types, which depends on the main executive function on the installation (drilling, production, other), and the oil fields on which they are located.

When talking about installations' demands, as already mentioned, we imply the demanded amount of cargo to deliver to an installation and visit frequency of the installation, which should be executed during a week. That is why our goal now is to discover all available and useful information about visit frequency and delivered amount of cargo in tons and lifts, providing data analyses.

We assume that the main cargo measure is the amount in tons. This assumption is made, because vessels' deck capacity is measured in tons. Therefore, it is easier to operate with tons when comparing the total cargo value to a vessel's deck capacity than using the number of lifts. Taking into consideration this argument: it is more reasonable to provide modelling of cargo demands in tons.

Service time on installations depends on the amount of delivered cargo: the more cargo is delivered to the installation, the more time unloading operations will take. Loading and unloading operations are managed by the crane, which lifts cargo from a vessel to an installation. As described above, one lift in average takes 8 minutes. Thus, simultaneously with the cargo amount in tons, the number of cargo lifts will be calculated, in order to be able to estimate service time on installations.

In this Chapter particular methods of statistical analyses will be used. Among them there are Students' t-test, Fisher's F-test, correlation analyses.

6.1 Analyses of vessels' departure from supply base

With regard to supply base, we built a chart with the total executed number of departures to installations by days (Figure 6.1, Figure 6.3) for a planned schedule, which was actual for weeks 18 – 26.

Figure 6.2 shows for each week (18 – 26) by weekdays (1 – 6, where 1 is Monday and 6 is Saturday) the total number of departures to installations at that day. Figure 6.3 shows for each weekday the total number of executed installations' visits by weeks. For other weeks schedule equivalents of Figure 6.2 and Figure 6.3 can be found in Appendix A.

From Figure 6.2 it is apparent that the total number of departures to installations differs from week to week. For example, for week 18 the total number of departures to installations is equal to 19, while on week 24 this value is 17 and on week 26 it is 20. Moreover, for some weeks (week 18, 22, 23, 24) the total number of departures to installations (19, 19, 19, 17 respectively) differs from one, which was actually planned (in total 20 departures) (Figure 6.2).

Thereby, not looking at the fact that there is a defined planned schedule for the season, it is never executed exactly, how it was planned, since there exist ad-hoc situations with demand increase or unplanned additional visits, which lead to the usage of spot vessels and idle charter vessels (Figure 6.2).

Likewise, the differences in the number of the executed installation visits occur from week to week during the season (see Figure 6.2 with Appendix A together or Figure 6.3 with Appendix A) because of changes in installations' activities, the number of drilling operations and rig relocations. Thereby, from the spread in the number of weekly departures to installations it is almost impossible to define any patterns, except some.

1. Firstly, we can notice (Figure 6.1 with Appendix A) that supply base has following working hours: there are no departures on Sundays, not taking into consideration some exceptions on weeks 35, 40 and 44 (Appendix A).
2. Moreover (Figure 6.3, Table 6.2), on the example of weeks 18 – 26 we can see that the number of scheduled departures to installations for Monday and Tuesday (days 1 and 2) have the lowest Range:

$$Range \ = \ Maximum - Minimum, \tag{6.1}$$

which is equal to 1 in both cases, and Variation Coefficient:

$$Variation\ Coefficient \ = \frac{Standard\ deviation}{Mean} * \ 100\ \%, \tag{6.2}$$

which is equal to 15.79% and 17.65% respectively and has the meaning of "*extent of variability in relation to the mean*" of an observing sample (Coefficient of variation 2015). These values show us that the total number of departures to installations for Monday and Tuesday were estimated quite accurately, while for the rest of the week the number of departures to installations vary substantially and is very uncertain (Figure 6.3, Table 6.2). That shows us one more time the importance of construction of robust planned schedule.

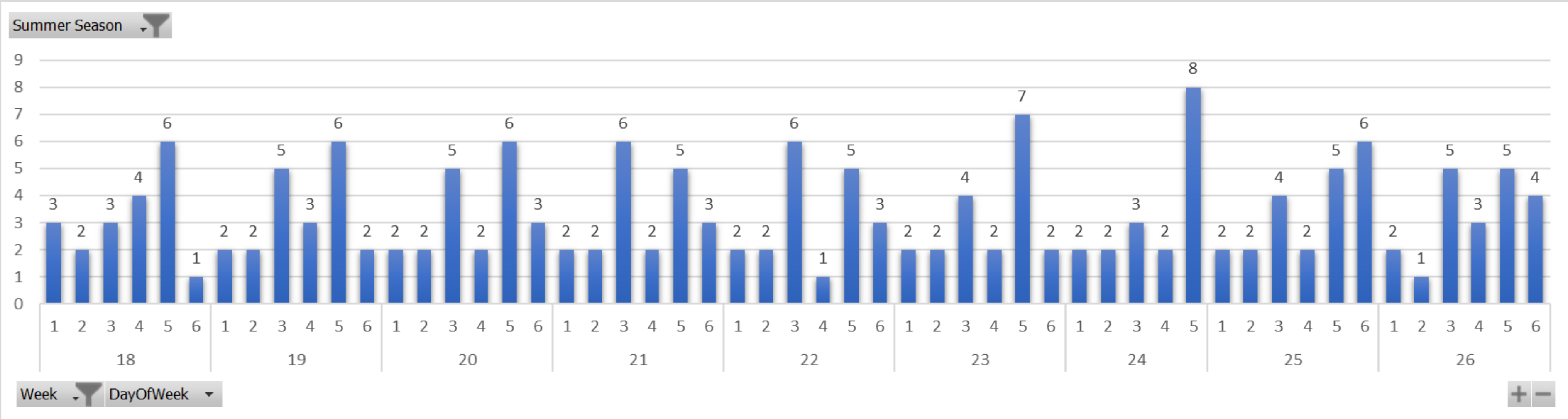


Figure 6.1 The number of installations' visits for all departures from supply base by days for weeks 18 – 26

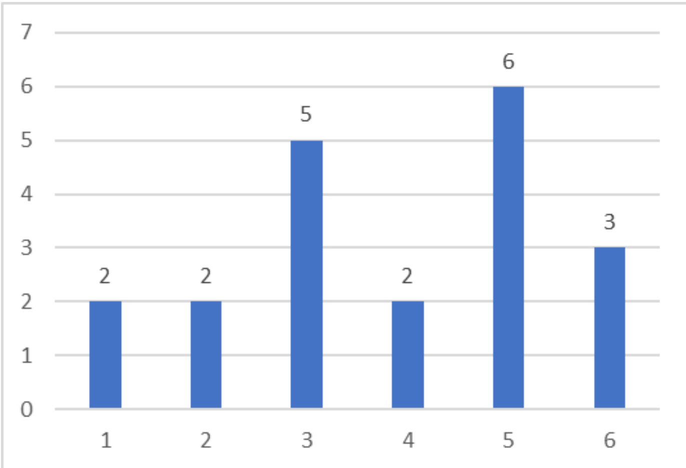


Figure 6.2 The number of planned installations' visits for all departures from supply base for weeks 18 - 26

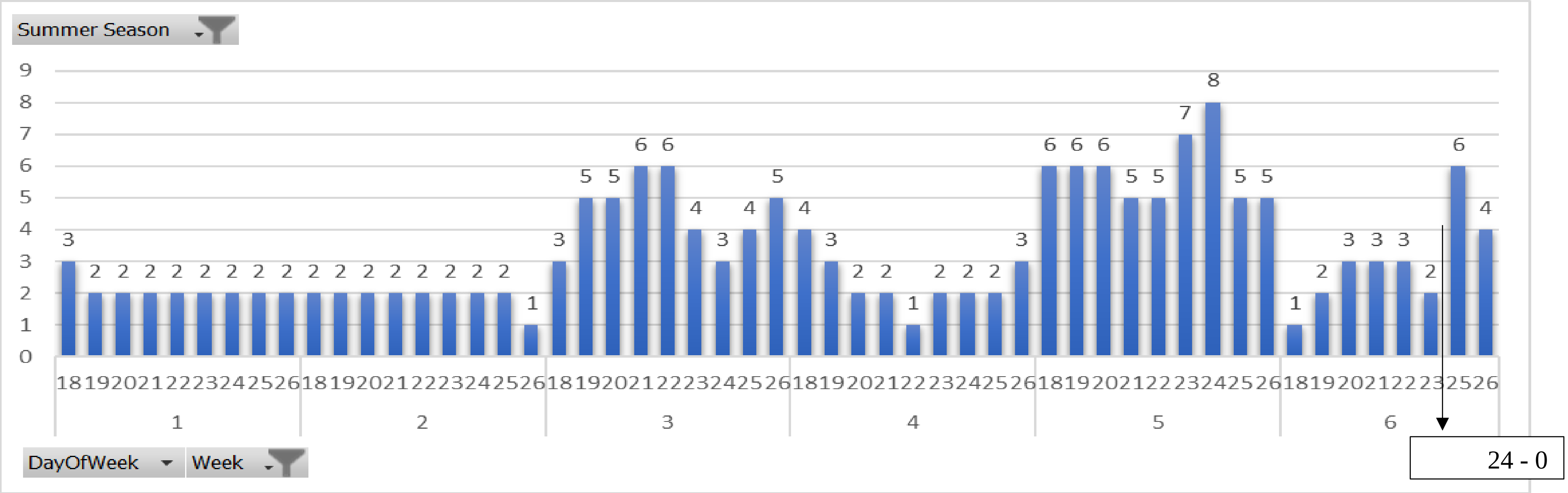


Figure 6.3 The number of installations' visits by weekdays for weeks 18 – 26

Table 6.2 Descriptive statistics of the number of installation visits for weeks 18 – 26

Day	Min	Mean	Max	Variation Coefficient	Range
1	2	2.11	3	15.78947368	1
2	1	1.89	2	17.64705882	1
3	3	4.56	6	24.81340238	3
4	1	2.33	4	37.11537445	3
5	5	5.89	8	17.89968487	3
6	0	2.67	6	64.95190528	6

3. At first glance, we could assume that on Wednesday, Thursday and Saturday, such large Variation Coefficients and Ranges can be explained by the assignment of departures to drilling installations (Table 6.2). However, from Figure 6.1 and Table 6.3 we can see that uncertainty of the number of departures to installations by days does not depend on the planned number of departures to drilling installations. For example, on Monday and on Saturday the number of departures to drilling installations is equal to 2 for both, while they are the least and the most uncertain installations respectively (Table 6.2).

Table 6.3 The planned number of departures to drilling installations by days

Monday	2
Tuesday	1
Wednesday	2
Thursday	1
Friday	1
Saturday	2

4. Thereby we can make the conclusion that the planned number of departures to drilling installations does not influence the difference in the number of actual departures from its estimated value.
5. From Figure 6.2 and Table 6.2 we see that on Wednesday, Friday and Saturday there were planned more departures to installations than on other weekdays, and exactly these days have shown the most uncertainty in comparison with others. Here we make a conclusion that the more visits are planned, and the more visits are planned for the same day, the more the number of actual visits differs from the planned value.

Table 6.4 shows us statistics of the total amount of cargo delivered to installations by days for weeks 27 – 30. For weeks 27 – 30, only on Wednesday were two vessel departures planned, and for other weekdays, 1 vessel. According to the logistic planner, the vessels' deck capacity is 600 tons. Hence, on Wednesday, total available deck capacity is 1200 tons, and for the rest of the weekdays, 600 tons. From Table 6.4 we can see that on Saturday there were in total delivered more than 600 tons (the maximum value for day 6 is 620.68). This visually proves to us the existence of ad-hoc situations with exceeding deck capacity, and once more underlines the importance of finding the way to build a more robust seasonal schedule.

Table 6.4 Total amount of cargo delivered to installations by days for weeks 27 – 30

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6
Standard deviation	77.21	68.62	353.54	111.00	147.62	192.87
Mean	142.55	182.02	503.73	194.85	316.68	426.57
Variation Coefficient	54.16	37.70	70.19	56.97	46.61	45.21
Min	66.10	127.00	233.92	86.60	180.80	189.20
Max	220.90	271.85	1022.56	334.04	473.75	620.68
Range	154.80	144.85	788.64	247.44	292.95	431.48

Here, in Table 6.4, the Variation Coefficient and Range on Wednesday (day 3) have the highest value in comparison to other weekdays and, on the other hand, exactly for these days there were planned departures to the highest number of installations (6 installations) and one of the highest numbers of departures to drilling installations (2 installations). This allows us to make the supposition, that the more visits and the more visits of drilling installations on the same weekday are planned; the more likely that cargo demand value will be more uncertain than for other weekdays.

The number of drilling operations in processes' diagram from May to October (Figure 6.4) does not have any changes from May to October, what shows to us that this diagram does not contain any useful information for analyses.

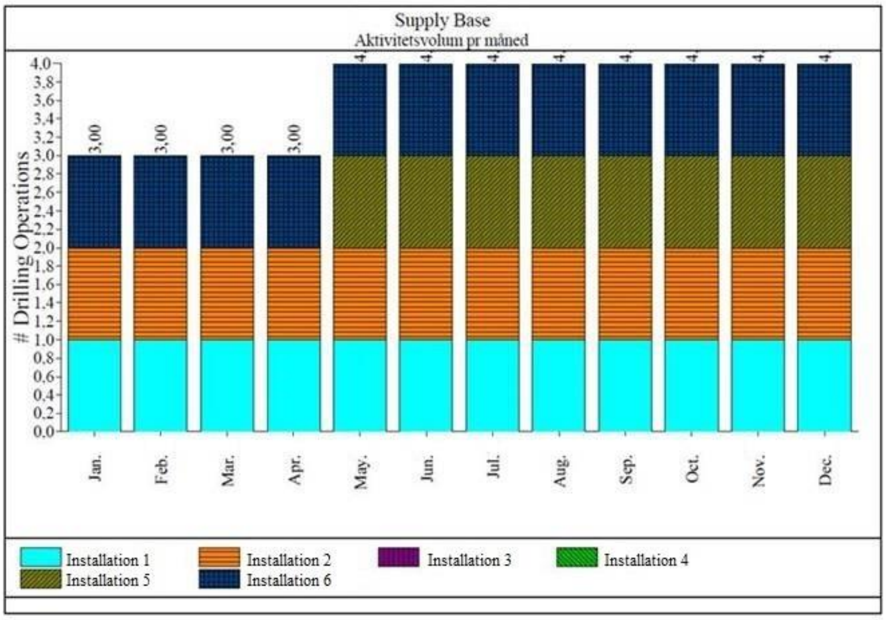


Figure 6.4 Drilling activity plan diagram (Provided by Statoil)

6.2 Analyses of cargo delivered to installations

With regard to such supply chain actors as installations, firstly, it is important to mention that in the planned schedule, there is never planned more than one departure to the same installation during the same day (for example see Table 2.1 Seasonal vessel schedule). While in reality two or more departures to the same installation during the same day can occur, because of ad-hoc situations. That is why, in order to analyse the value of total cargo demand for each installation per day, we need to calculate the aggregated value of delivered cargo for all voyages that start at the same day. In other words, we will analyse the values of cargo demand in tons for each installation grouped by days.

After applying filtering of data for the summer season and cargo demand aggregation, we calculate the numbers of available observations for each installation (Table 6.5). By available observations, we mean executed departures to installations.

Table 6.5 The number of available observations for each installation for summer season

Installation	# of Observations
I1	26
I2	86
I3	26
I4	71
I5	73
I6	31
I7	31
I8	85
I9	34
I10	31
I11	24
I12	5
I13	3
Total	526

As we can see from Table 6.5, in total we have 13 installations. For I12 and I13 the number of available observations is extremely small. Since our data is too uncertain, there is no guarantee that conclusions made for installations with small sample size will provide us any adequate information. That is why the cargo demand values of installations I12 and I13 will be added to other installations. However, before providing these merges, we need to know to which installations it is worth to add them and determine characteristics, which are not influencing the data of installations to which we add cargo demand values of installations I12 and I13.

6.2.1 Type of installation

Firstly, it is worth to have a look at demand uncertainty from the perspective of installations' types.

An installation can provide drilling, production, processing, accommodation, quartering and other functions, but we will divide into 3 groups:

- drilling;
- production
- other (accommodation, quarter, processing – the most stable demand).

This division is performed because, according to the opinion of Statoil's logistic planner, these types of functions are associated with, respectively, huge demand uncertainty, average uncertainty and quite stable demand changes.

In order to prove the expert opinion about differences of cargo demands between installations, depending on installations' processes, we will check if variances between cargo demands for installations with different functions are equal. With other words, we will test the next hypothesis:

$$H_0: \sigma_i \ = \ \sigma_j \tag{6.3}$$

$$H_1: \ \sigma_i \neq \sigma_j, \tag{6.4}$$

where $i \neq j$, σ_i and σ_j are variances of a sample of cargo demand for installations, with provided on them processes *i* and *j*, which are from the set {drilling, production, other}.

For testing these hypotheses, we will use F-Test (F-Test n.d.). The results of F-Test execution can be found in Table 6.6.

According to the rules of F-test, if F value is more than F Critical, then we reject the hypothesis about equality of variance (F-Test n.d.). As we can see from Table 6.6, all hypothesis about variances' equality with the probability 95% are rejected, what shows us, that we cannot prove the hypothesis that installations with different functions provide the same demand variance. The variances of installations show us that drilling installations have the most variable cargo demand, production installations – have less variable and other types have the least variable cargo demand (Table 6.6).

Table 6.6 Results of F-Test on the equality of variances for different installations' types

	Drilling	Production	Other
Mean	110.6949288	55.28019355	36.72900645
Variance	9073.076181	1471.044256	765.0522246
Observations	309	62	155
F-Test Two-Sample for Variances			
	Drilling-Production	Production-Other	Drilling-Other
F	6.16777921	1.922802403	11.85942069
P(F<=f) one-tail	5.65528E-14	0.000678594	2.85574E-48
F Critical one-tail	1.417460444	1.402769761	1.265250351

Here we can suppose that installations of different types have different variances, hence, provide different uncertainty. However, in order to make a conclusion about different variances for different types, we need to be sure that variances inside type groups are similar. Otherwise, it can occur such a situation that, for example, among drilling installations there was only one installation, which showed a huge variance, while others were quite stable.

In our case for production and other types there is no need to provide F-Tests inside the group, because in Table 6.6 shows that their variance values are not significant.

Two results of testing hypothesis for different installations, belonging to the same drilling type group, can be found in Table 6.7 (the rest is in Appendix B). Here F-Test has shown that variances of installations I2 and I5 are similar (F value is not higher than F-critical), while for I8 and I2 we cannot make this assumption. The Table in Appendix B shows that installations of drilling type inside the group have different variances. It is important to be careful here and not to conclude that just one installation has significant variance and the rest is stable. The difference of variances for drilling installations can just mean, that all variances are significantly huge, but in a different way. Moreover, it is exactly what we see in our data: not just one installation has a significant variance, but all installations (Table 6.7 and Appendix B).

We can conclude that uncertainty for different installations types is different, but cargo demand values of all installations should be analysed independently from each other.

Table 6.7 Results of F-Test on the equality of variances for several drilling installations

	I2	I5	I8
Mean	148.6239	94.45836	103.0541
Variance	8784.585	6513.884	14283.88
Observations	86	73	85
F-Test Two-Sample for Variances			
	I2-I5	I8-I2	
F	1.348594	1.626016	
P(F<=f) one-side	0.09645	0.013264	
F critical	1.459713	1.43287	

6.2.2 Installation location

One more parameter, from the perspective of which we have not looked at our demands yet is an oilfield, on which an installation is located. We will check an idea that the average demands of installations, which are located at the same oilfield, are similar (Formulas 6.5, 6.6). Drilling installations, since they are very uncertain, will not be taken into the consideration for testing our assumption about mean demand equality on the same oilfield.

$$H_0: \mu_{ik} = \mu_{jk} \tag{6.5}$$

$$H_1: \mu_{ik} \neq \mu_{jk} \tag{6.6}$$

where $i \neq j$, μ_{ik} and μ_{jk} are mean values of cargo demands for installations *i* and *j*, which are located at the same oilfield *k*.

For testing mean demand equality we will use t-Test, for specifying which, firstly, we will provide F-Test for variances (Formulas 6.3, 6.4).

In our case we can test only installations on one oilfield, since others or have one installation on an oilfield, or are located on the oilfield together with a drilling installation, or have too small sample size of one of the installations.

F-test shows us that for t-Test we need to assume unequal variances (F critical < F) (Table 6.8). From Table 6.9 in conclusion, we cannot reject an assumption that installations from the same oilfield have a similar mean value of cargo demand.

Table 6.8 F-Test on the equality of variances for two installations, located at the same oilfield

F-Test Two-Sample for Variances		
	I4	I3
Mean	44.37467	39.285
Variance	957.5345	403.8348
Observations	71	26
F	2.371105	
P(F<=f) one-side	0.008768	
F critical	1.800824	

Table 6.9 t-Test on equality of means for two installations, located at the same oilfield

t-Test: Two-Sample Assuming Unequal Variances	
	I4-I3
Hypothesized Mean	0
t-statistics	0.959611
P(T<=t) one-side	0.170351
t one-side critical	1.667916

However, we do not have more data, in order to reject or accept our assumption that is why currently we will assume that cargo demand average value equality between two installations, which are located at the same oilfield, is permissible.

6.2.3 Descriptive statistics

Now, we are coming back to the question about merge of installations I12 and I13.

Using results of Chapters 6.2.1 and 6.2.2 cargo demand values of installations I12 and I13 will be added to installations I4 and I11, accordingly, based on the close allocation, belonging to the same oilfield and execution of similar functions (have the same installation type).

After merging, we are going to work with 11 installations, the numbers of observations for which can be found in Table 6.10.

Table 6.10 The number of available observations for each installation for summer season after installations' merging

Installation	# of Observations
I1	26
I2	86
I3	26
I4	76
I5	73
I6	31
I7	31
I8	85
I9	34
I10	31
I11	27
Total	526

The statistic information for each installation about cargo demand value in tons per each delivery day is presented in graphical and numerical view in Figure 6.5 and Table 6.11, respectively.

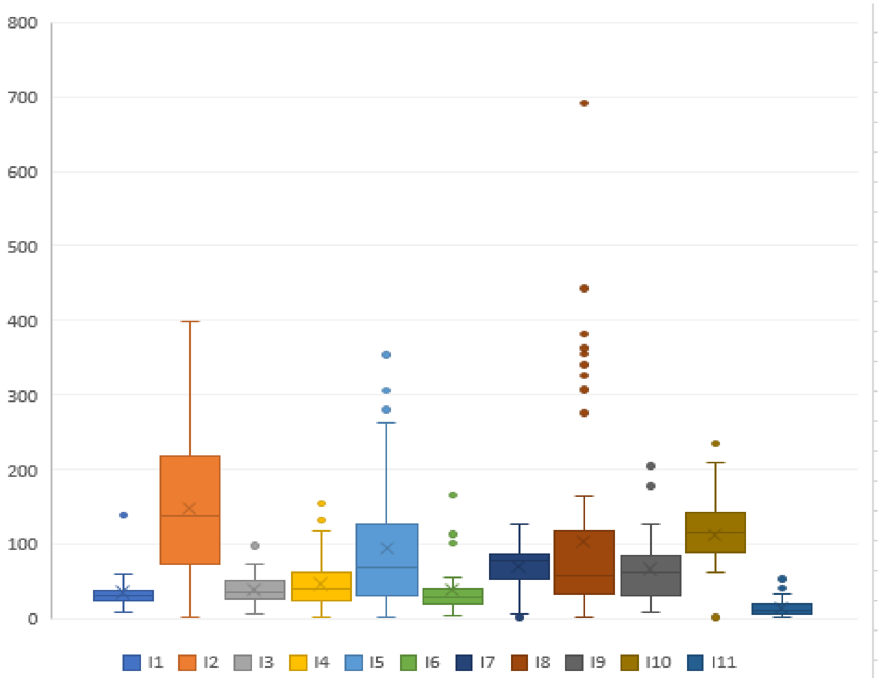


Figure 6.5 Box-and-Whiskers diagram of cargo demand values in tons for each installation

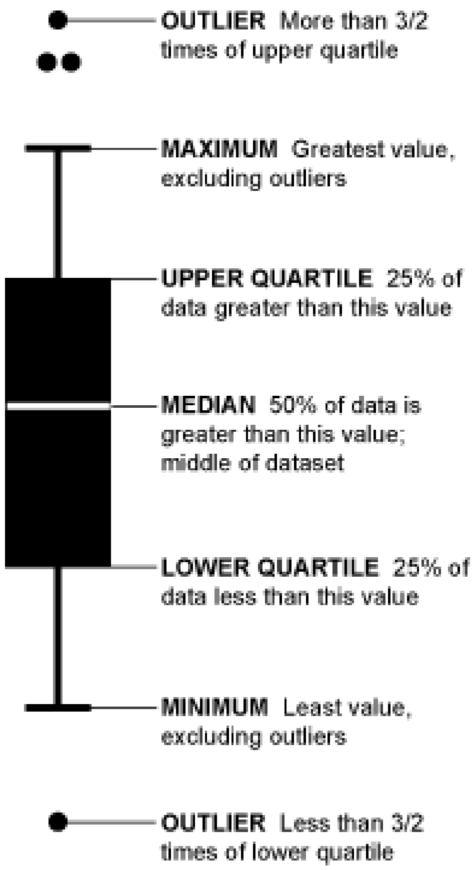


Figure 6.6 The interpretation of Box-and-Whiskers diagram elements (How to Read and Use a Box-and-Whisker Plot 2008)

Before saying any analyses conclusion made with the help of Figure 6.5, it is important to understand all element of it. For it have a look at Figure 6.6.

From statistics we can see that the difference between maximum and minimum amount of supplied cargo in tons have high variation (Figure 6.5, Table 6.11). For some installations, this difference can be not very significant, for some - can be huge. For example, installation I11, which provides not drilling and production operations, has the range only 50.4 tons, while installation I8, which provides drilling operations, showed ton values in a range from 2.1 to 691.36. Moreover, in comparison with other installations, I8 has the highest Variation Coefficient – 114.8%. These values show us again an existence of uncertainty in data and could give us an idea to check correlation between cargo demand values on the installation and executed on it functions, but according to the results of Chapter 6.2.1, this assumption is rejected.

We are paying attention to Figure 6.5 and Table 6.11 once more and see that none of the installations has a Normal Distribution, because of one of the next reasons:

Table 6.11 Descriptive statistics of cargo demand values in tons for each installation

	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11
Mean	35.62	148.62	39.29	46.84	94.46	39.86	70.70	104.28	67.10	112.47	15.54
Median	31.55	138.79	34.75	40.85	68.43	29.70	77.30	58.70	63.40	115.50	10.60
Standart deviation	23.40	93.73	20.10	32.22	80.71	35.72	34.98	119.72	44.94	57.65	12.60
Variation Coefficient	65.67	63.06	51.15	68.78	85.44	89.61	49.48	114.81	66.97	51.25	81.12
Kurtosis	16.49	-0.23	1.55	1.22	1.09	5.02	-0.12	6.97	1.98	0.33	2.70
Skewness	3.71	0.53	0.96	1.08	1.20	2.28	-0.50	2.40	1.19	-0.29	1.71
Min	8.4	3	6.8	2.3	1.9	4.3	2.6	2.1	10.2	2	3
Max	139.4	399.03	97.86	155.10	353.90	165.65	127.85	691.36	204.70	235.30	53.40
Range	131	396.03	91.06	152.80	352	161.35	125.25	689.26	194.50	233.30	50.40
Number of observations	26	86	26	72	73	31	31	84	34	31	24

- the median is usually located closer to upper or lower quartile, while for Normal Distributed values it should be located in the middle, meaning that there are usually more cargo deliveries with small cargo demand value or otherwise, not the mean one (Figure 6.5);
- the median and mean values are located quite far from each other for all installations, what shows us that cargo demand distributions have tailed shape (Figure 6.5, Table 6.11);
- kurtosis and skewness are giving far different from Normal Distribution Values, which are respectively 3 and 0 values. Where "*the kurtosis parameter is a measure of the combined weight of the tails relative to the rest of the distribution*" and "*skewness is as a measure of a dataset's symmetry – or lack of symmetry*" (McNeese 2016).

6.3 Distribution

In order to prove that cargo demand of installations value does not have Normal Distribution and find out, which distributions these values have, we build histograms of cargo demand values for each installation.

For it, firstly, we identify the optimal number of bins (histogram bars) for each installation using Sturges' formula (Sturges 1926):

$$k = 1 + [\log_2 n] \tag{6.7}$$

For example, the number of histogram bars for installation I4, the number of observations of which is 72, can be calculated using Formula 6.7 and is equal to the values 7. The histogram for I4 you can see in Figure 6.7. On the Figure 6.7 X- and Y-axes show us respectively interval of cargo demand values in tons and occurrence frequency of ton value in the interval.

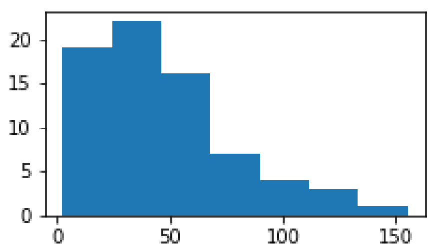
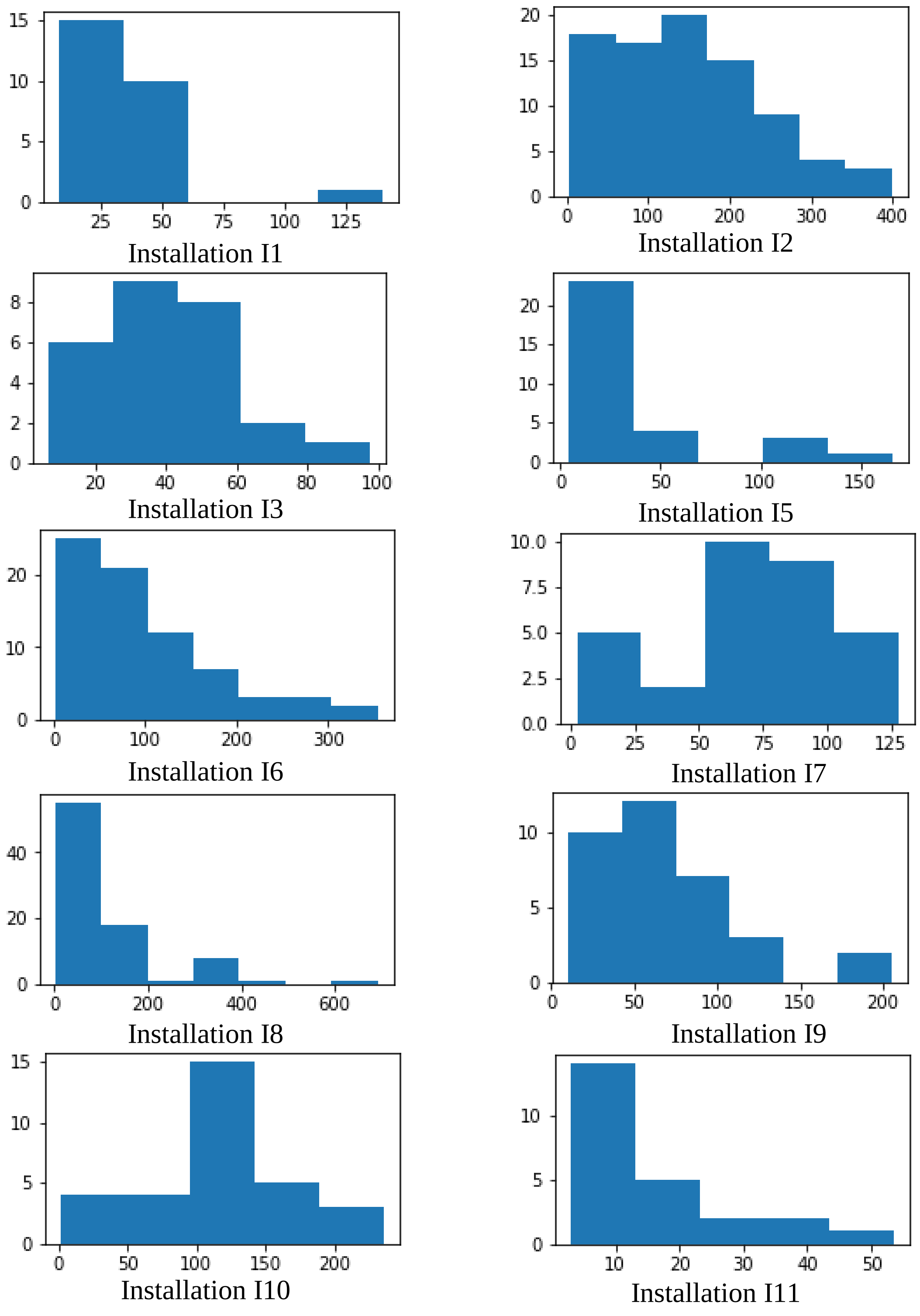


Figure 6.7 Histogram for DECK OUT (TON) value for installation I4

Table 6.12 Histograms for DECK OUT (TON) value for all installations (I1 – I11) except I4



From all histograms' plots we can see that some of installations have a skewed right unimodal asymmetric distribution (I4, I2 and other), while others can be left skewed (I7) or symmetrical (I10) (Figure 6.7, Table 6.12).

Distributions for all installations are different and since we do not have information about deliveries for previous years and have a lack of information for the observing year, to make assumptions about distributions is not correct. However, the view to these plots can show us once more that uncertainty of demand exists. Therefore, the information, which can be useful from the provided statistical data analyses, is the information about minimum, maximum, mode, mean cargo demand values.

6.3.1 Processes

One more parameter, dependence of cargo demand value with which we should find out is the estimated number of drilling operations.

During the whole summer season, there were drilling operations on four installations: I2, I5, I8, I9 (Figure 6.4).

Statoil's logistic planners construct schedule for a season, paying attention on the number of drilling operations, which is estimated to be processed. We have Figure 6.4, which shows the number of drilling operations for observed by us supply base for one year.

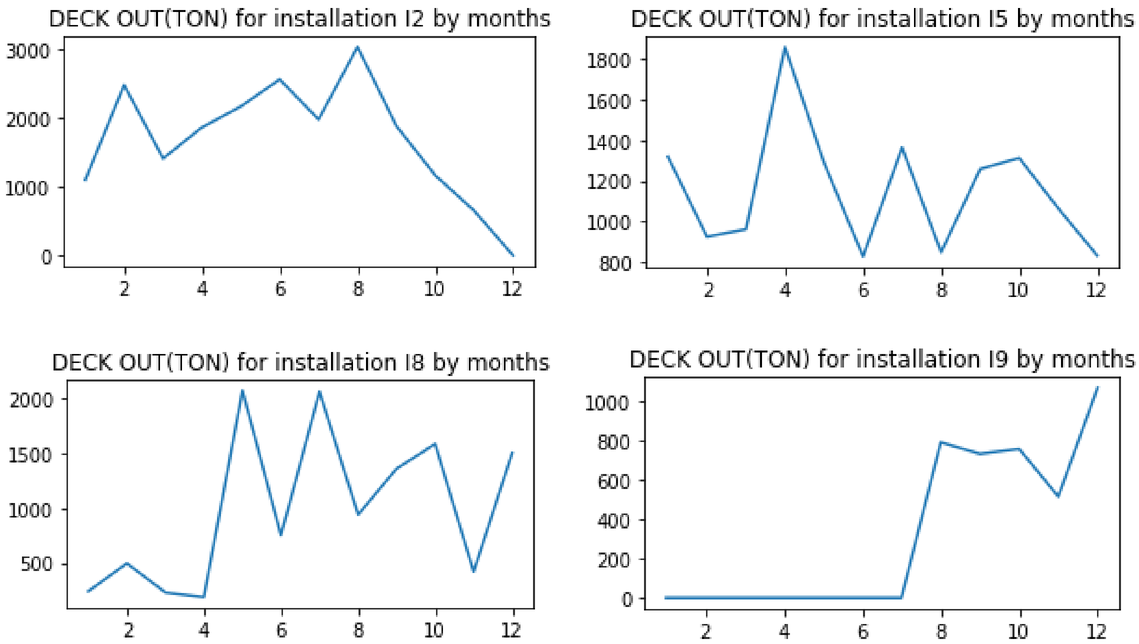
Using Figure 6.4 only for summer season analyses of one year, there is no possibility to see, how the number of drilling operations will influence on demand, because there were no estimated changes in number of drilling operations.

In order to understand if there is any influence of estimated number of drilling operations, we will have a look overall the whole year dynamic of cargo demand values in tons, aggregated by months for all drilling installations, for which we have estimated value of the number of provided drilling operations (Table 6.13).

We can notice that drilling operations on I9 were estimated from May, but actually, deliveries there have started from August. It shows to us that, while making demand prediction on the estimated number of drilling operations, logistic planners should be very careful, since absence of drilling operations can hint that there are no deliveries for this or that period, but not otherwise.

In total processes analyses for our data does not give any reasonable information and that is why it should not be considered for our future generations of cargo and visit demands.

Table 6.13 Dynamic of cargo demand values in tons by months for drilling installations I2, I5, I8, I9.



6.4 Analyses of the number of installations' weekly visits

We should not forget that the demand in our problem is not only cargo amount, but also installation's visit frequency. For it, we build cumulative weekly histograms of visit distributions for each planned schedule we had before. From Figure 6.8, built for the period of weeks 18 – 26, we can notice that for some installations (I6 and I1) there were no changes per weeks in the number of visits (they had only 1 visit during the whole period), while for some (I4 and I8) there are lots of changes. I4 has the number of visits in a range from 3 to 5, I8 – from 2 to 5. The number of visits increases (decreases) on installations have been occurring on different weeks during the whole season (I4 had 5 visits on week 21, while I8 had 5 visits on week 26).

Looking at Figure 6.8 and its equivalents in Appendix A we again can be convinced that all installations are different and can have changes in weekly visit demand not depending on the time period.

Moreover, the number of visits during summer season is laying in borders from 16 to 20 visits per week and when schedule changes in September (week 33) have occurred – from 20 to 25 visits. As the conclusion for the noticed by us facts, we can claim that the number of visits for a week in total varies plus-minus one visit.

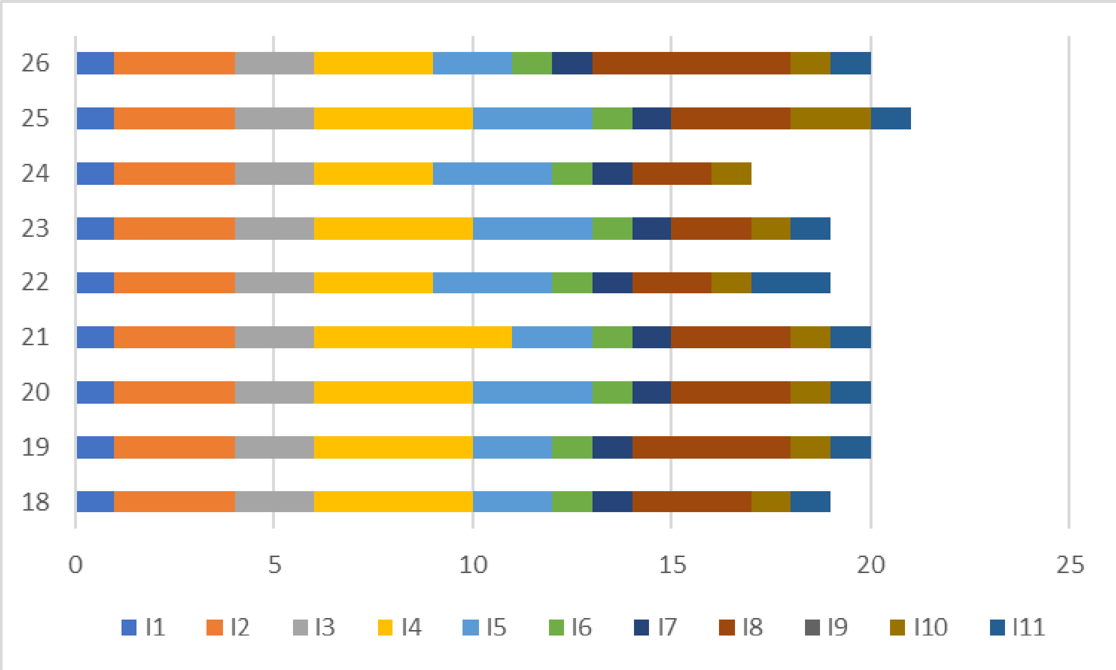


Figure 6.8 The number of visits for each installation for weeks 18 - 26

6.5 Data analyses conclusions

Provided analysis of constructed schedule and executed voyages have help us to underline the next statements:

- cargo demand values will be modelled in tons and based on these values will be calculated the cargo lift number;
- the planned seasonal schedule is never executed in the way it was constructed
- in total processes analyses for our data does not give any reasonable information and that is why it should not be considered for our future modelling of cargo and visit demands;
- finding the way to build a more robust seasonal schedule is an important problem
- from the perspective of supply base:
    - the total number of installations' visits differs from week to week days and does not depend on the number of departures to drilling installations;
    - there are no departures from supply base on Sunday;
    - the more visits are planned for the same weekday, the more the number of actual visits differs from the planned value and the total amount of cargo demand values are uncertain than for other weekdays.
- from perspective of supply base:

- variances of cargo demand amount for different installations' types are different. But all installation should be analysed independently from each other;
- cargo demand average values equality between two installations, which are located at the same oilfield, is permissible;
- the difference between maximum and minimum values of cargo demand in tons for different installations varies a lot;
- none of the installations have Normal Distribution cargo demand values;
- distributions of different installations have different characteristics, concerning symmetry and tailed-skewness;
- while making demand predictions based on the estimated number of drilling operations, it is important to be very careful, since estimation of drilling operations for this or that period cannot hint on their actual execution;
- installation' visits demand values can have changes in demand not depending on the time period;
- the number of weekly visits in total varies plus-minus one visit.

Based on data analyses we need to develop a methodology, which will not take into consideration the absence of possibility normally to forecast demand values, because forecasting should be made on samples of bigger size and of several years. Therefore, we should find a way to model data taking into consideration statistical values, which we got in this Chapter.

7.0 Assumptions

The problem description and the data analyses showed to us the complexity of the studied problem. To make this research possible, we will use following assumptions:

- Supplies of the installations provided from one supply base;
- Maximum one departure to each installation per working day can be arranged on the supply base;
- For supply base assigned homogeneous fleet;
- Cargo demand of one installation cannot be split between several vessels.

Basing on the data analyses part, to this list we can add one more assumption:

- There are no departures from supply base on Sunday.

8.0 Decision support tool

In this chapter, we are going to describe developed approach for robust seasonal schedule construction in respect that visit frequencies and cargo amount are unknown or highly imprecise.

Before definition of the tool's work, we made broad analyses of the demand uncertainty, which described in the Chapter 6.0. The result of the analyses showed that it is almost impossible to forecast demands of installations using historical data on executed voyages and installations behaviour prediction. Because of this reasons we should find another way how to include uncertainty in the approach.

In Figure 8.1, you can see the scheme of the developed solution method for PSVPP with uncertainty. The solution method was implemented as a decision-support tool. It consists of two phases. The first phase is schedule construction, which includes two steps:

1 - Feasible voyages generation. On this step tool generates feasible voyages, which is characterized by departure time from the supply base, sequence of installations to service, duration, probability of voyage's violation and its cost. By the probability of voyage violation is meant a probability that the total amount of cargo on the voyage will exceed the capacity of assigned vessel. The output of the first step is the list of feasible voyages, which is an input for the second step.

2 - Seasonal schedule construction. On this stage, the tool solves by Simplex method mathematical model of PSVPP-FC. The output of this step is an optimal schedule, which is characterized by the optimal fleet size, assigned voyages to supply vessels with departure times and its cost. The constructed schedule on this step is called *planned schedule*. The planned schedule used as an input for the second phase.

The second phase is simulation. This step is dedicated to simulation of the planned schedule with demands variations. The simulation included recourse action, which applies on the operational level changes of the planned schedule in order to ensure 100% service level of installations. The results of the second phase is a expected cost of the schedule and simulation's statics, which reports costs of executed voyages.

When two phases are completed, it is possible to compare costs of the planned schedule and simulation results. The high difference between these costs points on the fact that the planned schedule required reconstructions, using recourse actions in order to provide 100% service level of installations supplies more often than in the case of small cost differences. Thereby, planned schedule has low robustness level. Robust planned seasonal schedule is a schedule, which does not have changes during the season.

In order to define, how robust is planned seasonal schedule, we will use such metrics as *robustness level*. Robustness level, taking into consideration the previous paragraph, we calculate with the help of Formula 8.1.

$$Robustness\ level\ = \left(1 - \frac{expected\ cost - planned\ cost}{planned\ cost}\right) \times 100\% \tag{8.1}$$

From Formula 8.1 we see that the closer planned and expected costs are, the higher is robustness level.

The goal of this research is to build a seasonal schedule with the highest robustness level.

In order to make the planned schedule more reliable the next step is to decrease upper bound probability of the routes violation and repeat schedule construction and simulation. Do it until the upper bound probability equals to 0 or planned cost approximately equals expected cost.

The difference between costs is the highest on the first iteration. On the next iterations, the difference between costs is going down until the point, where planned and expected costs will be intersected. The cost of simulation is always greater, but can be very close to it, of the planned schedule cost, because of demand uncertainty. In Figure 8.2, you can see an example of this effect. By efficient solution is meant the value of upper bound probability parameter with the lowest simulation cost.

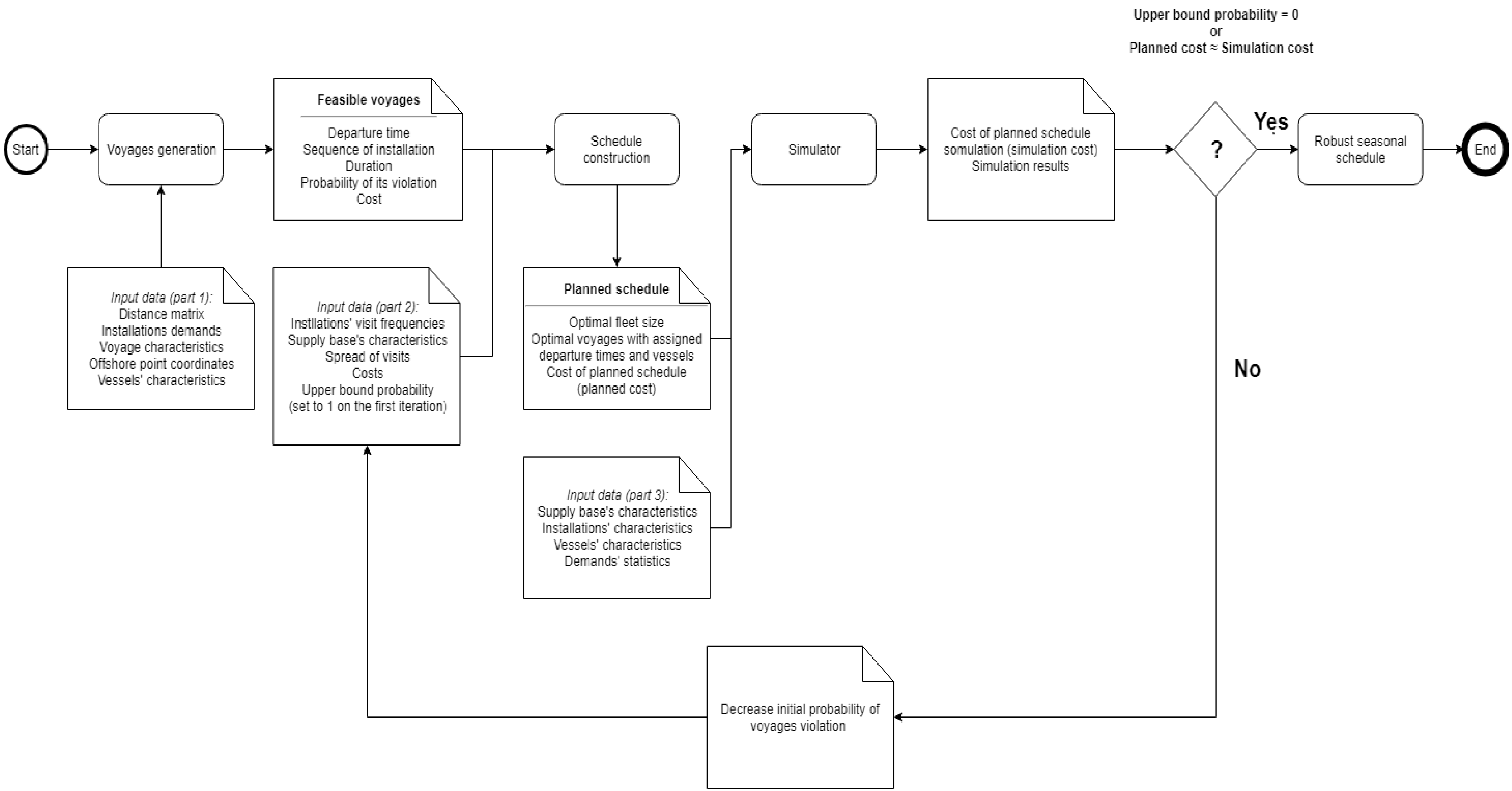


Figure 8.1. The developed solution method

The tool represents two-phase iterative method, which suggests the most efficient seasonal schedule for the installations' supply. The detailed description of its phases you can find further in this Chapter.

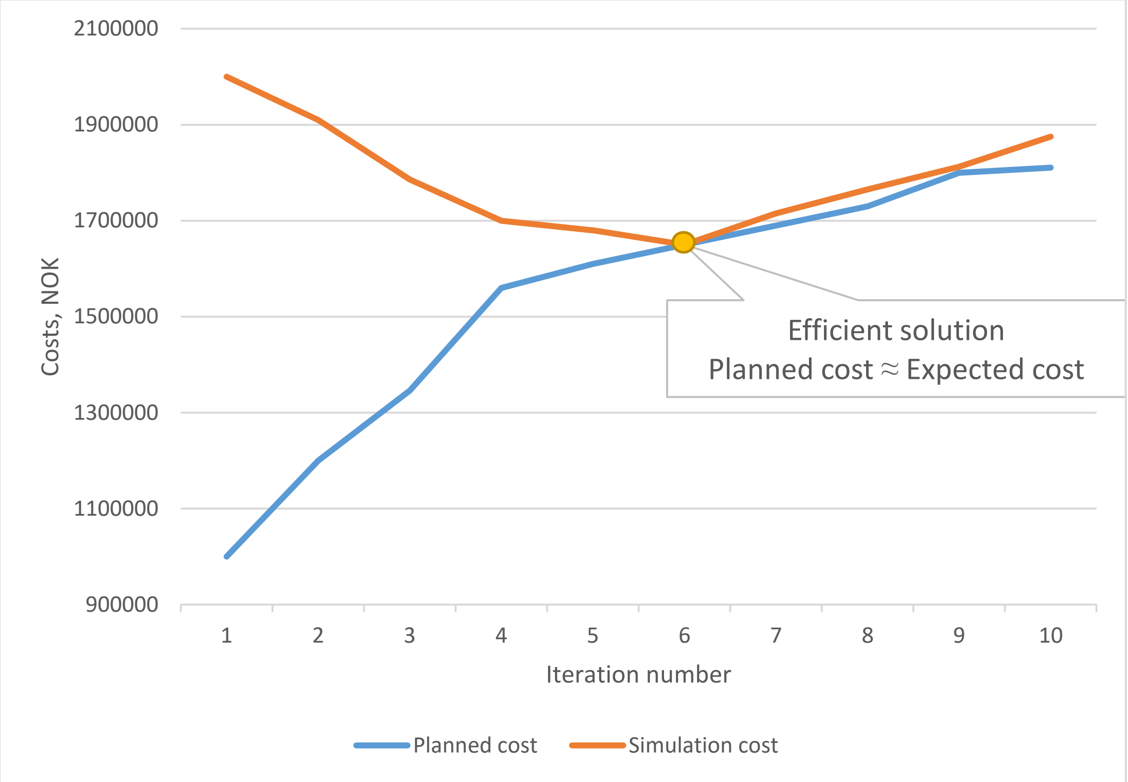


Figure 8.2. Planned and simulations costs behaviour

8.1 Voyages generation

Voyages generation is the first step of the first phase of the decision-support tool, on which all feasible voyages are defined. The developed algorithm constructs the voyages. The algorithm will be described below. It is implemented to the tool using C# programming language.

The input data for the voyages generator is separated into three files: data on installations and a supply base, data on vessels characteristics and voyage execution historical data. The data file about installations and the supply base consists of the distance matrix, minimum and maximum number of installations per voyage, load factor, acceptance time factor, coordinates of offshore point and the list of installations assigned to the supply base with parameters of their time windows, visit frequencies, service times and coordinates of their location.

In the vessel's deck, there could be columns, technical and insurance facilities, paths between containers etc. Thus, *load factor* is a parameter, which takes into account the fact that it is impossible to use all deck space. It is represented as a percentage of on how much the vessel's deck capacity overestimated.

Acceptance time factor takes into account inaccuracy of the time calculations. In the real life cases if, for example, vessel is late for 5 – 10 minutes, installation or supply base will anyway service it. The voyage generator has to know allowable error percentage on the time in which the vessel can still follow the schedule.

The input file about vessels' characteristics consists of the name of the vessel, its capacity, speed, fuel cost per ton and consumption rate of sailing, possible start time and stay time on the supply base and installation. Available vessels for the fleet composition of the supply base are listed in this file.

From the file of voyage execution, we can get a set of cargo demand for each installation. This set is used for further modelling of demand data file. The demand data file consist of 10 000 entries of the cargo amounts for each installation. Based on the demand data file, firstly, we calculate probabilities of the cargo amount appearance for each installation. We calculate it for every 10 tons of possible cargo amount until maximum amount of cargo from all installations. Pseudo code of the demand probability calculation described in the Algorithm 1.

For the voyage construction, it is necessary to know installations demands in order to evaluate its feasibility. In our case, as an input to the voyages generator we are using mode of cargo amount, calculate on the historical data. Mode is a value of the most frequent appearance data. In the described problem, the most often formed demands. Logistic planners in Statoil for planning process use mode of demands too, but they calculate it on the data of the two lasts month, whereas we calculate mode of the demands using all historical data provided by Statoil. For the voyage generator we use only mode of cargo amount for each installation. The mode of visit frequency is used in schedule construction.

Algorithm 1. Demand probability calculation

```
for each installation i
Set interval = 0, set count = 0
while interval != div(MaxCargo, 10) + 1 do
  for j = 0 to 10 000 do
    if cargo[i][j] ≥ interval and cargo[i][j] < interval +10
      count++
    end if
```

```
        j++
      end for
      probability[i][interval] = count/10 000
      interval += 10
    end while
    return probability matrix
```

When demand probabilities of each installation are calculated, we can define probability of violation. It will be calculated, as one minus probability of the fact, that total cargo amount of the voyage will not exceed the vessel's capacity (probability of fulfilment).

$$Probability\ of\ violation\ =\ 1 - Probability\ of\ fulfillment \tag{8.2}$$

There are three methods how to calculate probability of fulfilment (Medvedev 2001). Let describe the first method on the example of two independent random variables X and Y. $f_S\ (s)$ is a density function of random variable s. In our case, s is a vessel's capacity and X, Y is a cargo amounts from installations on the voyage.

$$f_S\ (s)\ =\ Probability\ (\ X\ +\ Y\ \leq\ s) \tag{8.3}$$

In the problem, X and Y are continuous nonnegative random variables. In this case probability of fulfilment can be calculated as follows in Formula 8.4, where S is a random variable S = X + Y, F_s and F_X are distribution functions of corresponding random variable (S and X) andf_Y – density function of Y random variables (Medvedev 2001).

$$F_s(s) =\ F_X\ *\ F_Y\ = \int_0^s F_X(s - y)\ f_Y\ (\ y)\ dy \tag{8.4}$$

In order to calculate probability of fulfilment of random variable $S\ = X_1 + X_2 + \cdots + X_n$, where X_i – independent random variable, we use a convolution function (Medvedev 2001), which is shown in Formula 8.4:

$$F_2 * F_1 = F^{(2)}, F3 * F^{(2)} = F^{(3)}, \dots, F_n * F^{(n-1)} = F^{(n)} = F_S \tag{8.5}$$

In Formula 8.5 F_i – distribution function of random variables X_i, where$F^{(k)}$ – distribution function of the sum of k random variables

In the studied problem voyage can consist of visits of up to six installations and demands vary for each installation from 0 tons to a ton value, which is bigger than vessel capacity. However, taking into consideration complexity, size of solving by us problem and the number of integrals, which we have to take in order to calculate probability of voyage fulfilment, using Formula 8.4, implementing this method will make it only more complex.

The second method is the method of moment-generating functions. In this method probability of fulfilment can calculated with the help of moment-generating function $M_S(t)$, which is defined for independent random variables $X_1, X_2, \dots, X_n$ by Formula 8.6 (Medvedev 2001).

$$M_S(t) = E[e^{tS}] = E\left[e^{t(X_1+X_2+\cdots+X_n)}\right] = E[e^{tX_1} \times e^{tX_2} \times \dots \times e^{tX_n}] = \qquad (8.6)$$
$$= [Since\ X_i\ random\ variables\ are\ independent] =$$
$$= E[e^{tX_1}] \times E[e^{tX_2}] \times \dots \times E[e^{tX_n}] = M_{X_1}(t) * M_{X_2}(t) * \dots * M_{X_n}(t)$$

In Formula 8.6 E is an expectation value. Calculation of moment-generation function can be a complex and time consuming operation. Especially, when random variable distribution function is not known or is not standard. That is why we prefer to find other method for calculating probability of voyage fulfilment.

The last method to calculate probability of fulfilment and the one we use in the voyage generation tool is to calculate it, using generated cargo demand values for each installation and a probability of occurrence of two independent events A and B at the same moment (Formula 8.7) (Further Concepts in Probability n.d.).

$$P(A\ and\ B) = P(A \cap B) = P(A)P(B) \qquad (8.7)$$

For our method, events A and B can be interpreted as occurrence of some cargo demand values for an installation. Moreover, the total demand of these two events does not exceed deck capacity of a vessel, because otherwise they are not satisfying capacity fulfilment requirement.

In order to understand this step better, we give an example. Assume we know that cargo demands of installation 1 and 2 are equal to 200 and 300 tons, correspondently, and probability of occurrence of this cargo demand values are 0.1 and 0.05. Therefore, probability of occurrence of these two events at the same moment can be calculated, using Formula 8.7 and is equal to value 0.1 * 0.05 = 0.005.

Now we calculate, occurrence of all events, for which summarized cargo demand values of two installations give a value, which does not exceed vessel capacity. For it we use Formula 8.8 of probability additive rule (Further Concepts in Probability n.d.):

$$P(C \cup D) = P(C) + P(D) \tag{8.8}$$

In Formula 8.8, C and D events never occur together, but are interchangeable: occurs or event C, or event D.

For example, our installations 1 and 2 can have not only cargo demands 200 and 300, but also 150 and 250, with probabilities 0.2 and 0.1, correspondently. Then probability that vessel the total demand does not exceed vessel's deck capacity is equal to 0.1*0.05 + 0.2*0.1 = 0.005 + 0.02 = 0.025.

In case of more than two variables, we use Formulas (8.9) and (8.10).

$$P(X_1 \cap X_2 \cap \ldots \cap X_n) = P(X_1) \times P(X_2) \times \ldots \times P(X_n) \tag{8.9}$$

$$P(X_1 \cup X_2 \cup \ldots \cup X_n) = P(X_1) + P(X_2) + \cdots + P(X_n) \tag{8.10}$$

This method was implemented to the voyage generator algorithm in order to calculate and assign voyage probability of violation.

Now we will describe gradually, how the voyage generator is working:

- Read the input data;
- Calculate distances between supply base, offshore point and installations;
- Calculate for each installation probability of appearance of cargo amount for each 10 tons until maximum possible value (Algorithm 1);
- Generate all possible the shortest voyages for every possible start time;
- Construct unique combinations of installations;
- Calculate voyage probability, as described above;
- Check feasibility of the voyage. If it is feasible create new feasible voyage, otherwise - create new infeasible voyage;

- By recursion find the best sequence for the voyage, calculate departure and waiting time and duration. For this step we used recursive procedure introduced by Kisialiou, Gribkovskaia and Laporte in the article “The periodic supply vessel planning problem with flexible departure times and coupled vessels“;
- Calculate voyage cost;
- Save the results to the output file.

The output file includes the list of feasible voyages, which are characterized by departure time, sequence of installations, duration, probability of violation and cost. Moreover, the output file is formatted and includes all the data for the second step of the first phase as an input file.

8.2 Schedule construction

The second step of the first phase is a schedule construction stage. It used as an input generated feasible voyages from the first step of the first phase and installations’ visit frequencies (mode, calculated on historical data), supply base characteristics (coordinates, opening hours, available departures), spread of visits, fuel and chartering costs and upper bound probability parameter.

To construct schedule we need to solve PSVPP. For the implementation to the decision-support tool we chose the most expanded mathematical model of PSVPP PSVPP-FC (Kisialiou , Gribkovskaia and Laporte 2018). The solution of the PSVPP-FC implemented to the tool by the AMPL programming language, which uses CPLEX solver.

8.2.1 PSVPP-FC mathematical model

The following notation is used for the Periodic Supply Vessel Planning Problem with Flexible departures and Coupled vessels mathematical model:

Sets

I – set of installations, assigned to the supply base ($i \in I$);

D – set of days, on which can be departures from the supply base (during a week) ($d \in D$);

V – set of vessels’ types ($v \in V$);

R – set of all feasible voyages;

T – set of possible departure times in the planning horizon ($t \in T$);

Variables

$x_{vrt} = \begin{cases} 1, if\ voyage\ r\ \in R\ assigned\ to\ vessel\ type\ v \in V\ departure\ at\ time\ t \in T \\ 0, otherwise \end{cases}$;

y_v – the number of vessels of type $v \in V$ used (integer and ≥ 0);

Objective function

$$minimize \sum_{v \in V} f_v y_v + \sum_{v \in V} \sum_{r \in R} \sum_{t \in T} c_r x_{vrt} \qquad (8.11)$$

f_v - charter cost of vessel of type $v \in V$;

c_r – fuel cost of voyage $r \in R$.

The first part of the objective function represents chartering cost of the supply vessels from which consist fleet of the supply base. The second part represents the cost of execution of planned voyages in the constructed schedule.

Subject to

1) The required visit frequencies of installations must be met:

$$\sum_{v \in V} \sum_{t \in T} \sum_{r \in R_{vt}} a_{ri} x_{vrt} = n_i\, , \forall i \in I \qquad (8.12)$$

$R_{vt} \subseteq R$ – subset of voyages assigned to vessels' type $v \in V$ departure at time $t \in T$;

$a_{ri} = \begin{cases} 1, if\ installation\ i \in I\ is\ visited\ on\ voyage\ r \in R \\ 0, otherwise \end{cases}$;

n_i – requested visit frequency of installation $i \in I$ within a week.

2) The number of departures on each day should not exceed defined maximum:

$$\sum_{v \in V} \sum_{t \in T_d} \sum_{r \in R_{vt}} x_{vrt} \leq B_d\, , \forall d \in D \qquad (8.13)$$

$T_d \subseteq T$ – subset of possible departure times during day $d \in D$;

B_d – maximum number of departures from supply base on day $d \in D$.

3) The number of used vessels of the type at any moment shouldn't exceed the number of available vessels of this type:

$$\sum_{l \in T_t^L} \sum_{r \in R_{vt}} b_{vrlt} x_{vrl} \leq y_v, \forall v \in V, \forall t \in T \tag{8.14}$$

$T_t^L \subseteq T$ – subset of possible departure times from supply base in the time interval $[t - L, t]$;

$$b_{vrlt} = \begin{cases} 1, vessel\ of\ type\ v \in V\ start\ voyage\ r \in R_{vt}\ at\ time\ l \in T_t^L\ till\ next\ departure\ at\ t \in T \\ 0, otherwise \end{cases}$$

This constraint holds overlapping of the voyages in the schedule, if the only one vessel of the type is used. Other way, it allows overlapping and, moreover, enables couples of two vessels of the same type.

4) Limitation on the number of available for chartering vessels:

$$y_v \leq K_v, \forall v \in V \tag{8.15}$$

K_v – the number of available vessels of type $v \in V$

5) Each installations has only one departure from the supply base per day:

$$\sum_{v \in V} \sum_{t \in T_d} \sum_{r \in R_{vt}} a_{ri} x_{vrt} \leq 1, \forall i \in I, \forall d \in D \tag{8.16}$$

6) Spread of departures:

$$m_i \leq \sum_{v \in V} \sum_{t \in T_{it}} \sum_{r \in R_{vt}} a_{ri} x_{vrt} \leq M_i, \forall i \in I, \forall t \in T \tag{8.17}$$

$T_{it} \subseteq T$ – subset of possible departures from supply base to installation $i \in I$ in time interval $[t, t + h_i]$;

m_i – minimum number of departures within sub-horizon h_i for installation $i \in I$;

M_i – maximum number of departures within sub-horizon h_i for installation $i \in I$.

Installations require visit frequency from supply base service. For example, one installation required two visits per week. For us it is obvious that visit should be evenly distributed during a week. It is a good case if an installation will have service on Tuesday and Friday, however it can be so that service will be on Monday and Tuesday. In this case, installation will struggle with storage capacity and will operate without any service for almost a week. To avoid such situate this constraint is developed. It limits the number of days between visits of installation, depending on required visit frequency.

7) Voyage violation probability parameter should not exceed upper bound probability:

$$p_r \le P_0, \forall r \in R \tag{8.18}$$

p_r – probability of violation of voyage $r \in R$;

P_0 – upper bound of probability of violation for all voyages (upper bound probability parameter).

After the second phase, we have planned schedule and its cost. The next stage is its simulation and evaluation.

8.3 Schedule simulation modelling

In order to analyse planned seasonal schedule, expected cost, which is most of all close to a real practical schedule execution cost and provide enhancement of model solution, we propose usage of not only an optimization modelling, but also use optimization with simulation.

Therefore, in the thesis we deal with simulation modelling. For defining the type of simulation modelling, which we will use, firstly, we will look at the definitions in simulation modelling of such words as System, State and Event (L. Kelton 2000).

"*System – is composed of objects called entities that have certain properties called attributes;*

State – a collection of attributes or state variables that represent the entities of the system;

Event – an instantaneous occurrence in time that may alter the state of the system"

The studied PSVPP can be represented as combination of "vessel departures" and "installation cargo demand value occurrence" events. The departures occur by the defined time in the planned schedule. At the departure time the cargo demand, which should be delivered to each installation, can be cumulated. Since the cargo demand is not deterministic on each installation, and can occur demand exceeds exactly at this moment. We implemented decision strategies to handle described changes in order to provide 100% service level. These changes are called *recourse actions*.

Events occur only at countable points of time. And by this reason, we use in the work approach of Discrete event simulation (DES).

Discrete event simulation is considered as "*the modelling of a system as it evolves over time by a representation in which the state variables change instantaneously at separate points in time*" (Kelton og Law 1991). DES approaches span its use across various life areas, ranging from manufacturing logistics to transportation modelling, through communications systems.

The usage of DES is convenient, because it provides possibility to make cost estimations. Some more benefits of DES usage are:

- ease for understand;
- lower realization cost than real-life testing;
- high customization of the technique.

Today exist variety of simulation languages: GPSS, Simscript, SLAM, and SIMAN. They require time to understand how to use them in an effective way (W. Kelton 2007). On the other hand, nowadays it is much faster to use built-in libraries of ordinary programming languages, such as C++SIM for C++, SimPy for Python, or develop your own library (Mattlof 2008).

High-level simulators (AREANA Simulator, JaamSim) provide high graphical visibility and ease of use, however have a restricted functionality.

In our work we use Python language since it is easy to use, readable, elegant and powerful (Matloff 2015). It contains a big amount of various libraries. Thus, it is possible to use lots of functions. Moreover, python is considered to be a strong statistical tool and there is a huge number of resources, in which answer for any questions about Python realization can be found fast.

8.4 Logical model of the simulator

During simulation process there is generated uncertain demands. These generated demands differ from the demands, which were used for building seasonal schedule. The difference between these demands influences the amount of supplying cargo on voyages and a length of service time at installations. Voyage durations should be recalculated due to service time changes. Thereby depending on demand, which was generated for a voyage, we can talk about acceptance and violation of described constraints:

- vessels' deck capacity constraint. It can be violated if supplying demand exceeds vessel's capacity;
- voyages overlapping constraint. It can be violated if voyage duration has increased, and consequently the vessel did not manage to return back to supply base before the start of its next voyage.

If any of the described above constraints is violated, some recourse actions (strategies) may be applied to insure schedule feasibility.

For estimating cost of constructed schedule, we run one simulation process, which consists of 1000 replications. Each replication is proceeded for 4 weeks. For each week it is initially used the same constructed schedule, which can be modified during simulation process, if such need occurs.

Simulation flow, introduced in Figure 8.3, starts with the specification of replication number ("Replication number = 1"). Since it is only a start of the simulation, the result of check "Replication number ≤ 1000" will evidently lead us by the true branch. Then generation of demand and respective to it service time occurs for the whole replication period ("Generate Demand and Service time on each installation").

On the next stage looping of "Week number" from 1 to 4 and of "Day number" from 1 to 7 start. If there is a violation in vessels' capacity or voyages' overlapping constraints for any of the voyages of the day occur ("Are there violations in any voyage for the day?"), then changes of planned schedule are done to provide 100% service level ("Recourse actions"). If there are no violations and need to provide schedule changes, we assume that the schedule was proceeded as it was planned. Not depending on the result of constraint validation, we remember statistics and all changes for the day ("Remember statistics for the day").

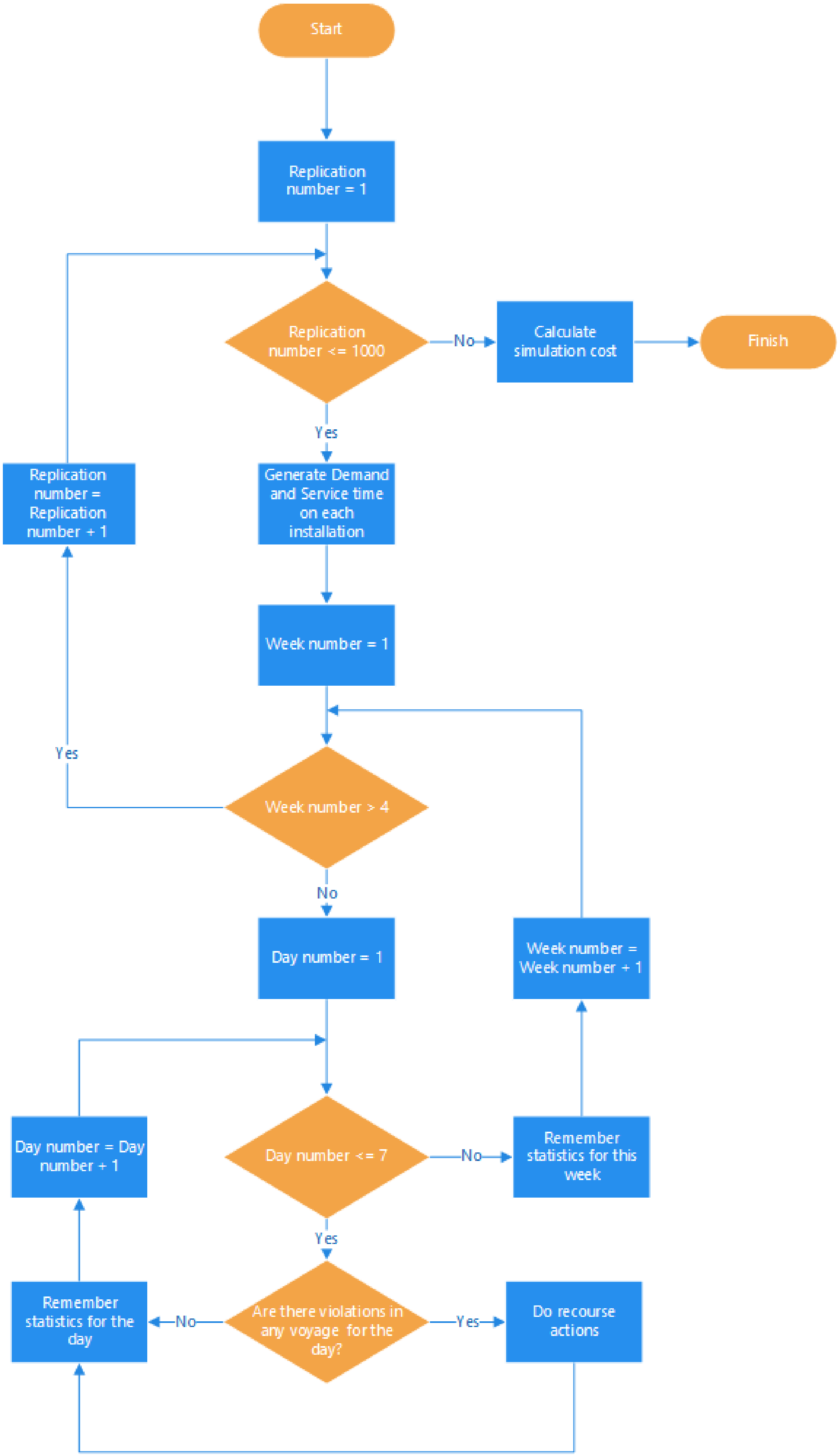


Figure 8.3 The workflow of the developed simulator

Then we go to the next day ("Day number = Day number + 1") and proceed the same constraint validation actions again. When "Day number ≤ 7" decision takes false value, we follow its false branch and come to the next week ("Week number = Week number + 1") and repeat the same actions. After "Week number > 4" takes true value, we remember statistics for current replication and go to the next one ("Replication number = Replication number + 1"). When there is executed 1000 of replications ("Replication number ≤ 1000" takes on a false value), we finally calculate expected cost of schedule execution, by calculating the average weekly schedule execution cost.

8.5 Recourse actions

As already was written above, recourse actions can occur in the case of violations:

- cargo, which needs to be delivered, exceeds vessel capacity (loaded cargo for the voyage greater than its capacity):

$$\sum_{i \in I} Demand_i * (1 + \alpha) > Capacity \tag{8.19}$$

where:

I – a set of all installations from a voyage;

$Demand_i$ – cargo demand of installation i, known for this day;

α – load factor, because of unknown shape of the cargo. Statoil, according to the words of the logistic planner expert, currently is using α = 20%;

- occurs overlapping of voyages for one vessel (vessel does not return back from current voyage before the next voyage starts). It happens because of increase of delivered cargo amount.

Below we provide strategies to handle both these situations, in order to provide 100% service level. It is important to mention, that these recourse actions were developed based on cations, which are made in reality to handle occurrence of deck capacity exceeds and possible voyages overlapping situations.

8.5.1 Recourse actions strategies

Strategy 1 (Scheduled charter vessel)

According to this strategy cargo, demand of one or more installations is shifted to another voyage from the scheduled voyaged as an additional installation to visit. Only voyages executed during the same or the next days are taken into consideration as violated voyages. In that situation, only vessels for this or the next day are observed, because it is in our interest to deliver a cargo to all scheduled installations at the required time. Thus, if we will look at vessels, which start their voyage on a day after the next, it can be already very late to deliver this cargo, hence, service level decreases.

For better understanding, we will provide an example of this strategy.

Let us assume that occurs the situation, which is possible to see in Figure 8.4.

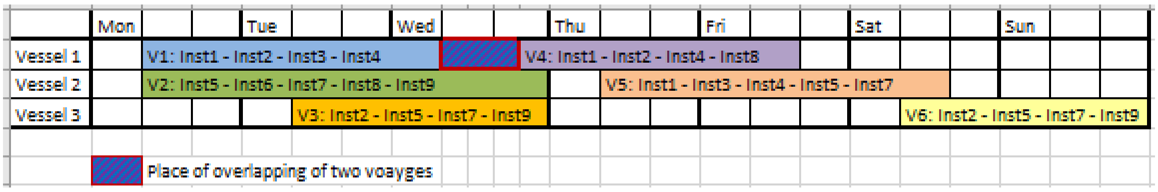


Figure 8.4 A schedule example for strategy 1

On voyage 1, which starts on Monday on vessel 1, there is increased cargo demand so, that according to calculations before the start of this voyage 1, supply base understands that vessel 1 will not manage to return back before the start of the next voyage (V4).

This situation means that overlapping violation takes place. In order to provide 100% service level and has no overlapping, cargo demand of one or more installations from voyage 1 (Installation 1, 2, 3, 4) needs to be shifted. We will check all other voyages, which start on Monday or Tuesday. There are available voyages 2 and 3, which start on Monday and Tuesday respectively. It is possible to see from Figure 8.4, if we shift some cargo demand from voyage 1 to voyage 2, there may occur another overlapping: voyage 2 will overlap voyage 5. While shifting of cargo to voyage 3 does not lead to any overlapping violations. If capacity constraint on voyage 3 with shifted to it cargo is satisfied, then a cargo can be shifted to the voyage 3, if not – other strategies will be considered.

Strategy 2 (Idle charter vessel)

Here cargo demand of one or more installations is shifted to an idle charter vessel for a suitable time. Hence, we are talking about a new voyage for the vessel. Availability of an idle charter is checked for the current and the next days. Charter is counted to be available if it satisfies overlapping restrictions:

1. there are no voyages for this vessel, which are not finished before the current day (or the next day, if we check an idle vessel for the next day);
2. the idle vessel, to which there will be shifted installations to supply, will manage to return back to the supply base before there will be started its loading for the next scheduled voyage.

For this strategy can be given an example shown in Figure 8.5.

	Mon			Tue			Wed			Thu			Fri			Sat			Sun		
Vessel 1		V1: Inst1 - Inst2 - Inst3 - Inst4									V4: Inst1 - Inst2 - Inst4 - Inst8										
Vessel 2		V2: Inst5 - Inst6 - Inst7 - Inst8 - Inst9												V5: Inst1 - Inst3 - Inst4 - Inst5 - Inst7							
Vessel 3																	V6: Inst2 - Inst5 - Inst7 - Inst9				

	Demand	Demand * (1 + α)	Vessel Capacity	Delta
V1	590	708	600	108
V2	500	600	600	0

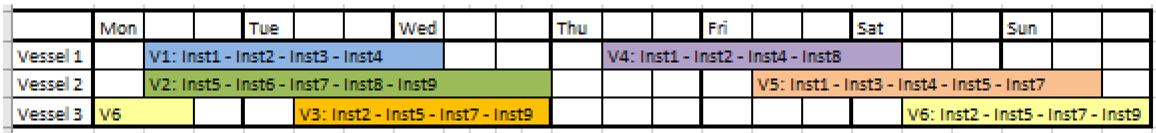
Figure 8.5 A schedule example for strategy 2

In Figure 8.5 vessel 1 should start voyage 1 (V1) on Monday and has the total cargo demand to deliver to installations equal to 590 tons. Taking into consideration load factor, we get 708 tons, what is for 108 tons more than vessel capacity. On Monday there is only one more voyage started (V2), which has no free deck to shift an additional cargo. On Tuesday there are no vessels to departure. Hence, we are looking for an idle charter vessel. There is vessel 3, which can start a voyage on Monday. If we shift to it cargo demand of one or more installations from voyage 1 so, that there will be no violations of overlapping or cargo demand constraints on both vessels, then we can shift this cargo and send vessel 3 to an additional voyage. In example from Figure 8.5, it is easy to see that this possibility exists.

Strategy 3(Spot vessel)

According to the third strategy, cargo demand of one or more installations is shifted to a spot vessel. In comparison with previous strategies, this one gives the highest additional cost, but, on the other hand, provides the fastest delivery of the cargo.

The situation, when a need in a spot vessel occurs can be seen in the Figure 8.6.



	Demand	Demand * (1 + α)	Vessel Capacity	Delta
V1	590	708	600	108
V2	500	600	600	0
V3	480	576	600	-24

Figure 8.6 A schedule example for strategy 3

Cargo demand on voyage 1 exceeds capacity for 108 tons and cannot be shifted to any other voyage of Monday or Tuesday, since other vessels are busy at that moment or have not enough free deck capacity. Hence, there is a need to fright a spot vessel in order to serve all demand and provide 100% service level.

It is important to mention, shifting of installation's cargo demand occurs without splitting of the cargo demand value in this thesis. For example, if we shift cargo demand of installation 1, which has value 200 tons, from a voyage, where value of exceeded total cargo demand is 100 tons, then we shift to another vessel all installation's demand – 200 tons.

The application of strategies depends on cost and can be executed combining several of them. As a recourse action, will be applied that combination, which has the lowest cost of execution.

8.5.2 Recourse actions execution

In order to understand cargo demand of which installation according to which strategy to shift, firstly, we need to define amount of cargo, which exceeds capacity, in order to understand, if we really need to proceed any recourse actions and for how many vessels we need to spread exceeded cargo demand. This amount we calculate with the help of the next formula:

$$delta = \sum_{v \in V} \sum_{i \in I(v)} Demand_i * (1 + \alpha) - Capacity \tag{8.20}$$

where:

V – set of all voyages v, on which violation has occurred;

I(v) – a set of all installations of the voyage v, which belongs to the set V;

$Demand_i$ – demand of installation i, known for this day;

α – load factor, because of unknown shape of the cargo.

It is important to notice, that we calculate this exceeded delta value not for each voyage, which is violated today, but for all voyages of this day. This logic is implemented, because it can be cheaper to shift the cargo of several installations from all violated voyages in one voyage than shifting it to each separate voyage.

If there is no cargo demand, which exceeds capacity of the vessel's deck, but violation occurs because of overlapping there is no need to calculate this value. However, the calculation will not influence for the further work of the simulator.

Since among our strategies there is an option to shift installations to a charter vessel, which departures to a voyage according to the planned schedule during the current day or the next day (strategy 1), we need to define, if this possibility exists. For it, we check the total available deck space on unviolated voyages, which start from the supply base on the current day or the next day. Additionally, we check if overlapping and capacity constraints are not violated on the vessels, on which this unviolated voyages are executed.

The next step is to define if the amount of the total free deck is enough to deliver delta cargo. If it is enough, there is no need in an additional vessel. Otherwise, we calculate the number of vessels, which is needed, in order to satisfy a shifting of the cargo, the amount of which is equal to a difference of delta cargo and the total free deck. This number can be calculated with the help of the next formula (Formula 8.21):

$$\begin{aligned} &Number\ of\ additional\ vessels \\ &= \ (delta - free\ deck) \ * \ (1 \ + \alpha) \ / \ Capacity \end{aligned} \tag{8.21}$$

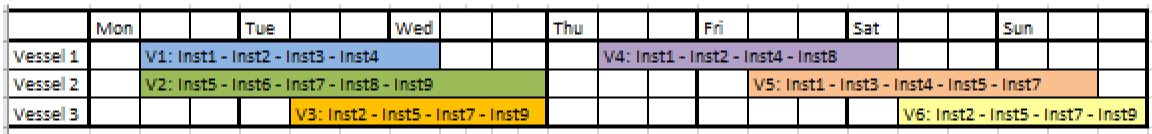
After the number of scheduled charter vessels with available free deck and the number of additional vessels are known, we calculate the number of vessels, between which we will try to spread our exceeded cargo. We will call this number as a *spread vessel number*. This number consists of the number of scheduled charter vessels, the number of additional vessels and one additional free vessel. The need in one additional free vessel occurs, because we do not split shifted demand of installations and there can occur such situations, when shifting cargo demand simply cannot be fulfilled with the total available free deck.

For example, the total available free deck and delta value are equal to 100 tons both, while the smallest installations' cargo amount, which we can shift, is 60 tons. Therefore, in such a situation, we need to shift at least 2 installations' cargo demands, one of which is 60 and another is at least 60. Hence, we have to shift at least 120 tons, what cannot be fulfilled with 100 tons of the total free deck.

On the next step, we combine all installations from violated voyages into one set of installations and spread them between vessels. The number of vessels for spread was defined earlier. Therefore, we simultaneously provide extract and insert operations.

We give an example for work of simulator here, in order to understand the work on this stage.

As an example, we are assuming the situation from Figure 8.7.



	Demand	Demand * (1 + α)	Vessel Capacity	Delta
V1	510	612	600	12
V2	520	624	600	24
V3	450	540	600	-60

Figure 8.7 A schedule example for understanding extract and insert installations stage

In situation in Figure 8.7 there are cargo demand violations on voyage 1(V1) and voyage 2(V2). These demands can be shifted to voyage 3. However, it can occurs that none of the installation from V1 or/and V2 will have a demand less than 80, for instance. In this case, since we do not permit split of the demand, the complete exceeded demand will be not possible to shift to V3. That is why we need to consider an additional vessel and, thus, spread vessel number of vessel between which we will spread the total cargo demand is equal to 2.

The list of installations, which we will consider for shifting, consists of installations from V1 and V2: Installations 1, 2, 3, 4, 5, 6, 7, 8, and 9.

Before coming to spreading of installations, we need to be sure which number of installations will be enough for shifting, in order to satisfy constraints. Thus, in the current example, we check if it will be enough to shift only installation 1, or it should be shifted in combination with some other installation.

In addition, in order to cut the number of permutations, we do not consider those combinations, which were allowed for spreading on a step before. It means, if shifting of installation 1 was enough, in order to cover constraints requirements, we will not consider any combination with this installation, for example (1,2), (1,3,4) or other combinations with installation 1.

On the next step, we provide spread of the set of considered for shifting installations into two vessels. Therefore, we can spread the set of shifting installations in the next ways (Figure 8.8):

1. 1 installation and one free vessel;
2. 2 installations, where each one is assigned to a separate vessel;
3. 2 installations into one vessel and one free vessel;
4. 3 installations into one vessel and one free vessel;
5. 2 installations into one vessel and 1 free vessel;
6. and so on.

Vessel 1	1	empty	2	...	3	4	...	3, 4	empty	...	5, 6, 7	...	5	6, 7	...
Vessel 2	empty	1	empty	...	4	3	...	empty	3, 4	...	empty	...	6, 7	5	...

Figure 8.8 An example installations spread between two vessels

After all possible spreads of vessels are defined, we are coming to the installations' insertion step.

In the example, as it was already mentioned before we have two vessels to insert, what means that we have 2 variants: shift installations to voyage 3 of vessel 3 and shift them into an empty spot vessel (for understanding, why spot, look Chapter 8.5.1 Recourse actions strategies).

If we calculated that the total cargo demand value of installations 1 and 5 is enough to shift, in order to satisfy requirements of our constraints, then we check the next variants:

- Installations 1 and 5 total cargo demand amount is shifted to voyage 3;
- Installation 1 cargo demand amount is shifted to voyage 3, while installation 5 – to a free spot vessel;
- Installation 5 cargo demand amount is shifted to voyage 3, while installation 1 – to a free spot vessel;
- Installations 1 and 5 total cargo demand amount is shifted to a free spot vessel.

Now we need to find out, which exactly combination of these new voyaged gives the best cost. For it, firstly, we provide voyages re-optimization, by checking the cost of all possible permutations of new voyage and defining the best among them. If re-optimized voyaged give better value than all previous observed combinations, then we remember this combination of new voyages as the best.

When all voyages were observed, we execute recourse actions, which correspond to the best combination of voyages. It means we write in the statistics, how installations were served by vessels, which departure from supply base on the current day and how installations should be served by vessels, which departure the next day.

After it, the simulator continues its work as it was written in Chapter 8.4.

9.0 Experiments

This Chapter is dedicated to the evaluation of developed decision-support tool's work. At the beginning of the Chapter we provide description of methods, with the help of which we have been modelling data for our experiments (Chapter 9.1). Then we go straight to the description of the results and, finally, to the results of their analyses.

As mentioned above, our decision-support tool has two stages: schedule construction and simulation modelling.

Schedule construction part was implemented using C# and AMPL programming language on a computer with 4 GB of RAM and Intel Core 2 processor of 2.20 GHz under the Windows operating system. Simulation modelling experiments were conducted using Python programming language on a computer with 6 GB of RAM and AMD Core 4 processor of 2.30 GHz under the Windows operating system.

For the experiments we are using the instance with 11 installations and 1 supply base, provided by Statoil.

For our decision-support tool we use two groups of input data: the data for schedule construction and for the simulation modelling, which repeat several times, with changing probability of vessel's deck violation. Probability of vessel's deck violation changes from 1 down to 0 value with step 0.01.

The input data for the two-phase optimization approach involves the data on the supply base, installations, vessels, modelled demand data and probability of vessel's deck violation. The input to the simulation modelling includes data on the same installations, the supply base, vessels, modelled demand data and constructed schedule. As it is possible to notice, on both phases there are involved demand data, the modelling of which is described in Chapter 9.1.

9.1 Data modelling

9.1.1 Demand generation for seasonal schedule construction

As far as seasonal schedule construction part is concerned, we need to use discrete values for both: the visit frequency and cargo amount.

For visit frequency we use its executed voyages' historical data average value and round it up to the closest integer, because we want to build as more robust schedule as possible and have as less additional visits' ad-hoc situations as possible.

According to the information provided by Statoil logistic planner, while planning a schedule for a new season, they are using a median value of the amount of the cargo for the last two months. However, we are using a mode value of the demands, calculated from the executed voyages' historical data for the whole summer season. By definition, mode is the value, which appears most frequently, and, hence, can lead to the most effective usage of resources.

A mode value for a discrete dataset is calculated by the next formula:

$$mode = L + \frac{(f_m - f_1)h}{(f_m - f_1) + (f_m - f_2)} \quad (9.1)$$

Where:

"*L – lower limit of modal class,*

f_m – frequency of modal class,

f_1 – frequency of class preceding the modal class,

f_2 – frequency of class succeeding the modal class,

h – size of class interval" (Mode n.d.).

9.1.2 Demand generation for simulation modelling

As far as simulation modelling part is concerned, visit frequency demand is modelled, using the same logic as for the seasonal schedule construction – rounded up average value to the closest integer.

To simulate uncertain cargo demand for each installation or a cluster of installations, may be used several approaches based on historical data:

- find a distribution function;
- build a regression model, for which as input will be used some stochastic data;
- use a distribution, which shows demand uncertainty, with the use of statistics of historical data;
- use sampling of data.

To find distribution functions is not reasonable, because we have only one-year data for one year summer season grouped by weeks, what means we have a lack of data for making assumption about any distribution.

Moreover, there are different processes, which are executed on each installation and on which cargo demand amount depends. However, information about these processes is not known for us, that is why there is no chance to find out a distribution or build a good regression.

Alternative variants of demand modelling: usage of a distribution, which could show uncertainty of demand or providing data sampling. We use the first approach, because data analyses were already provided and its results can be used.

In simulation modelling applied Modified PERT Distribution (Figure 9.1, Formula 9.2), which is often used for modelling an expert opinion, who predicts minimum, maximum and most likely meeting value, with selecting a shape, which mostly fits the opinion of the expert (Modified PERT distribution 2017). Moreover, it is applied in cases, when there is not enough observed data or sample size is small.

Since we need to model variation and Modified PERT distribution, taking it into consideration amount of cargo, demand modelling in our work is provided using this distribution for each replication.

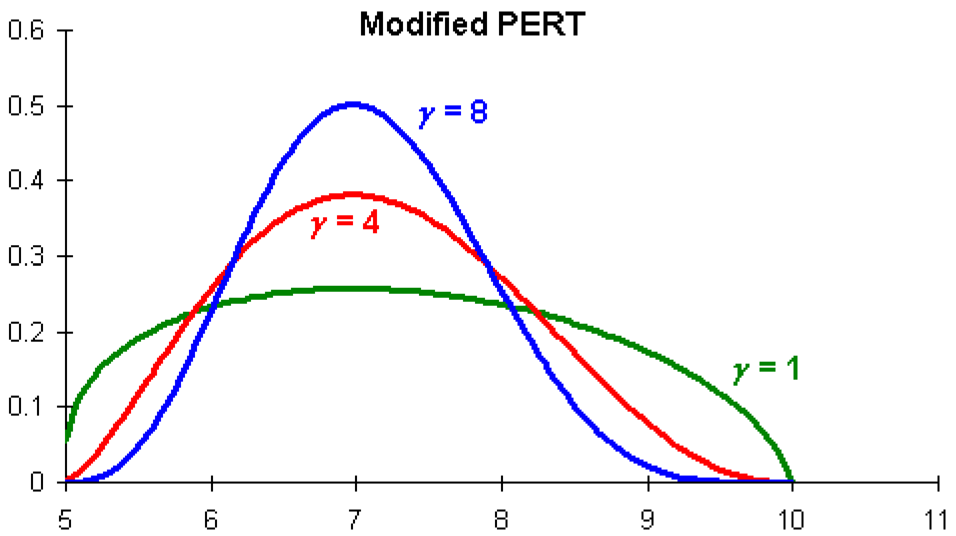


Figure 9.1 Modified PERT distribution (Modified PERT distribution 2017)

$$f(x) = \frac{(x - min)^{\alpha_1 - 1}(max - x)^{\alpha_2 - 1}}{B(\alpha_1, \alpha_2)(max - min)^{\alpha_1 - \alpha_2 - 1}}, \tag{9.2}$$

where $\alpha_1 = 1 + \gamma \left(\frac{mode - min}{max - min}\right), \alpha_2 = 1 + \gamma \left(\frac{max - mode}{max - min}\right)$, $B(\alpha_1, \alpha_2)$ – Beta function.

In comparison with triangle distribution, Modified PERT distribution provides probabilistic estimates of more bell-shaped uncertainties. That is why the preferences were given to this distribution.

As an input for generation of random values, distributed by Modified PERT, used the next parameters:

- min – minimum value of sample;
- max – maximum value of sample;
- mode – mode value of sample;
- shape – shape of probability density function.

Min, max, mode were calculated for each installation, using provided to us data on executed voyages. While modelling cargo demand amount, we add 20% to minimum and maximum values of estimated values, in order add little bit more uncertainty and do not lose lots of values inside.

Shape value was calculated using formula of Modified PERT mean value (Formula 9.3) (Pouillot 2016):

$$\mu = \frac{min + shape * mode + max}{shape + 2} \tag{9.3}$$

From Formula 9.3 we calculate shape value, using the next transformations:

$$\begin{gathered} \mu(shape + 2) = \ min + shape * mode + max \Longrightarrow 2\mu - min - max = \\ = shape * mode - shape * \mu \Longrightarrow shape = \ \frac{mode - \mu}{2\mu - min - max} \end{gathered} \tag{9.4}$$

9.1.3 Service time generation

Service time consists of several parts: vessel arrival, delivered cargo unloading and pick up cargo loading operations.

Vessel arrival consists of number of activities, which should be done in order to be sure that the vessel can start unload operations on the installation (choose needed speed for the vessel, check weather conditions and check satisfaction of other requirements). This time can range from 20 minutes to several hours. We will assume that there is 1 hour.

Delivered cargo unloading and pick up cargo loading depend on the number of lifts, which are performed. One lift, which consists of unloading of delivery and loading of pick up, according to the words of company logistic planner, is 8 minutes. That is why, firstly, we need to generate cargo demand in lift values.

Since demand is generated in tons and approximate dependence of ton values and the number of lifts should be found, we build a correlation plot and calculate a correlation value (Figure 9.2).

The value of correlation is equal to 0.790662 and shows to us an existence of dependences between tons amount and the number of lifts. However, looking in Figure 9.2, we can understand that saying that there is a linear correlation between these two parameters would be wrong, because we can see such phenomenon, which known as heteroscedasticity. That is why we cannot predict number of lifts, using a linear regression.

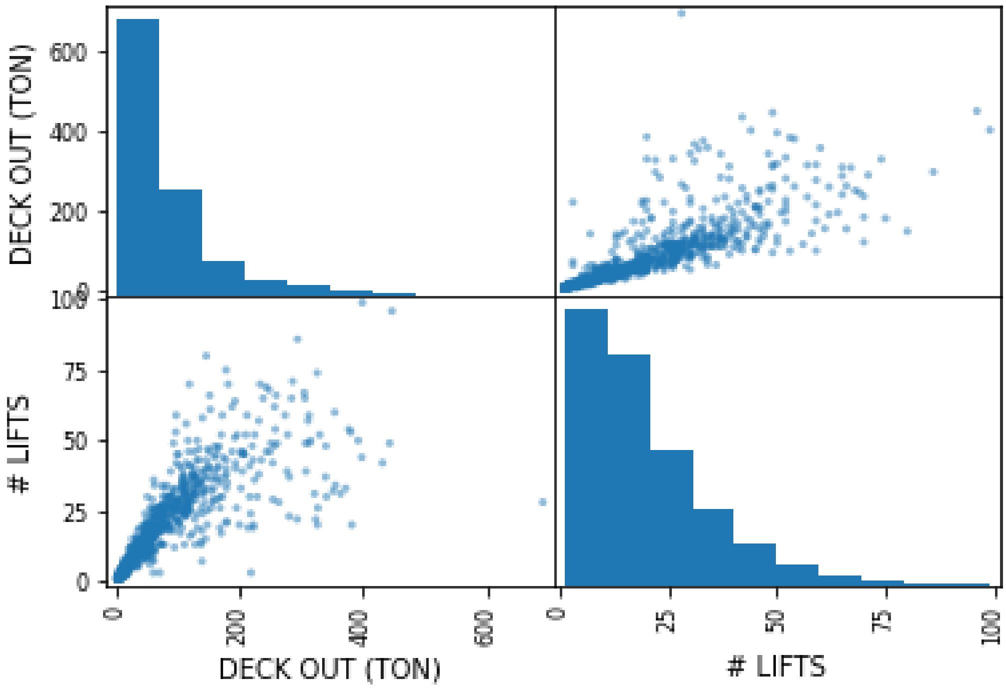


Figure 9.2 Correlation plot of cargo amount in tons and the number of lifts

But as a conclusion from Figure 9.2, we can understand that for modeming of cargo demand in the number of lifts values, we need to take into consideration lifts' ranges for different value of demand in tons (Formula 6.1). What means, that while generating number of lifts, we should take into consideration that for small ton values there are not significant ranges of lifts and for bigger tons' values, ranges increase.

In order to model cargo demand in lift values, we separate our demand in ton values for several bins and for each bin we will find minimum, maximum and mode value of the number of lifts (Formula 6.7). And later, when an amount of supplied to the installation cargo in tons will be known in simulation, we define to which bin it belongs and generate the number of lifts by a triangle distribution, using minimum, maximum and mode values, defined before.

9.2 Tests

In this section, we conduct computational experiment. First, we define several scenarios with different demand data of cargo amount. Second, we apply our solution tool for each scenario for each scenario of input data.

9.2.1 Tests setup

In the thesis, in order to evaluate the work of the developed decision-support tool, we provide two scenarios. The first scenario is based on statistics of provided by Statoil data. The data for the second scenario is obtained by modification of the real data (of the first scenario), where the mode values of cargo amount are increased by 50%. The second scenario is provided with the aim to compare tool work performance in these two scenarios.

Minimum and maximum values of cargo amounts for the corresponding mode values are adjusted according to formulations in Formula 9.5 and Formula 9.6.

$$\min_{new} = \text{minimum}\left(0, mode_{new}\left(1 - \frac{mode - \min}{mode}\right)\right) \tag{9.5}$$

$$\max_{new} = mode_{new}\left(1 + \frac{\max - mode}{mode}\right), \tag{9.6}$$

where $\min_{new}$, $\max_{new}$, $mode_{new}$ are new calculated min and mode values.

9.2.2 Results

In this section we run decision-support tool with different values of upper bound probability parameter.

In Table 9.1 and 9.2 we provide generated schedules for different values of upper bound probability parameter which equals to 1 (that means there are no requirements on robustness) and to the value of upper bound parameter which corresponds to the minimum simulating cost (efficient point). As defined before, efficient solution is a point, where planned and expected costs are approximately equal (Figure 8.2).

In schedules there are given (Table 9.1, Table 9.2):

- planned cost,
- vessel (v1, v2, v3),
- weekdays (Mon - Monday, Tue - Tuesday, …),
- voyages (for instance, voyage (1,4,8,11) starts on Tuesday by vessel 1, when probability of violation is equal to 1) (Table 9.1).

From both Tables we see that corresponding different values of upper bound probability parameter we get different schedules with different voyages and different costs.

Table 9.1 Results of schedule construction for scenario 1

Upper bound probability parameter = 1	Planned cost:			2016690				
		Mon	Tue	Wed	Thu	Fri	Sat	Sun
	v1		1,4,8,11		1,2,3,9,11			
	v2	1,2,3,9,11		2,4,5,6,7,10			2,3,4,5,6,10	
Upper bound probability parameter = 0.97	Planned cost:			2900370				
		Mon	Tue	Wed	Thu	Fri	Sat	Sun
	v1		2,4,11		1,2,3,9		4,5,10	
	v2	1,2,3,9		1,3,8,10			2,6,7,11	
	v3			4,5,6,11				

Table 9.2 Results of schedule construction for scenario 2

Upper bound probability parameter = 1	Planned cost:			2032110				
		Mon	Tue	Wed	Thu	Fri	Sat	Sun
	v1		1,2,4,11		1,2,3,4,11		3,5,6,8,9,10	
	v2	1,2,3,4,11		2,5,6,7,9,10				
Upper bound probability parameter = 0.97	Planned cost:			2908860				
		Mon	Tue	Wed	Thu	Fri	Sat	Sun
	v1		2,4,11		1,8,10,11		1,3,5,9	
	v2	2,3,6,10			2,4,6,7		2,4,11	
	v3			1,3,5,9				

On the simulation modelling stage as the result, we got the cost of schedule simulation, taking into account recourse actions. An example of this stage results you can see in Table 9.3. In Table 9.3 we provide an example of output of our simulation tool for the first week of one replication of the first scenario.

In Table 9.3 in the column Day there are given weeks:

- expected cost or an average cost of the whole simulation (Average cost of simulation),
- replication number,
- week number,
- weekdays (Day, where 0 is Monday, 1 – Tuesday, …),
- vessel number (Vessel, where positive numbers are charter vessels, negative number is spot vessels),
- voyages (on Day 1 vessel 1 has started a voyage (1, 4, 8, 11)),
- voyage expected cost.

We can notice in Table 9.3 that for the planned schedule with probability 1 there were done recourse actions: on day 5 installation 3 and 6 were shifted from voyage (2,3,4,5,6,10) and they were supplied with a spot vessel, departure on the same day (Table 9.1). That shows to us once more that the schedule with violation probability 1 cannot reach the highest robustness level.

Table 9.3 Results of simulation for scenario 1, replication number 0, week 0

Avg cost of simulation:	2261303		
Replication number:	0		
Week:	0		
Day:	Vessel:	Voyages:	Cost:
0	2	1, 2, 3, 9, 11	84087.75
1	1	1,4,8,11	84203.72
2	2	2, 4, 5, 6, 7, 10	104804.43
3	1	1, 2, 3, 9, 11	74467.48
5	1	2, 4, 5, 10	95855.33
5	-1	3, 6	366985.18

Figure 9.3 and Figure 9.4 provide the results of the decision-support tool run for scenario 1 and scenario 2. For each value of upper bound probability parameter, there are provided corresponding planned cost and expected cost. The results of the experiments are provided in Table 9.4, Table 9.5 and are shown graphically in Figure 9.3 and Figure 9.4.

Looking at Figure 9.4, we see that with the decrease of the value of upper bound probability parameter, the planned schedule cost increase, while expected cost decreases. Such an effect is observed until an efficient point is reached (upper bound probability parameter equals 0.95). After that both types of costs goes close to each other. As far as results of scenario 1 are concerned (see Figure 9.3), efficient point is reached for the largest value of upper bound probability parameter.

In both Figures we can see that planned schedule costs surges occur. Surges can be explained by the fleet size increasing by one vessel on schedule construction stage. That occurs due to increase of the requirements on robustness, while manipulating the value of upper bound probability parameter.

In comparison with results of scenario 1, we see that the best solution in scenario 2 was found later on the third step. This result can be explained by the fact that the variance in scenario 2 is higher and that is why we get the best solution later.

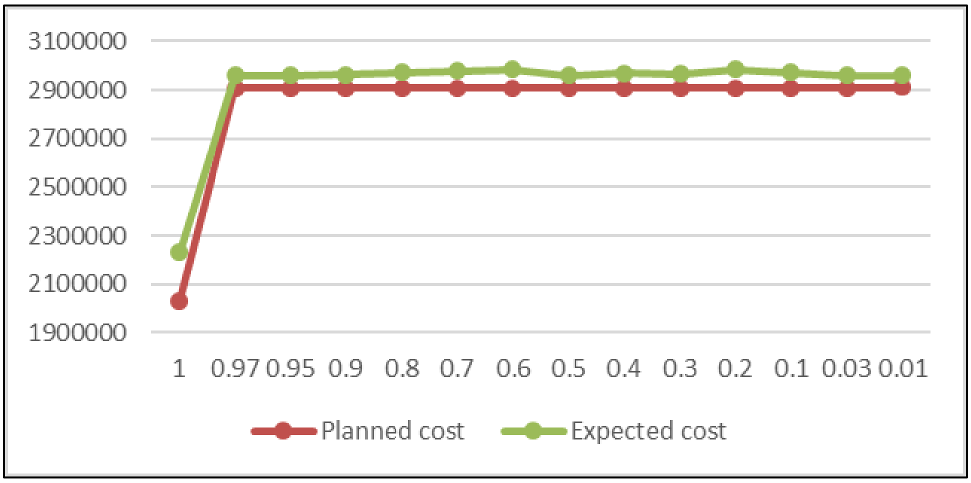


Figure 9.3 Test results for scenario 1

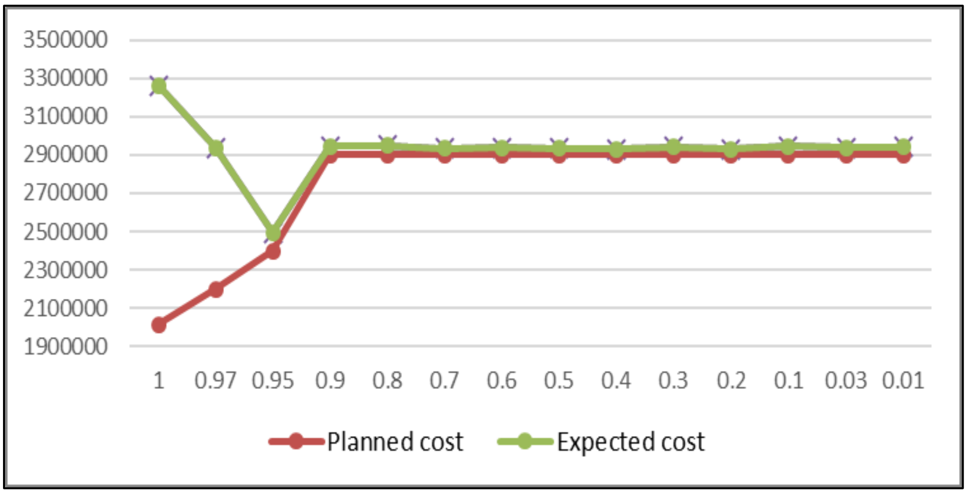


Figure 9.4 Test results for scenario 2

Table 9.4 Test results for scenario 1

Probability	Planned cost	Simulated cost	Robustness, %
1	2016690	2261303	87.87
0.97	2900370	2937824	98.71
0.95	2900370	2935531	98.79
0.9	2900370	2943664	98.51
0.8	2900370	2949866	98.29
0.7	2900370	2933662	98.85
0.6	2900370	2937245	98.73
0.5	2900370	2932666	98.89
0.4	2900370	2929163	99.01
0.3	2900370	2939603	98.65
0.2	2900370	2930190	98.97
0.1	2900370	2943486	98.51
0.03	2900370	2938897	98.67
0.01	2900370	2940600	98.61

Table 9.5 Test results for scenario 2

Probability	Planned cost	Expected cost	Robustness, %
1	2016690	3261303	38.28
0.97	2200370	2937824	66.49
0.95	2400370	2495531	96.04
0.9	2900370	2943664	98.51
0.8	2900370	2949866	98.29
0.7	2900370	2933662	98.85
0.6	2900370	2937245	98.73
0.5	2900370	2932666	98.89
0.4	2900370	2929163	99.01
0.3	2900370	2939603	98.65
0.2	2900370	2930190	98.97
0.1	2900370	2943486	98.51
0.03	2900370	2938897	98.67
0.01	2900370	2940600	98.61

The total computational time for schedule construction and simulation execution are provided in Table 9.76 and Table 9.7. Voyage generation time for both scenarios is around 15 minutes. Optimization modelling time increases with the probability reduction. It occurs, because with probability decrease there are available only short voyages for optimization modelling. The number of permutations of short voyages is bigger than of a long one. That is why the optimization modelling time increases. Simulation modelling otherwise decreases with probability reduction and varies in range from around 46 up to 135 minutes.

We see that voyage generation for all experiments is similar, except simulation modelling time, where probability violation is equal to 0.97. It can be explained by the fact that there were applied more recourse actions in scenario 2. In total execution time for scenario 2 is a little bit.

Table 9.6 Speed of tool work for scenario 1

Case 1			
Voyage generation, min			15.24
Probability	*Optimization modelling, min*	*Simulation modelling, min*	*Total time, min*
1	3.11	118.20	121.31
0.97	3.35	46.23	49.58
0.95	4.17	46.26	50.43
...	...	...	...
0.01	23.58	46.23	69.81

Table 9.7 Speed of tool work for scenario 2

Case 2			
Voyage generation, min			15.2
Probability	*Optimization modelling, min*	*Simulation modelling, min*	*Total time, min*
1	3.17	135.60	138.77
0.97	3.87	58.20	62.07
0.95	5.01	47.13	52.14
...	...	...	...
0.01	25.78	47.23	73.01

10.0 Conclusion and future research

This master thesis is dedicated to a problem encountered by logistic planners in the upstream petroleum logistics in the oil and gas industry. The problem under the study is the Periodic Supply Vessel Planning Problem with demand uncertainty. Offshore installations receive all the necessary materials and equipment from an onshore supply base according to a weekly delivery schedule. The fleet of supply vessels chartered on the periodic basis provides deliveries to the offshore installations. The schedule performance is seriously affected by uncertain demand at installations. We developed optimization simulation methodology enabling to construct robust vessel schedules with minimised expected cost.

For the first step of the research involves an extensive demand data analyses, where we tried to define possible trends and correlations. After the results were obtained, we proceeded to the development of the solution methodology for the PSVPP with uncertain demand. The developed methodology involves combination of optimization and simulation approaches where vessel schedules are constructed using two-phase optimization method and discrete event simulation model is used to compute simulated schedules costs. To control the level of robustness optimization tool incorporates a specially developed mechanism setting an upper bound on the probability of a voyage's demand exceeds vessels capacity. Thus, multiple schedules are generated with different robustness level and subsequent simulation is used to define expected cost under uncertain demand conditions. The schedule with least expected total cost is finally selected.

The decision-support tool evaluation was provided conducting computational experiments for several scenarios with different demand data of cargo amount. One of scenarios is based on real life data statistics provided by Statoil. The experimentations allowed to build schedules with different robustness level for all scenarios. Moreover, the tests approved construction of robust schedules by the developed solution tool, which showed fast performance on testing instances.

In the future research the problem can be extended with consideration that supplies of installation can be managed from several supply bases with multiple flexible departures by heterogeneous fleet. Also in the problem can be added types of cargo and evaluation of the vessel capacity by tons and square meters. In addition, can be provided deep analyses of the installations' demands in order to find a way to their forecast, under condition that data on demands available for several years. Moreover, PSVPP can be studied with demand and weather condition uncertainties.

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Appendixes

Appendix A

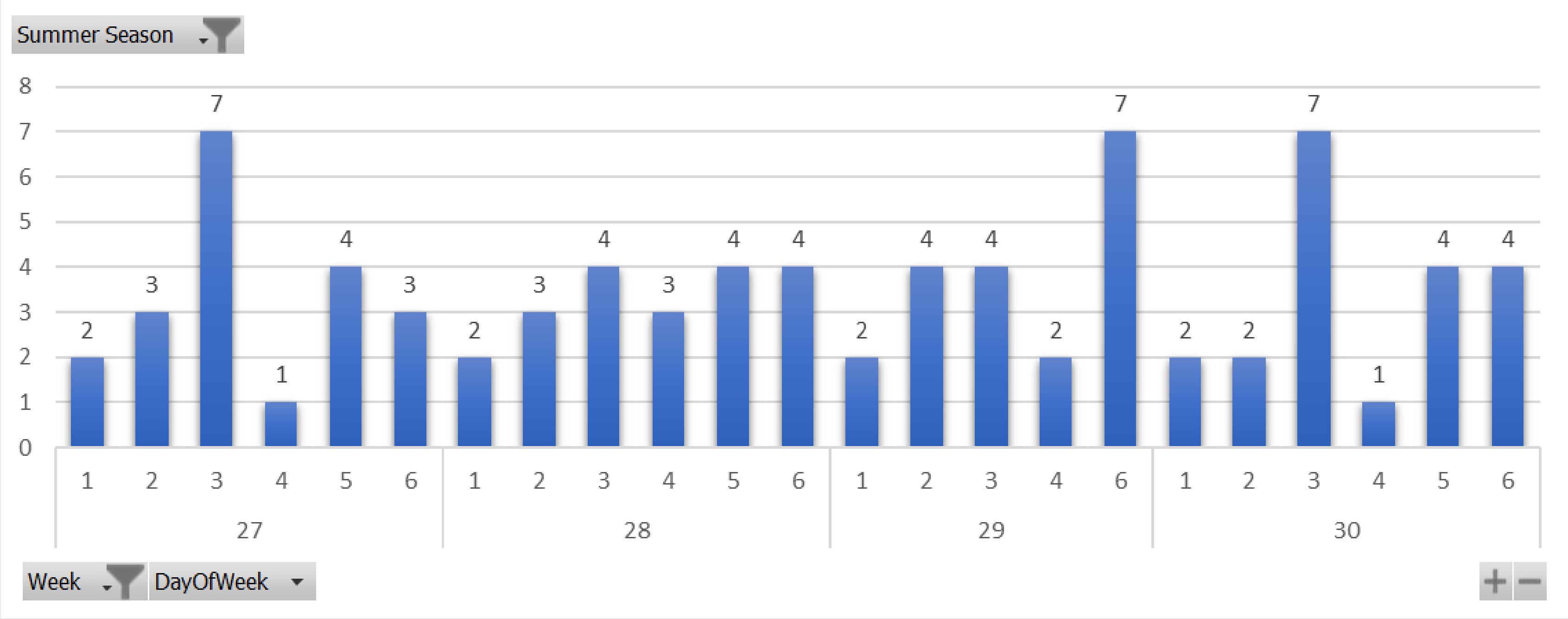

Figure A.1 The number of installations’ visits for all departures from supply base by days for weeks 27 – 30

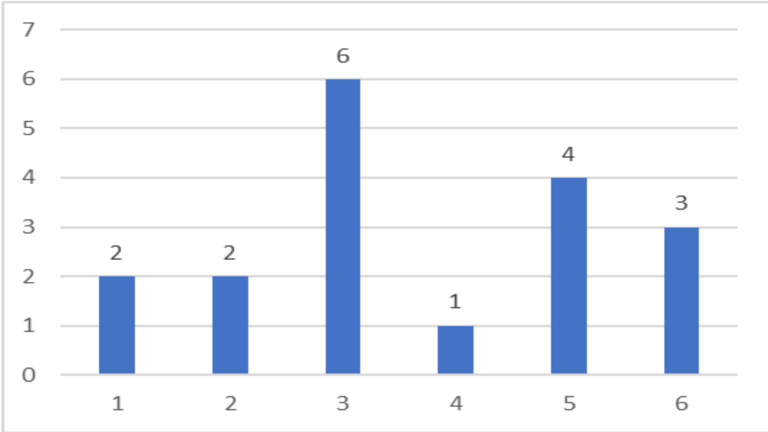

Figure A.2 The number of planned installations' visits for all departures from supply base for weeks 27 - 30

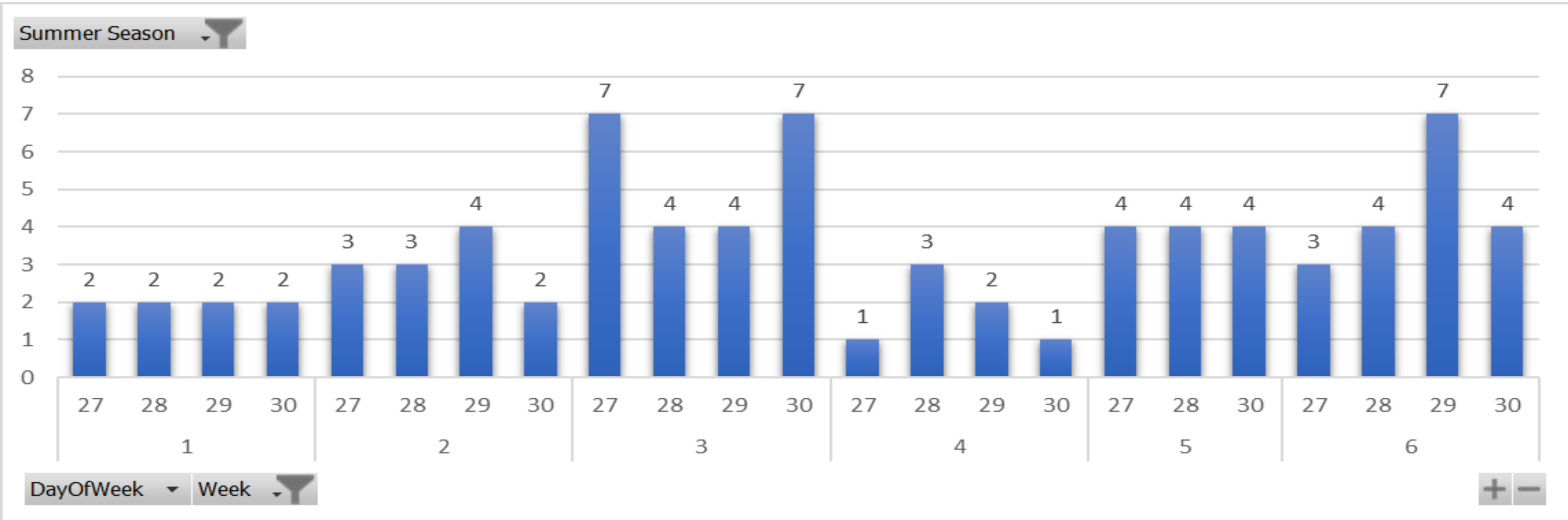

Figure A.3 The number of installations' visits by weekdays for weeks 27 – 30

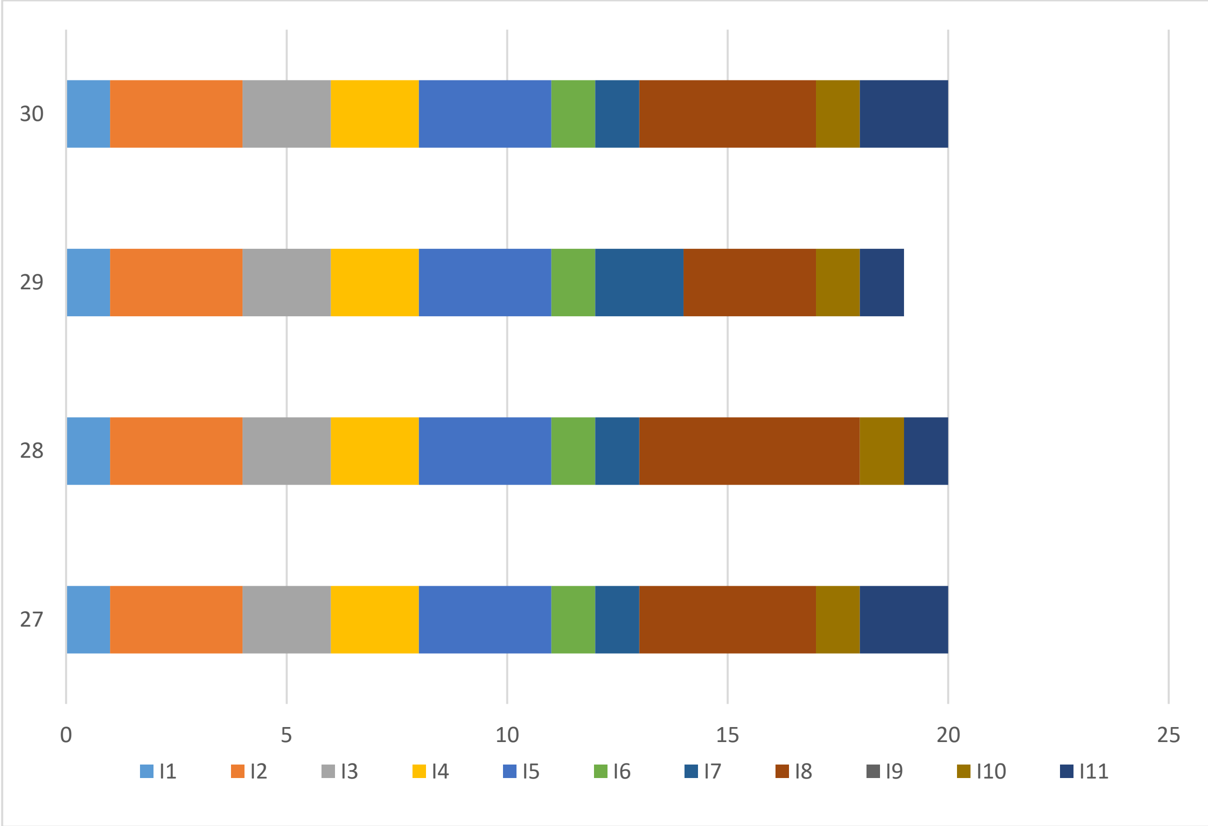

Figure A.4 The number of visits for each installation for weeks 27 - 30

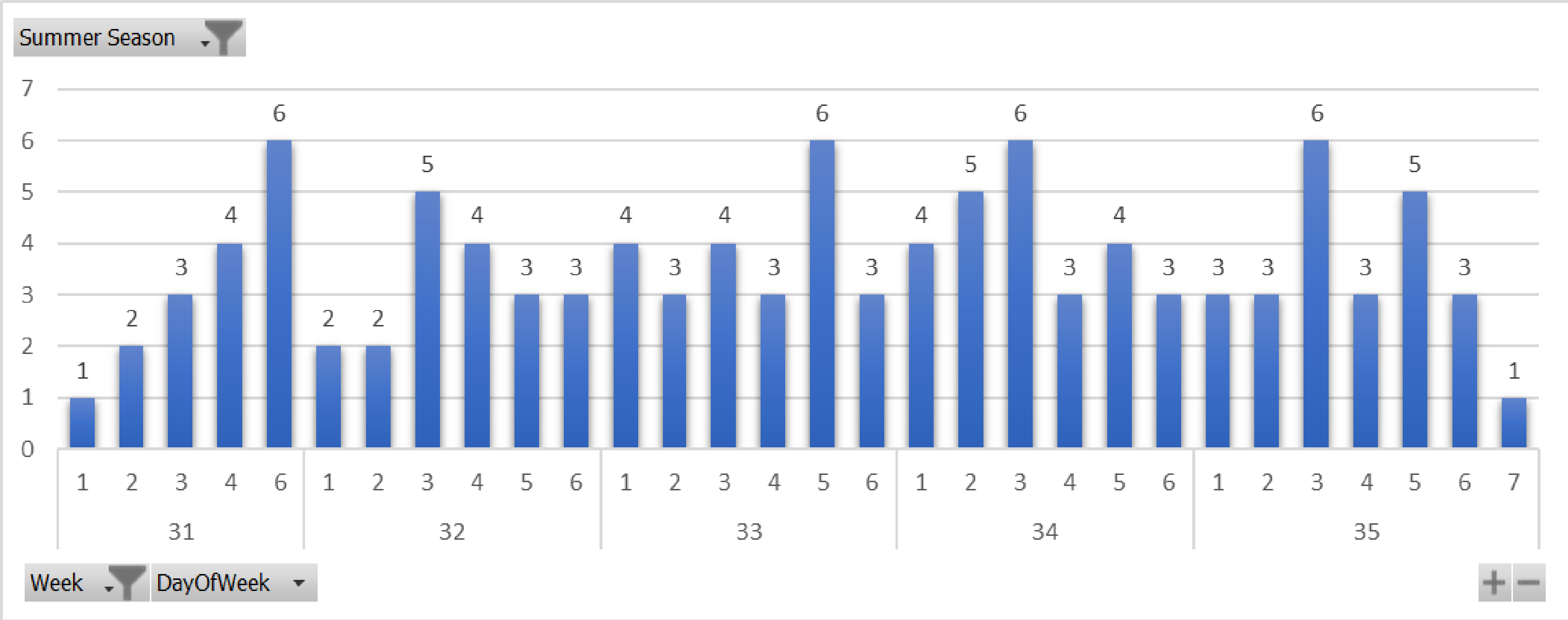

Figure A.5 The number of installations' visits for all departures from supply base by days for weeks 31 – 35

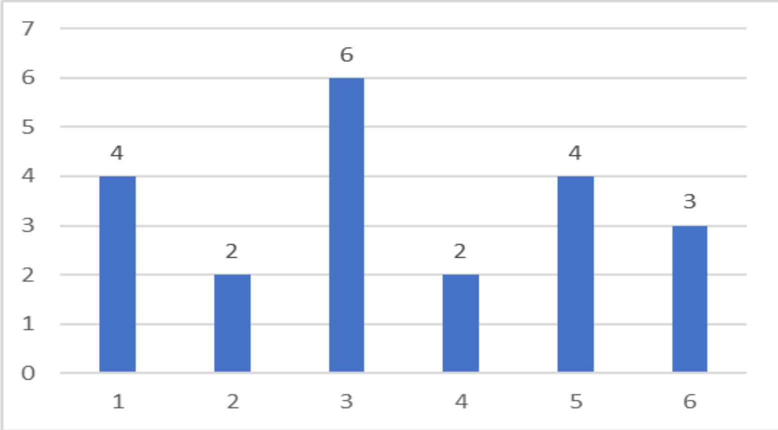

Figure A.6 The number of planned installations' visits for all departures from supply base for weeks 31 - 35

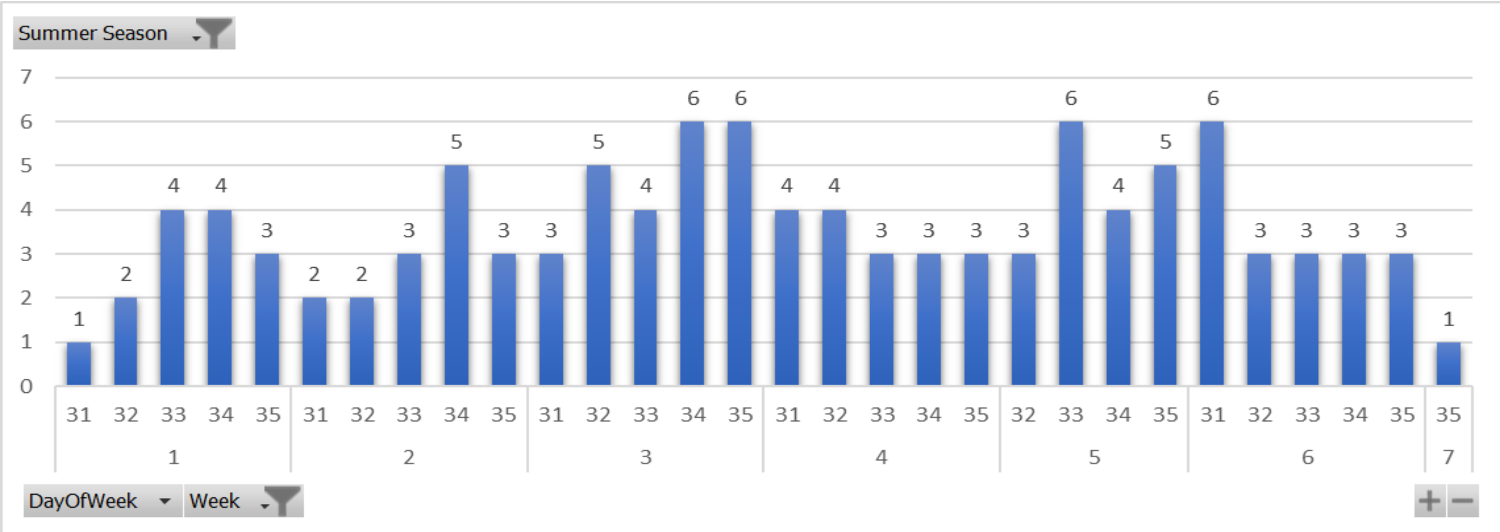

Figure A.7 The number of installations' visits by weekdays for weeks 31 – 35

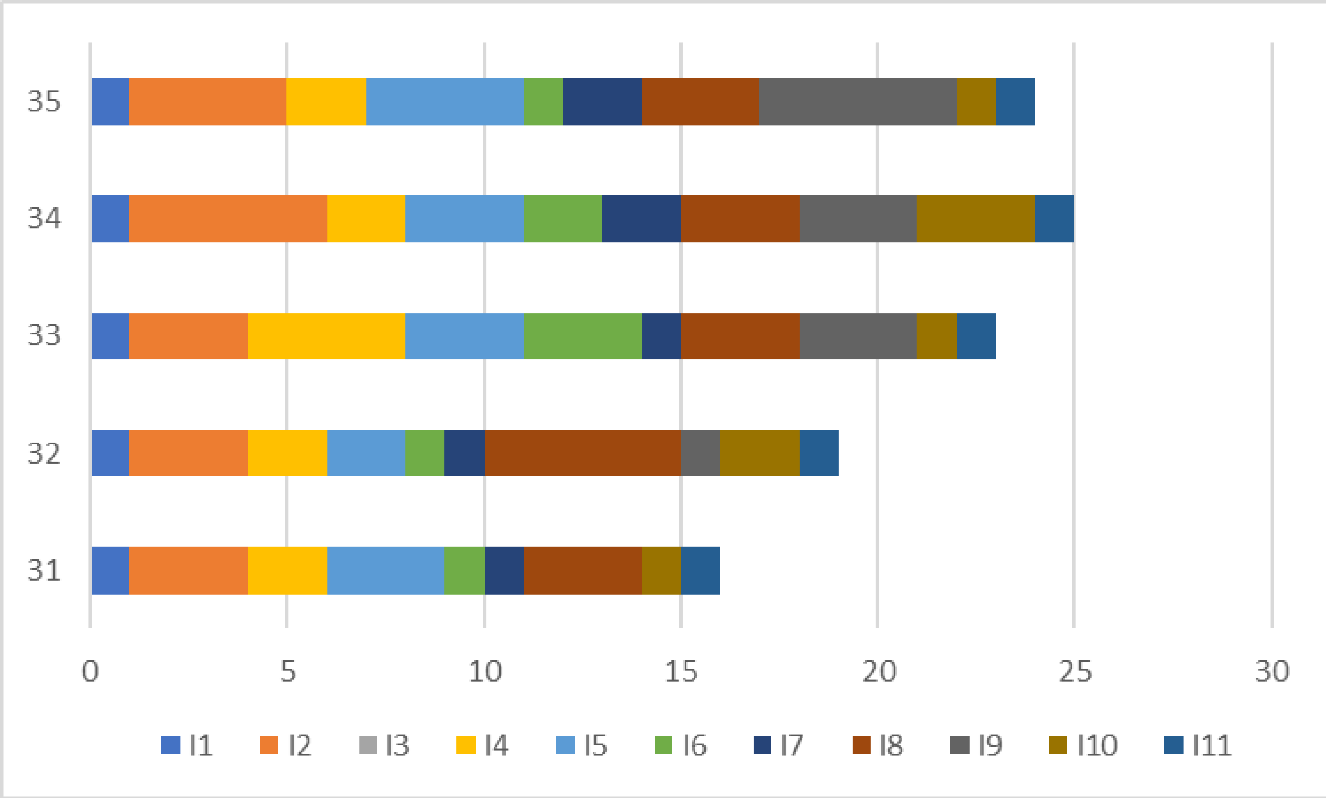

Figure A.8 The number of visits for each installation for weeks 31 - 35

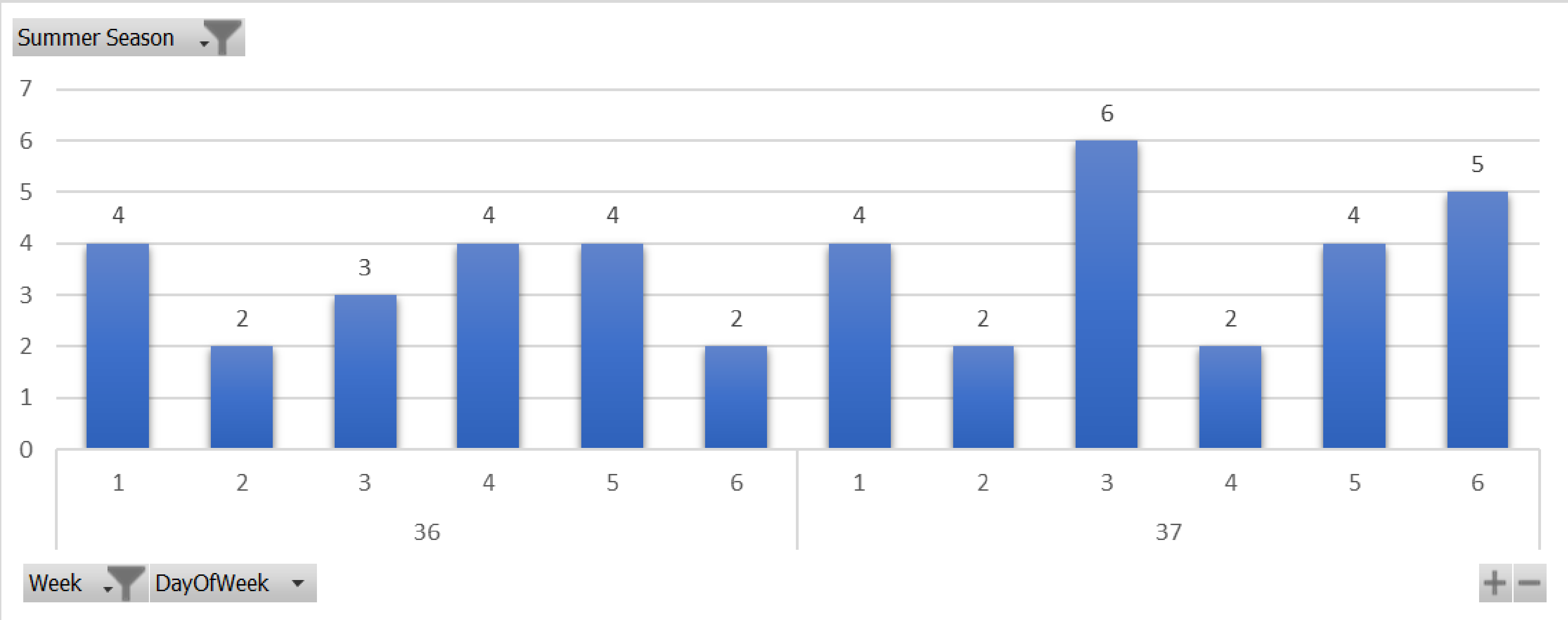

Figure A.9 The number of installations' visits for all departures from supply base by days for weeks 36 – 37

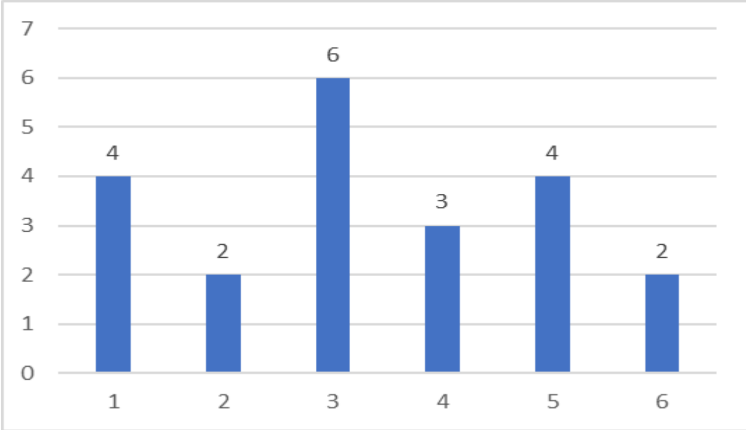

Figure A.10 The number of planned installations' visits for all departures from supply base for weeks 36 - 37

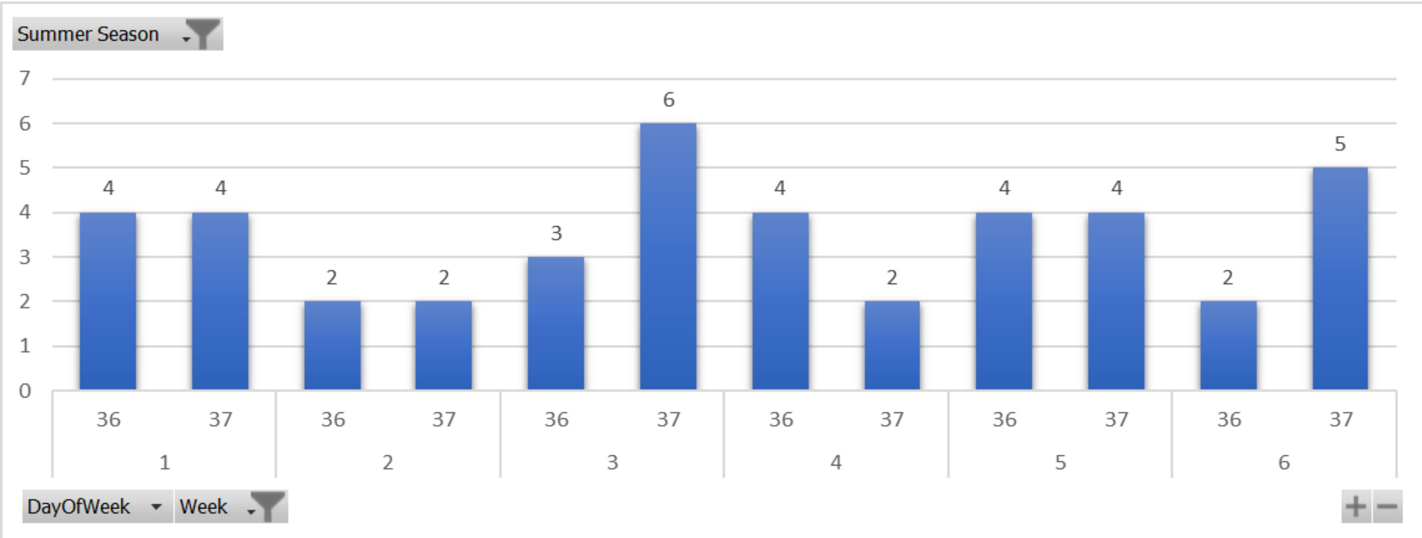

Figure A.11 The number of installations' visits by weekdays for weeks 36 – 37

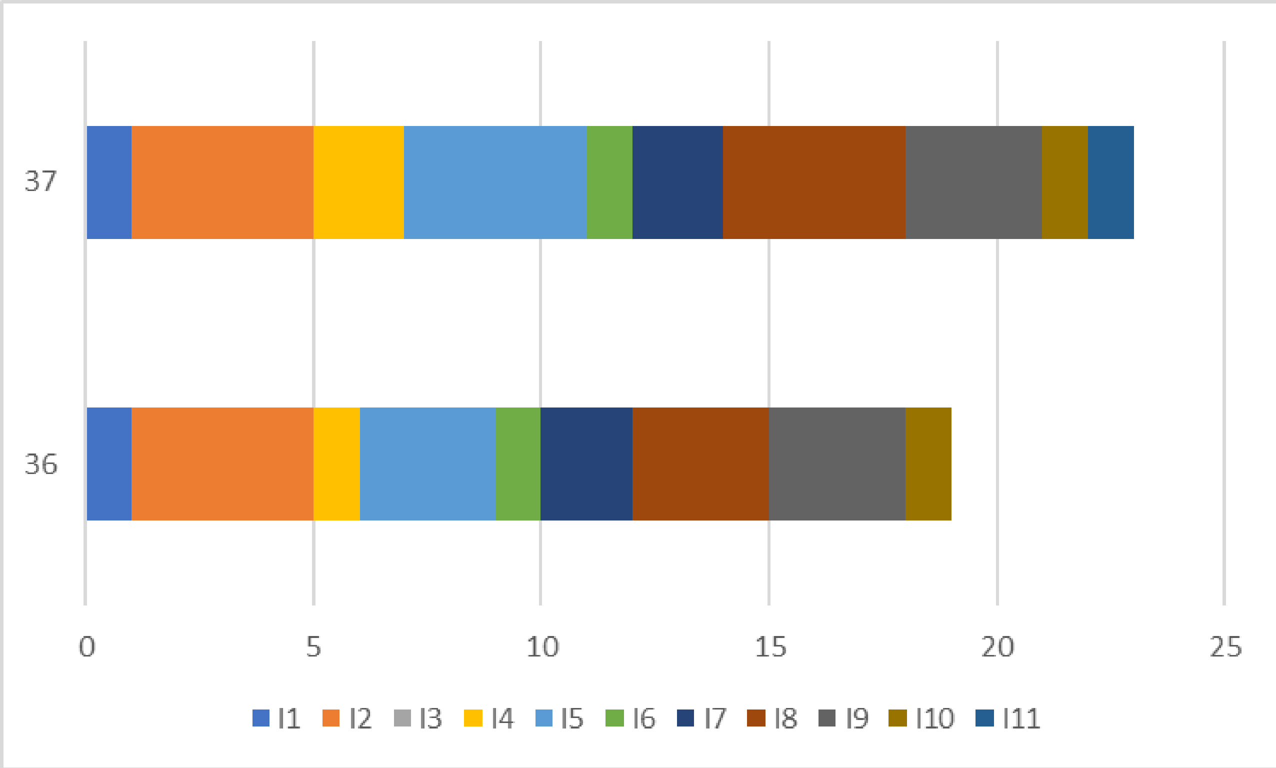

Figure A.12 The number of visits for each installation for weeks 36 - 37

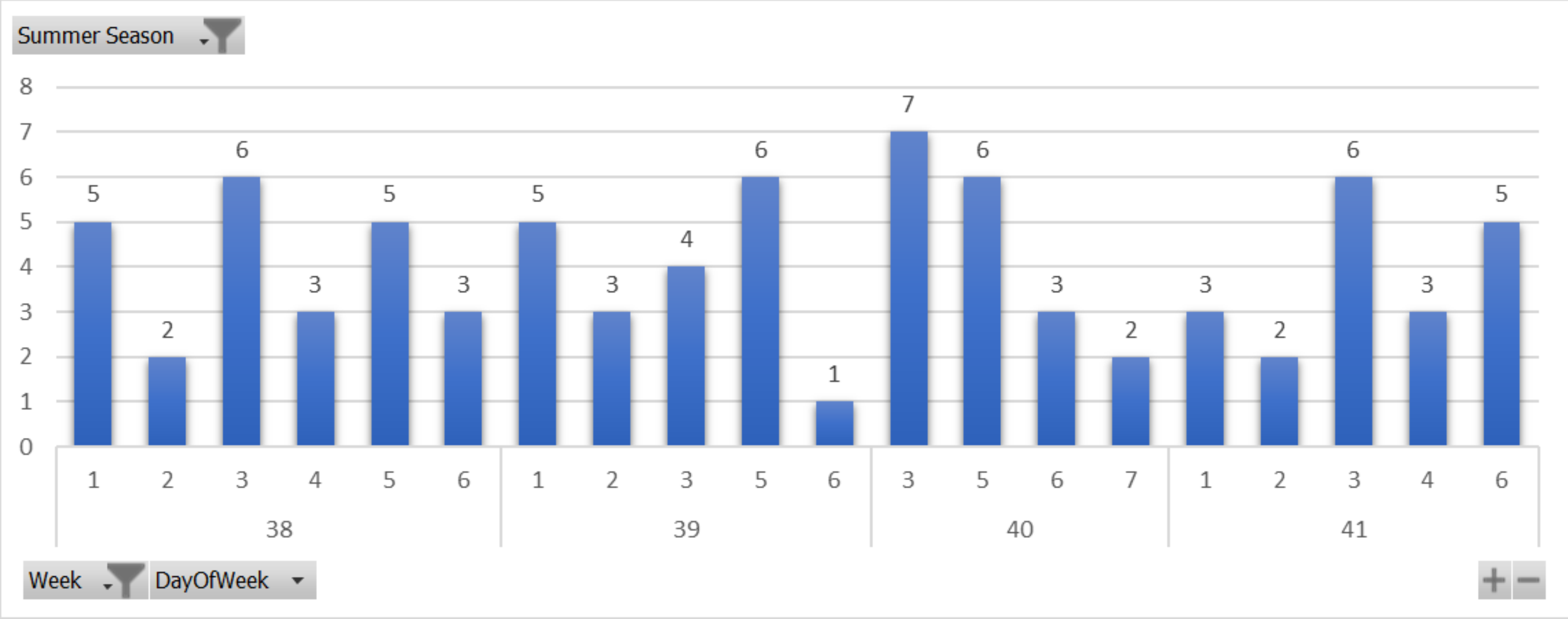

Figure A.13 The number of installations' visits for all departures from supply base by days for weeks 38 – 41

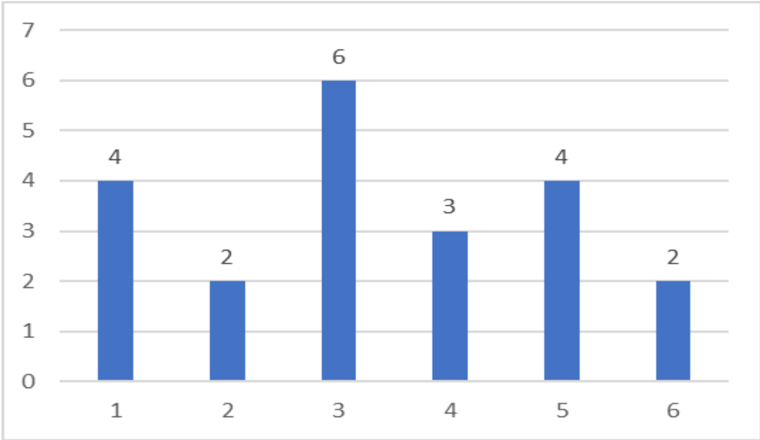

Figure A.14 The number of planned installations' visits for all departures from supply base for weeks 38 - 41

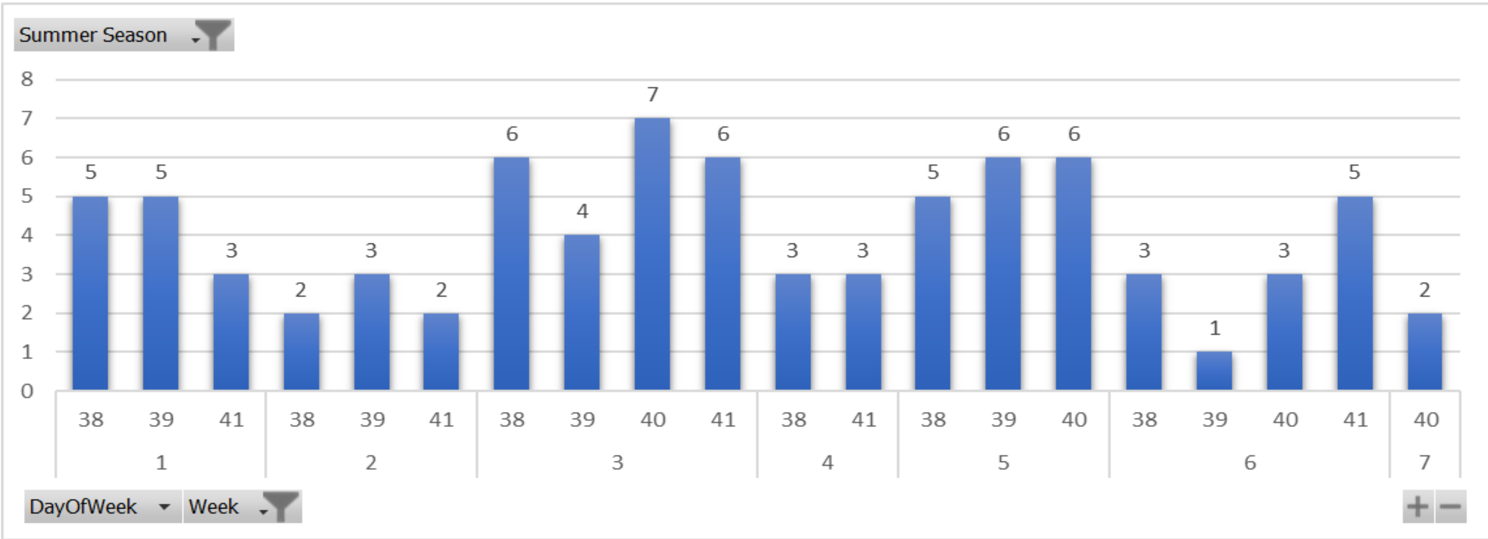

Figure A.15 The number of installations' visits by weekdays for weeks 38 – 40

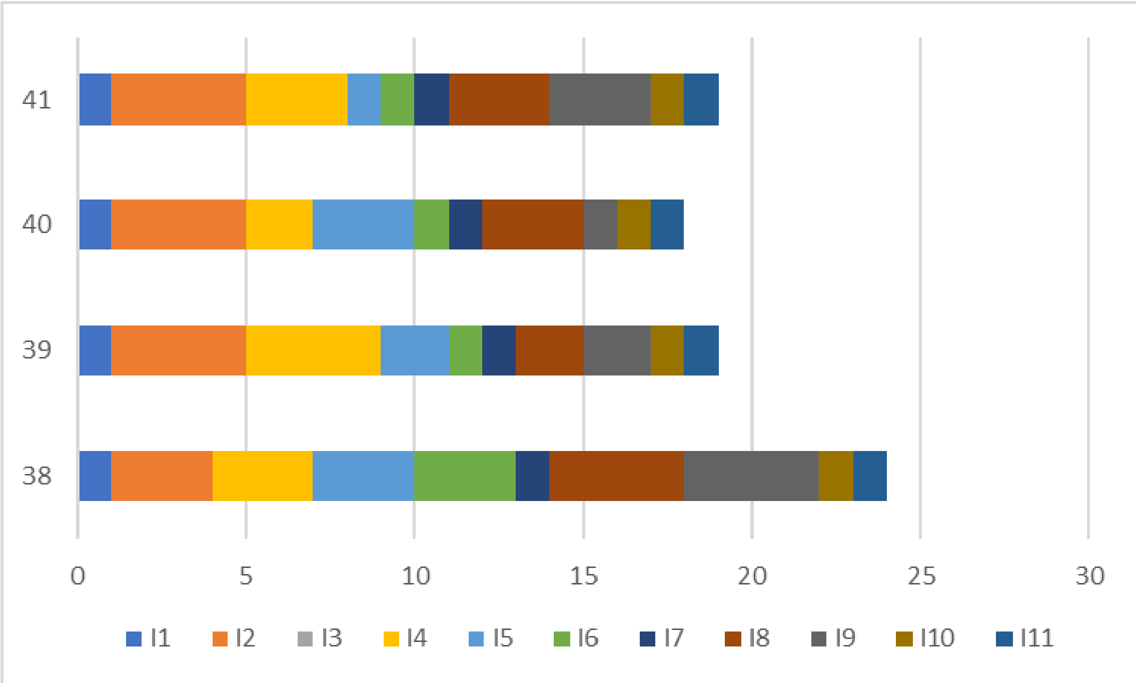

Figure A.16 The number of visits for each installation for weeks 38 - 41

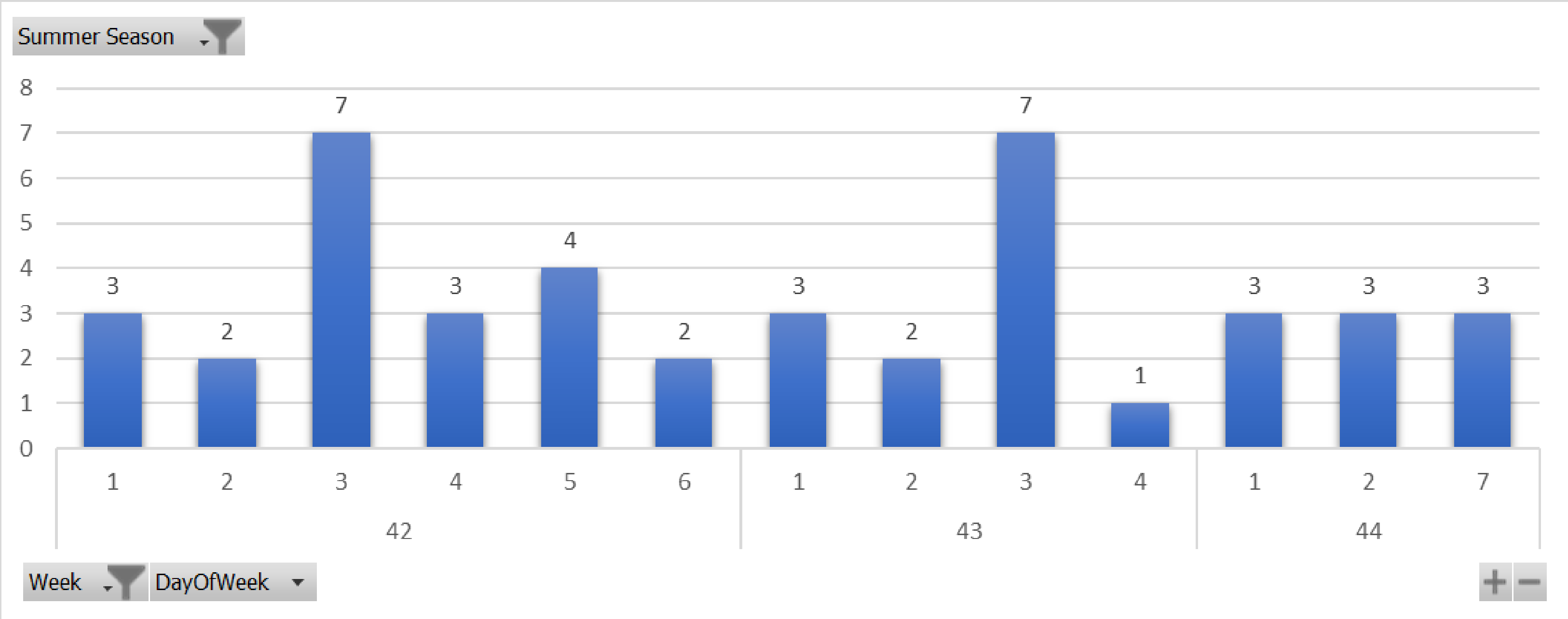

Figure A.17 The number of installations' visits for all departures from supply base by days for weeks 42 – 44

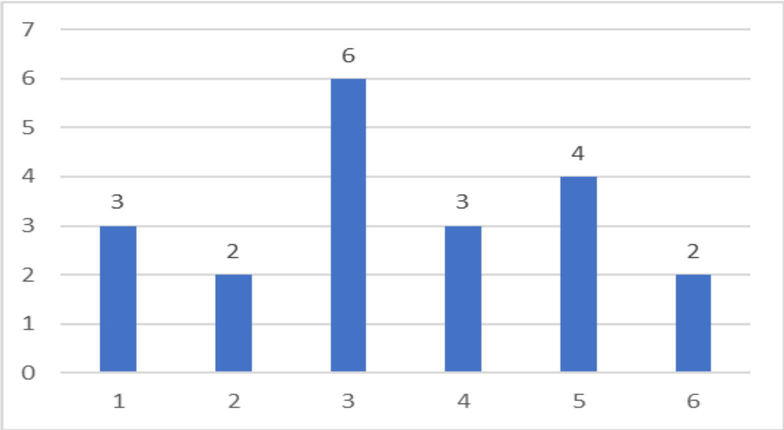

Figure A.18 The number of planned installations' visits for all departures from supply base for weeks 42 - 44

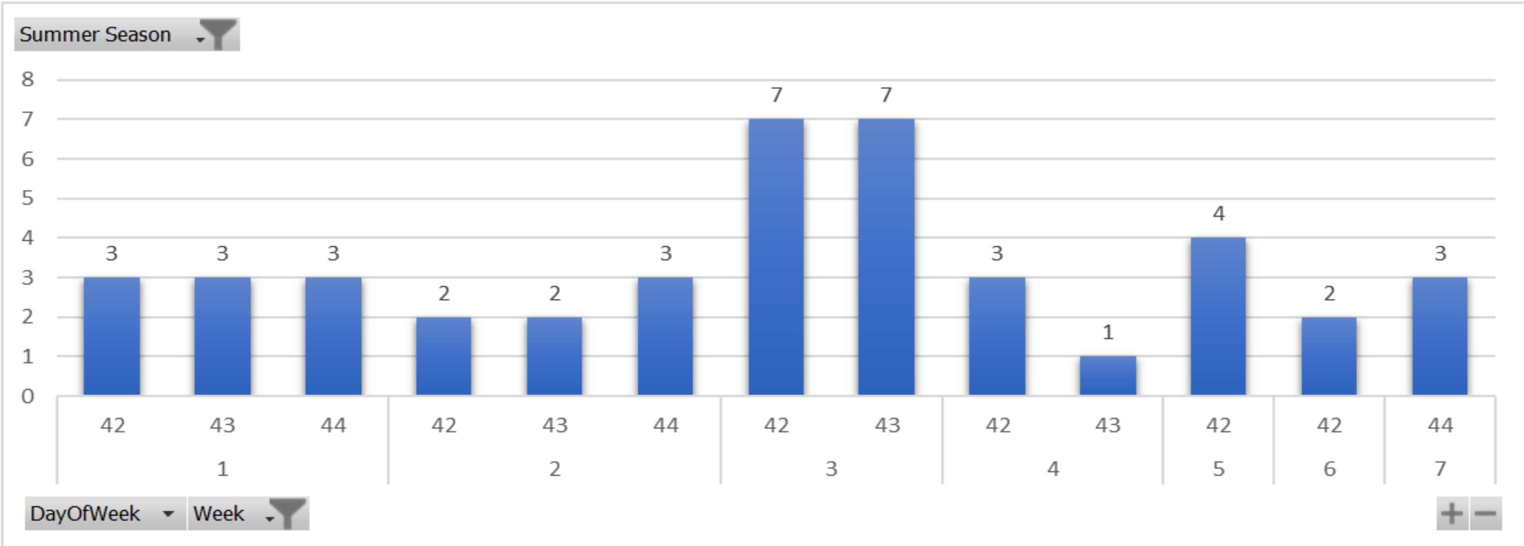

Figure A.19 The number of installations' visits by weekdays for weeks 42 – 44

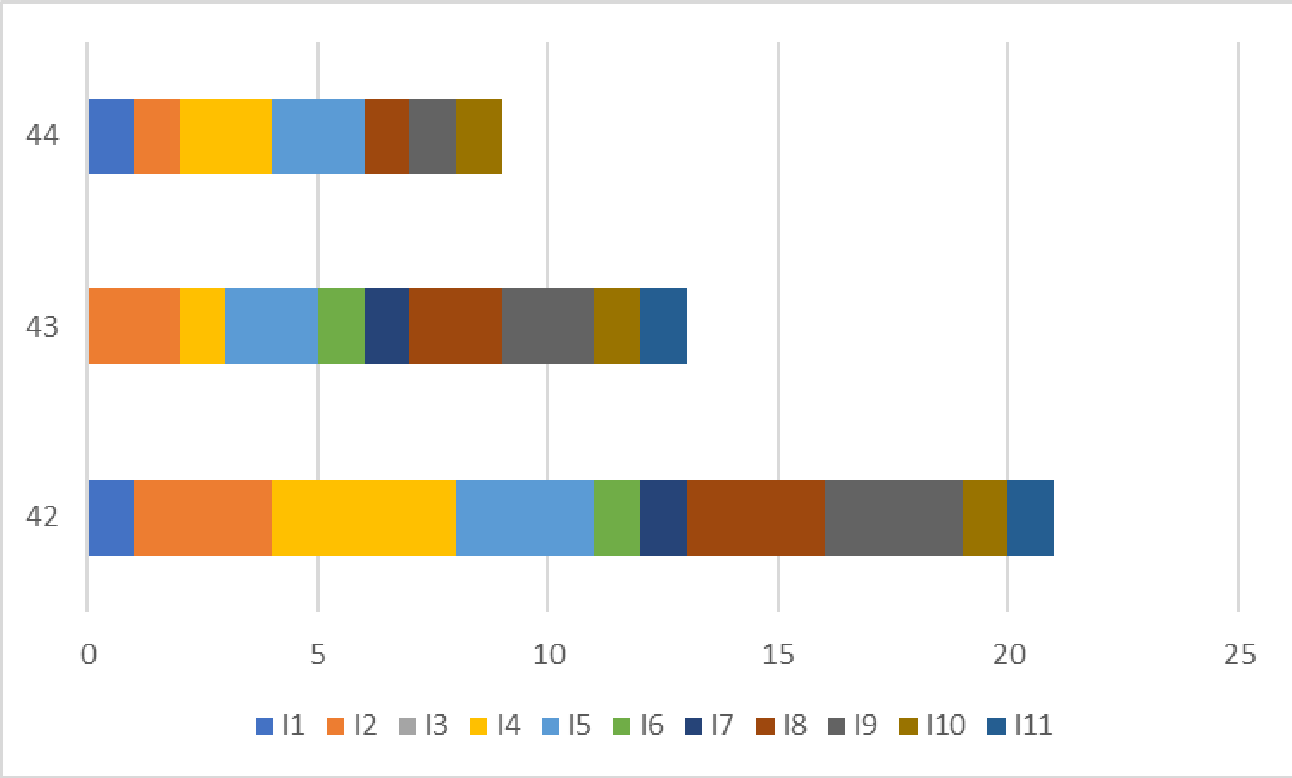

Figure A.20 The number of visits for each installation for weeks 42 - 44

Appendix B

Table B.1 Results of F-Test on the equality of variances for all drilling installations

	I2	I5	I8	I9	I10
Mean	148.6239	94.45836	103.0541	67.10382	112.4674
Variance	8784.585	6513.884	14283.88	2019.598	3323.154
Observations	86	73	85	34	31
	I2-I5	I8-I2	I2-I9	I2-I10	I8-I5
F	1.348594	1.626016	4.34967	2.643448	2.192836
P(F<=f) one-side	0.09645	0.013264	5.46E-06	0.001826	0.000383
F critical	1.459713	1.43287	1.669065	1.707097	1.460897
Test results		reject	reject	reject	reject

	I5-I9	I5-I10	I8-I9	I8-I10	I10-I9
F	3.225337	1.960151	7.072634	4.298289	1.645453
P(F<=f) one-side	0.000194	0.021379	1.07E-08	1.46E-05	0.082417
F critical	1.683688	1.721347	1.670039	1.708045	1.805636
Test results	reject	reject	reject	reject	