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# Simulation and Rescheduling of Operation for a RoRo-fleet

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## Abstract

This master thesis is a part of the MARFLIX (MARitime FLeet size and mIX) project. The research project MARFLIX is a collaboration between NTNU, MARINTEK, DNV and WWL. The overall aim for the MARFLIX project is to develop and test methods for improved support for fleet size and mix decision-making through quantitative methods.

Wallenius Wilhelmsen Logistics (WWL) is a global liner shipping company which delivers shipping and logistics solutions for manufacturers of car, trucks, heavy equipment and specialized cargo.

In this master thesis a framework model that is able to test and verify deployment models was developed. This framework model contains a simulation part and an optimization part. The simulation model is constructed to simulate the day to day operations of a fleet. In the day to day operation disruptions will occur. These disruptions are simulated by the use of two different probability distributions and Monte Carlo Simulation. Disruptions occur regularly in a global liner shipping network. About 70-80 % of the vessels experience delays in at least one port during each roundtrip. When a disruption occurs in a liner shipping network, the impact on the network should be minimized.

When a disruption occurs, the simulation model will first try to regain the delay by speeding up the delayed vessel. If speeding up is not sufficient, a rescheduling process is initiated. The simulation model will then call on the optimization model to perform a rescheduling. The optimization model considers omitting and changing the order of port calls, and space chartering cargo as possible recovery actions. It will then find the best way to recover from the delay. The new

solution will then be implemented as new schedules for the vessels in the fleet.

The optimization model is modeled as a set partition model, which can take use of the beneficial structure that appears in transportation problems. To solve a set partition model a column generation algorithm is needed. The column generation algorithm implemented in our model is a complete enumeration algorithm, which generates all possible routes that the vessels can sail. A benefit with the complete enumeration algorithm is that the same routes can be used for all reschedulings during a simulation.

There are several incidents, e.g. machinery problems, extreme weather and collision, that can cause delays for a vessel and with that create a need for a rescheduling. Each of these incidents have different impacts on ships, e.g. reduced speed, delayed, changed resistance, port call canceled etc.

The simulation and optimization model have been tested on several different problems with a different composition of ports, vessels and cargos. The time required to solve the different test instances varied between 30 and 240 seconds. The tests showed that the required computing time increased exponentially with an increase in the number of ports. The tests also showed that when the chartering cost increased, the number of chartered ships decreased and the rescheduling cost increased.

The new routes generated and implemented by the optimization model show similarities with the original routes; in most scenarios only one or two port calls are changed or left out. This is done contrary to what many shipping companies usually do when they experience delays; they often speed up until the delay is regained.

The simulation and optimization models developed in this thesis are able to test and verify the MARFLIX deployment model. In case of a delay the models are able to find good schedules for the fleet within a reasonable amount of time. The different output values provided by the simulation model should be sufficient to verify the deployment model.

## Sammendrag

Denne diplomoppgaven er en del av MARFLIX-prosjektet (MARitime FLeet size and mIX). Forskningsprosjektet MARFLIX er et samarbeid mellom NTNU, MARINTEK, DNV og WWL. Det overordnede målet for MARFLIX-prosjektet er å utvikle og teste kvantitative metoder for økt beslutningsstøtte av flåtestørrelse- og kombinasjonsproblemer.

Wallenius Wilhelmsen Logistics (WWL) er en global linjefartoperatør som leverer skipsfart og logistikk løsninger for fabrikanter av biler, tungt rullende last og spesialisert last.

I denne diplomoppgaven er det utviklet en rammemodell som er i stand til å teste og verifisere en distribusjonmodell. Denne rammemodellen inneholder både en simulerings- og optimeringsmodell. Simuleringsmodellen er konstruert for å simulere den daglige driften av en gitt flåte. I den daglige driften kan det forekomme forskinkelser. Disse forskinkelsene er simulert ved bruk av to forskjellige sannsynlighetsfordelinger og Monte Carlo-simulering. Forsinkelser forekommer regelmessig for et globalt linjefartoperatør. Ca 70-80minst en havn for hver rundtur. Når en forskinkelse oppstår, må innvirkningen på flåten være minimal. Ved en forskinkelse vil simuleringsmodellen først prøve å gjenvinne forsinkelsen ved å øke farten til det forsinkede fartøyet. Hvis dette ikke fjerner forskinkelsen, vil simuleringsmodellen kalle på optimeringsmodellen for å gjennomføre en reruting. Optimeringsmodellen bruker forskjellige løsningsmetoder, blant annet å utelate og endre rekkefølgen på havneanløp, og leie lasteplass på andre båter. Etter at optimal løsning er funnet vil optimeringsmodellen sende denne til simuleringsmodellen som fortsetter simulering av den daglige driften. Optimeringsmodellen bruker en to trinns

løsningsmetode. Det første trinnet går ut på å generere samtlige mulige ruter. De genererte rutene brukes når man i trinn to finner den optimale ruten. De ferdig genererte rutene bidrar til en god struktur på problemet. Rutegenereringen er en tidkrevende prosess. Rutene krever dog bare å bli generert en gang per simulering, og kan gjenbrukes hvis det skjer flere optimeringsprosesser per simulering.

Simulerings- og optimeringsmodellen har blitt testet på flere forskjellige problemer. Problemene har hatt forskjellige sammensetninger av skip, havner og last. Totalt brukt tid varierer fra 30 ti 240 sekunder. Testene viste at beregningstiden økes eksponensielt med en økning av antall havner. De valgte rutene av optimeringsmodellen er relativt like de opprinnelige rutene. Som regel endres kun et eller to anløp. Dette er ikke det samme som hva de fleste operatører pleier å gjøre, som er å øke farten til skipet helt til forskinkilsen er gjenvunnet. Simulerings- og optimeringsmodellen utviklet i denne avhandlingen er i stand til å teste og verifisere MARFLIX' sin distribusjonsmodell. Ved forskinkelser i en flåte er modellen kapabel til å finne en optimal rute innenn en forsvarlig tid.

## Preface

This master thesis is written as a part of the candidates' five year Master of Sciences degree in Maritime Technology with specialization in Design and Logistics, at the Norwegian University of Science and Technology, during spring 2013. The thesis is a requirement for completing the Master of Science degree in Marine Technology. Our master thesis is an extension of our project thesis carried out during the fall of 2012. The report counts for 30 credits, or 100% of a semester's work load.

The master thesis is a part of the MARFLIX project, which is collaboration between WWL, NTNU, MARINTEK and DNV. The main purpose of our study has been to develop a simulation model and a optimization model to evaluate deployment models in a liner shipping segment. The work has been time-consuming and challenging, but we are well satisfied with the result.

It has been an educational final semester. The master thesis work has provided us with a greater understanding on how to approach new subjects and how to work well in team. During the work we have had regular meetings. During these meetings we have updated each other on the progress, discussed problems and taken important decisions.

We would like to thank Professor Bjørn Egil Asbjørnslett and Post-doctoral Fellow Jørgen Glomvik Rakke, our supervisors at the department of Marine Technology, for their valuable advices and support during the work of this thesis. We would also like to thank our family, friends, girlfriends and office mates for their vital support.

Trondheim, June 10, 2013

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# 1

## Introduction

Maritime transport is the major channel of international trade. According to UNCTAD (2011), trade by sea has in terms of weight more than doubled from 1990 to 2010. The largest increase has been in container trade and dry bulks. Measured by weight, more than 80 % of world trade is carried by seagoing vessels (IMO et al., 2009). The shipping industry has almost monopoly on transportation of large volumes of cargo among the continents (Christiansen, Fagerholt, Nygreen, et al., 2007). Liner shipping vessels carry about 60 % of all goods measured by value moved internationally by sea every year (worldshipping 2012).

Efficient transportation is becoming more important in the maritime transport industry. Transportation costs can sometimes account for 20 % of the total cost of a product (Hoff et al., 2010). Increased consumption, growth in the economy, and globalization tend to increase the need for transportation. The competition between transport companies and between cargo owners are strong, this lead to higher demand for efficiency, cost reduction, and customer service in transportation (Hoff et al., 2010).

The Roll on/Roll off (RoRo) vessel industry is no exception for strong competition. RoRo vessels transport cars, trucks, farming equipment and other rolling cargo. In 2011 the global car trade grew by 12 %. Between 2006 and 2012 there was a 3 % growth in number of RoRo vessels, but an 11 % growth in overall deployed lane meters (MDS Transmodal 2012). In 2012 the RoRo fleet counted more than 2 400 vessels. However, more than half of the fleet is vessels smaller

## 1. INTRODUCTON

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than 10 000 dwt. Compared with the container shipping fleet, that counts more than 4 300 vessels, the RoRo fleet is small. The difference is more significant when comparing the number of deep sea RoRo vessels against deep sea container vessels (Lindstad, Asbjørnslett, and Pedersen, 2012). This is a threat for the RoRo industry; the container shipping segment can obtain a more efficient short sea feeder traffic out and in of the ports. The RoRo industry must continuously improve so that cars and other wheeled cargo are not transported by container ships.

In international vehicle trade, RoRo vessels sail between different regions of the world according to a predefined plan. Planning of operations in the maritime industry can be divided into three main categories by the time horizon. The first category is strategic planning; it has usually a planning horizon of several years. Strategic planning often involves fleet size and mix decisions. Planners decide how many and which ships to operate and own. The second category is tactical planning; it usually has a time horizon of several months. Tactical planning relies on the strategic plan, and often involves determining which vessels should serve which routes, and when they should arrive and leave each region. Operational planning is the third category. The time horizon for operational planning is often days or weeks. Decisions related to operational planning are often associated to a given voyage, such as vessel speed, weather routing and delays. Tactical plans are used as input in the operational plan. In case of disruption the planners have to decide how to get the vessels back on schedule with as little impact and cost as possible. In these planning levels the shipping company has to decide the robustness of their fleet.

In liner shipping networks disruptions and delays will cascade through the network and influence other ports and ships. This is given by the nature of many liner shipping networks (Theo Notteboom and Rodrigue, 2008). Maritime shipping networks are an example of transport mode that operates around the clock. In addition, the ships almost never get empty at any points, and freight forwarding obligations must be met during the recovery period. These facts make it hard to get a delayed vessel back on schedule; it can take days, or even weeks (Andersen, 2010). The operational planning phase can also be used to verify the tactical plan. If the shipping company constantly need to increase the vessel speed, omit port calls or charter in vessels to deliver the cargo on time,

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it can be advisable to do some changes on the tactical level, or maybe even on strategic level.

The planners have to balance the complexity and the scope when making these plans. Planning for longer periods and for a greater part of the fleet simultaneously increase the scope, and provides more flexibility. This can give good synergy effects, but planning a bigger problem makes it harder to solve. In addition solving larger problem requires more information.

Much of the maritime business environment has changed over the last decades, but Christiansen, Fagerholt, Nygreen, et al. (2007) claim the business methods of many shipping companies are still the same. Shipping companies are often conservative, low risk family businesses. As a result, several companies still rely on intuition and experience when doing strategic, tactical and operational planning. In many other industries operation research has been a popular area of study. The airline industry is one of the most successful examples of applying operation research methods and tools for the planning and scheduling of resources (Clausen et al., 2010). Operation research has in the later years also become more popular in the maritime transport industry. The reasons for harder competitions between the shipping companies are, decreasing margins for the companies, more complex operations through integrated planning into terminal operations and hinterland transport and a rapid development in computer technology. Operation research has been used extensively to design an optimal ship fleet, and to find good ways to managing a fleet of ships (Pantuso, Fagerholt, and Hvattum, 2013). On the other hand there has not been done much research in disruption management in liner shipping and in the maritime transport in general (Kjeldsen et al., 2012). In our work, we have only found two studies that deal with disruption management in liner shipping. Both studies are published within the two last years.

Disruption management in the maritime transport industry consists of getting ships and cargo back on schedule after a delay or disruption, with as little cost and impact as possible. In this thesis delay is used if a vessel is behind schedule. A disruption is an unplanned event which can cause a ship to be either ahead or behind schedule, i.e. a disruption does not need to cause a ship to be delayed. Vessels can experience delays due to mechanical breakdowns, bad weather and increased port time. Methods used to get a vessel back on the schedule can be to increase the vessel speed, to omit a port of call, and charter in an extra vessel. A route specifies the order in which the ports are to be

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called, while a schedule also specifies the time when the ports are to be called. Disruption management models can also be used to verify the deployment model already developed. To our knowledge, there is no studies that use a distruption management model to investigate the qualities of the corresponding deployment model in the maritime transport segment.

Maritime transport is an industry that experiences a high degree of uncertainty. A reason for this uncertainty is delays that occur during sailing or in port. Ship's long life time, often exceeding 30 years, influence on the uncertainty, due to the unknown marked situation.

This master thesis is a part of the MARFLIX (MARitime FLeet size and mIX) project. The research project MARFLIX is collaboration between NTNU, MARINTEK, DNV and WWL. The overall aim for the MARFLIX project is to develop and test methods for improved support for fleet size and mix decision-making through quantitative methods. The MARFLIX project intends to make a fleet size and mix (FSM) proposal. Since the time horizon for the MARFLIX deliverable is based on ship chartering contracts of 25-30 years, the model has some limitations with respect to routing, scheduling and day to day operations. A given FSM might look good in the MARFLIX model, but when encountering tactical and operational problems it may fall short. There has to be a verification process in which these problems are tested to the given fleet size and mix. The verification process has two steps, a 6 month deployment perspective and a day to day operational perspective. In this master thesis we are going to develop an operational model framework. In this operational model framework the deployment model from the MARFLIX model can be implemented. It will then be possible to examine how the fleet from the MARFLIX project is operating in a day to day perspective. The operational model can be used to verify the strategic and the tactical plan in the MARFLIX project. You may find an illustration of this in figure 1.1.

The operational model framework can be used to validate the deployment model, which is validating the fleet size and mix model. The operational model will check if the given deployment and FSM are valid in the daily business. Both the FSM proposal and the deployment proposal may work well, but if the fleet fail on operational level some changes have to be made. First on the tactical level, but if that is not sufficiant there will be necessary with changes on strategic



**Figure 1.1: Planning categories in the MARFLIX project -**

level. Different deployment scenarios can be tested and the best proposal can be found.

To our knowledge there are none that have used a simulation optimization model to investigate the day to day operation of a liner fleet.

The remainder of this paper is organized as follows: Section 2 describes disruption management and our problem more in depth, section 3 presents WWL briefly. The literature review is presented in section 4, in the literature review some different disruption management models and other literature are presented. Section 5 contains a review about the maritime transportation segment, while section 6 investigates the use of operational research in the maritime transport industry. Potential incidents causing delays are handled in section 7. Rescheduling actions are discussed in section 8. Probability of incidents and impacts and different distributions are discussed in section 9. In section 10 the models presented in section 4 are discussed, and different solution approaches for our problem are also discussed. Our optimization model is also presented in this section. In section 11 the choice of column generation algorithm is discussed and the chosen algorithm is presented. The simulation model is presented and discussed in section 12. In section 13 different input parameters are calibrated, and the effects of changes in these are discussed. The results are presented in section 14. In section 15 assumptions and the use of the model is discussed. Section 16 concludes the thesis.

## 1. INTRODUCTON

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## 2

# Problem Description

Liner shipping companies normally have a large set of published schedules. These schedules consist of sequences of ports where the time of each port call is fixed. A Europe – North America trade from WWL is illustrated in figure 2.1 below. In addition the network will be such that transshipping cargo between different services is an integrated part of operating the network. Most transshipments take place in designated hub ports which are frequented by two or more routes.



Figure 2.1: Europe-North America trade -

## 2. PROBLEM DESCRIPTION

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Disruptions occur often in a global liner shipping network. According to T Notteboom (2006) approximately 70-80 % of vessel roundtrips experience delays in at least one port. When a disruption happens in a liner shipping network, the effect on the network needs to be limited both in time and space. The time limitation leads to a decision on which time the vessels and cargoes must be back on schedule. The space limitation leads to a decision on which vessels and port calls to be used in getting the network back on schedule. All vessels and ports that are directly involved in the disruptions are included in getting the vessels and cargoes back on schedule. However, other vessels and ports may also be included, depending on their position relative to the disruption and their perceived ability to alleviate the effects of the disruption (Kjeldsen et al., 2012).

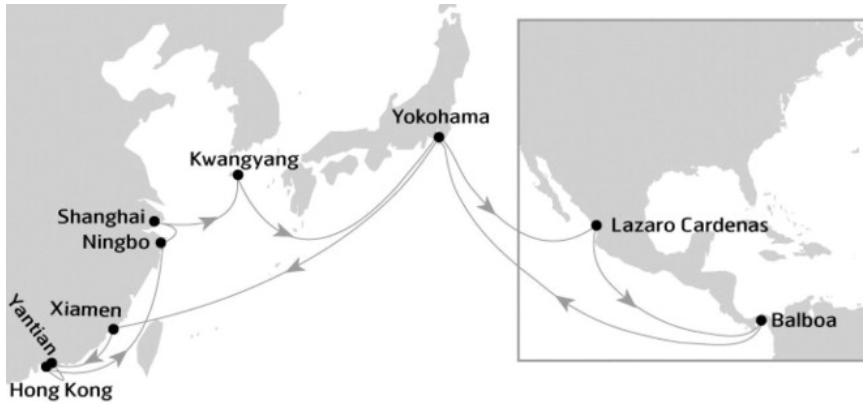
It is a challenge to find new schedules and cargo routings, given the capacity and port productivity, which are minimizing the operational cost. The operational cost consists of fuel cost and other costs for the vessels, all port related costs, transshipment costs and costs that concern delays.

An example from Brouer et al. (2013) illustrates the problem. Maersk Sarnia was deployed on a route between South–East Asia and Central America. The route is displayed in figure 2.2 below. During the pickup of cargo in South–East Asia the weather conditions cause the vessel to suffer a 30 hours delay when leaving Kwangyang in South Korea. The delay may cause the vessel to miss a scheduled port call in the transshipment port of Balboa in Panama. As a result of the missed port call, large parts of the cargo will miss their onward connections and most cargoes will not be delivered on time.

Maersk Sarnia has several options to mitigate the negative effects of the disruption. It can speed up significantly to try to reach Balboa on time, swap the port calls of Lazaro Cardenas and Balboa, omit one of the upcoming port calls, or it can accept the delay and catch up schedule returning to Asia from Bilbao.

The shipping company chose to increase the speed of Maersk Sarnia to recover from the delay, but nevertheless the speed increase did not ensure timely delivery of the cargo to the hub port of Balboa. The final recovery was done returning to Asia. As a result all the cargo was delayed and some of the cargo missed the onward connection at the hub. A recovery model proposed by Brouer et al. (2013) suggested omitting the last port call in Asia reaching the transshipment port without increasing the vessel speed. The cost saving,





**Figure 2.2: Asia-Central America trade** - (Brouer et al., 2013)

including a delay penalty, of the suggested solution was more than 20% (Brouer et al., 2013).

In this master thesis we are to build a model framework that can take in the deployment model from the MARFLIX project and investigate how well the deployment model operate on a day to day basis. The deployment model may look good in itself, but on a day to day basis there can be some problems. The model framework can check if there is the right amount of slack and robustness in the vessel schedules proposed by the deployment model.

If there is too little slack the vessels need to omit ports, increase the speed, and vessels need to be chartered in to meet the freight forward obligations. This gives an high extra cost that is not included in the deployment model. If there is too much slack in the vessel schedules the vessels may wait in port or stay idle for some time. A fleet of vessels where the vessels spend much time waiting in port is a fleet that is not well utilized. The operational model we are to develop will find the best way to distribute robustness to the vessel schedule.

In some cases an entire port can be shut down, e.g. due to labor strike, such events can be implemented in the operational model. It is possible to see how a fleet of vessels work under such conditions.

## 2. PROBLEM DESCRIPTION

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### 3

# Wallenius Wilhelmsen Logistics

Wallenius Wilhelmsen Logistics (WWL) is a company which delivers shipping and logistics solutions for manufacturers of car, trucks, heavy equipment and specialized cargo. WWL is also specialized in handling complex project cargoes such as rail cars, power generators, mining equipment and yachts. The core business is the ocean transportation, but provides other services in the field of supply management as well, such as terminal handling, inland distribution and technical services.

In 2011 WWL transported 4.3 million units, 1.8 million by sea and 2.5 million inland. The company is owned by Wallenius Logistics AB of Sweden and Wilhelmsen Ships Holding Malta Ltd. WWL employs 3 500 people and has around 60 RoRo vessels in operation, servicing 18 routes to six continents. The main trades are:

- Asia – North America
- Asia – Europe
- Europe – North America
- North America – Europe

### 3. WALLENIUS WILHELMSSEN LOGISTICS

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- Europe/ North America – Oceania
- Europe – Oceania

The schedule will not be the same for all ships serving the same trade. The trade gives which areas the ship visits, not the specific port calls, which depends on the current demand and supply in each port.

WWL's fleet is heterogenous. To detect the different types of vessels, the fleet is divided into four vessel categories:

- PCC – Pure Car Carriers
- PCTC – Pure Car Truck Carriers
- LCTC – Long Car Truck Carriers
- RORO – Roll-on Roll-off Carriers

All of the vessels are Roll-on Roll-off carriers, but WWL defines RoRo as vessels which has High and Heavy and Non-Containerized Cargo as the main cargoes, and cars are just supplementary cargo.

WWL's fleet consists mostly of PCTC, LCTC and RoRo-vessels. For more about the vessels, visit WWL's home page [www.2wglobal.com](http://www.2wglobal.com).

# 4

## Literature Review

During the last decades research on maritime transportation has increased (Christiansen, Fagerholt, Nygreen, et al., 2007). Much research has been done in how to design an optimal ship fleet, and how to manage a fleet of ships (Pantuso, Fagerholt, and Hvattum, 2013). On the other hand, there has not been done much research in disruption management in liner shipping and in maritime transport. In other transport segments and especially in the airline industry there have been made a significant amount of research on disruption management (Kjeldsen et al., 2012).

### 4.1 Optimization Models

#### 4.1.1 Liner Shipping Models

In liner shipping, Kjeldsen et al. (2012) and Brouer et al. (2013) have to our knowledge written the only papers that studies disruption management. The first study that dealt with distruption management in liner shipping was the doctoral thesis was *Rescheduling Ships and Cargo in Liner Shipping in the Event of Disruptions* by (Kjeldsen et al., 2012), the study was written in 2012. This thesis introduces a mathematical model for rescheduling ships and cargoes. Kjeldsen et al. suggest a model that constructs a set of ship schedules and cargo routings that allows resumption of scheduled service at the end of the planning period while minimizing the operating cost.

## 4. LITERATURE REVIEW

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To get the fleet of vessels back on schedule after one or more delays, the vessels can speed up, or cargo can be transshipped by another vessel than originally intended. Omitting port calls and swapping port calls are also possible recovery actions in the model. Kjeldsen et al. (2012) allow other vessels than the delayed vessel to take part in the recovery when a vessel gets disrupted. This yields a better utilization of the vessel fleet.

Kjeldsen et al. formulate the simultaneous ship and cargo rescheduling in the event of disruptions problem as a multicommodity flow problem with side constraints on a time-space network. The time-space network is given by a multigraph  $G = (V, A)$  with vertex set  $V$  and arc set  $A$ . The elements  $V$  and  $A$  are described below.

Ports, origins of ships and destinations of ships are represented by different vertices. The three sets are mutually exclusive.  $V_P$  represent ports,  $V_O$  represents origins of ships and  $V_D$  represents destinations of ships. The notation  $V_{pt}$  is used to denote the vertex representing location  $p \in V$  at time  $t$ . The arc set  $A$  is composed of a number of different types of arcs, representing flows of ships and cargoes. Any arc  $(i, j) \in A$  is directed from  $i = V_{pt}$  to  $j = V_{p't'}$  where  $t' > t$ .

For the ships there are three different types of arcs: Voyage arcs that represent ships that sail from one port to another, berthing arcs that represent ships berthed and under operation in a given port, and waiting arcs that represent ships waiting in a given port. There are also four types of arcs for the cargoes: Onboard arcs that represent a given cargo transported on a given ship, port arcs that represent a given cargo waiting in a given port, loading arcs that represent a given cargo loaded in a given port on a given ship, and discharge arcs that represent a given cargo discharged in a given port on a given ship. All these arcs are presented more in depth below.

Kjeldsen et al. (2012) let the binary variable  $x(V_{pt}, V_{p't'})_{VOY}^h$  take the value 1 if the corresponding arc is used, and the value 0 otherwise. Moreover they let  $x^h(i+)$  denote the sum of  $x$ -variables associated with voyage arcs for ship  $h$  out of vertex  $i \in V$ .  $x^h(-i)$  is then the sum of  $x$ -variables associated with voyage arcs for ship  $h$  into vertex  $i \in V$ . In addition,  $X^h$  is the set of all voyage arcs for vessel  $h$ . Since the vessel speed is a variable, there can be several voyage arcs from a given  $V_{pt}$ . There are two different costs associated with each voyage arc; the first is the fuel cost, the second is the cost associated with calling on the next port.  $SC_{ij}^h$  denotes the fuel cost, where  $i = V_{pt}$  and  $j = V_{p't'}$ , for vessel

## 4.1 Optimization Models

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$h$  from location  $p$  to  $p'$  at the speed corresponding to the time span  $t' - t$ .  $PC_j^h$  is the cost associated with the port call, which includes all one-off costs incurred when a vessel calls a port, such as pilotage and harbor dues (Kjeldsen et al., 2012).

$(V_{pt}, V_{p,t+1})_B^h$  represent that ship  $h$  is berthed and under operation in port  $p$  from time  $t$  to time  $t + 1$ . The binary variable  $y^h(i+)$  take the value 1 if the berthing arc out of  $i = v_{vp}$  is used. Similarly, let the binary variable  $y^h(-i)$  take the value 1 if the berthing arc into  $i = v_{vp}$  is used. The cost  $BC_i^h$  of a berth arc is the cost having ship  $h$  berthed at port  $p$  for one time unit. If a port is closed due to a disruption, the flow on the associated berthing arcs is fixed to 0 (Kjeldsen et al., 2012).

$(V_{pt}, V_{p,t+1})_W^h$  represent that ship  $h$  is waiting in port  $p$  from time  $t$  to time  $t + 1$ . The binary variable  $w^h(i+)$  take the value 1 if the waiting arc out of  $i = v_{vp}$  is used. Similarly, let the waiting variable  $w^h(-i)$  take the value 1 if the waiting arc into  $i = v_{vp}$  is used. A berthing arc can appear both after a voyage arc and between two berthing arcs. There is no cost associated with the waiting arcs (Kjeldsen et al., 2012).

The set of cargoes is denoted  $M$ . Each cargo  $m$  designated by a volume  $G^m$ , an origin vertex  $O_c^m = V_{pt}$ , where  $p$  is the origin port and  $t$  is the time cargo  $m$  gets available for loading, and a destination vertex  $D_c^m = V_{p't'}$ , where  $p'$  is the destination port, and  $t'$  is the planned delivery time. Kjeldsen et al. (2012) let  $B_-^m$  denote the set of vertices representing the destination of cargo  $m$  at the various times in the planning period at which cargo  $m$  may be delivered at the destination.  $B_+^m$  denote the set of vertices representing the destination of cargo  $m$  at the various times after the planning period at which cargo  $m$  may be delivered at the destination.

Each cargo has a given a unique delay cost,  $FC_i^m$ , which is the cost of delivering cargo  $m$  at  $time(i)$ . If the cargo is not late, i.e.  $time(i) \leq time(D_m^c)$  the cost will be 0.

In addition to the vessel arcs above, there are four types of cargo arcs. The first one is the *onboard arc*.  $(V_{pt}, V_{p't'})_O^{mh}$  represents the transport of cargo  $m$  onboard ship  $h$  from  $V_{pt}$  to  $V_{p't'}$ . Each vessel  $h$  has a given capacity,  $CAP^h$ . The continuous variable  $u(V_{pt}, V_{p't'})_O^{mh}$  denotes the fraction of cargo  $m$  transported on ship  $h$  from  $V_{pt}$  to  $V_{p't'}$ . Moreover let  $u^{mh}(i+)$  denote the sum of  $u$ -variables associated with onboard arcs for cargo  $m$  on ship  $h$  out of vertex  $i \in V$ .  $u^{mh}(-i)$

#### 4. LITERATURE REVIEW

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is then the sum of  $u$ -variables associated with onboard arcs for cargo  $m$  on ship  $h$  into vertex  $i \in V$ . In addition,  $U^{mh}$  is the set of all onboard arcs for cargo  $m$  on vessel  $h$  (Kjeldsen et al., 2012).

$(V_{pt}, V_{p,t+1})_P^m$  represent that cargo  $m$  is waiting in port  $p$  from time  $t$  to  $t+1$ . The continuous variable  $z^m(i+)$ , where  $i = V_{pt}$  represent the fraction of cargo  $m$  being held in port  $p$  from time  $t$  to  $t+1$ . Similarly, let the continuous variable  $z^m(-i)$ , where  $i = v_{pt}$ , represent the fraction of cargo  $m$  being held in port  $p$  from time  $t-1$  to  $t$  (Kjeldsen et al., 2012).

$(V_{pt}, V_{p,t+1})_L^{mh}$  represent that cargo  $m$  is being loaded on vessel  $h$  in port  $p$  from time  $t$  to  $t+1$ . The continuous variable  $s^{mh}(i+)$ , where  $i = V_{pt}$  represent the fraction of cargo  $m$  being loaded on vessel  $h$  in port  $p$  from time  $t$  to  $t+1$ . Similarly, let the continuous variable  $s^{mh}(-i)$ , where  $i = v_{pt}$ , represent the fraction of cargo  $m$  being loaded on vessel  $h$  in port  $p$  from time  $t-1$  to  $t$  (Kjeldsen et al., 2012).

Finally,  $(V_{pt}, V_{p,t+1})_D^{mh}$  represent that cargo  $m$  is being discharged from vessel  $h$  in port  $p$  from time  $t$  to  $t+1$ . The continuous variable  $r^{mh}(i+)$ , where  $i = V_{pt}$  represent the fraction of cargo  $m$  being unloaded from vessel  $h$  in port  $p$  from time  $t$  to  $t+1$ . Similarly, let the continuous variable  $r^{mh}(-i)$ , where  $i = v_{pt}$ , denote the fraction of cargo  $m$  being discharged from vessel  $h$  in port  $p$  from time  $t-1$  to  $t$  (Kjeldsen et al., 2012).

When loading and discharging cargo, the productivity  $PR_j^h$  of a port  $p$  for a given ship  $h$  must be taken into consideration. The transshipment cost per TEU,  $TC_j$ , in port  $j$  is incurred for any cargo  $m$  which requires a load on another ship in order for the cargo to arrive at  $location(D_c^m)$ , i.e., the cost is incurred for all cargos except those for which port  $j$  is the destination  $location(D_c^m)$  (Kjeldsen et al., 2012).

Given the time-space network above, as well as the operating constraints Kjeldsen et al. formulate the model as a mixed integer program. The objective is to minimize cost when reschedule the vessels and cargoes after a disruptions that have appeared. The model is formulated as follows:



$$\begin{aligned}
& \min \sum_{h \in \mathcal{H}} \sum_{(i,j)^h \in \mathcal{X}} x(i,j)^h_{VOY} (SC_{ij}^h + PC_j^h) \\
& + \sum_{h \in \mathcal{H}} \sum_{i \in \mathcal{V}} y^h(i+) BC_i^h + \sum_{h \in \mathcal{H}} \sum_{m \in \mathcal{M}} \sum_{i \in \mathcal{B}} FC_i^m r^{mh}(-i) \\
& \quad + \sum_{h \in \mathcal{H}} \sum_{m \in \mathcal{M}} \sum_{i \in \mathcal{V} \setminus \mathcal{B}} r^{mh}(-i) G^m TC_i,
\end{aligned} \tag{4.1}$$

subject to:

$$y^h(O^h+) + w^h(O^h+) + x^h(O^h) = 1, \quad \forall h \in \mathcal{H}, \tag{4.2}$$

$$\sum_{i \in \mathcal{D}} x^h(-i) = 1, \quad \forall h \in \mathcal{H}, \tag{4.3}$$

$$\begin{aligned}
& y^h(1+) + w^h(i+) + x^h(i+) - y^h(1-) \\
& \quad - w^h(i-) + x^h(i-) = 0, \quad \forall h \in \mathcal{H}, i \in \mathcal{V}
\end{aligned} \tag{4.4}$$

$$\sum_{h \in \mathcal{H}} (s^{mh}(O_c^m+) + u^{mh}(O_c^m+)) + z^m(O_c^m+) = 1, \quad \forall m \in \mathcal{M}, \tag{4.5}$$

$$\sum_{h \in \mathcal{H}} \left( \sum_{i \in \mathcal{B}_-} r^{mh}(-i) + \sum_{i \in \mathcal{B}_+} u^{mh}(-i) \right) = 1, \quad \forall m \in \mathcal{M}, \tag{4.6}$$

$$\begin{aligned}
& \sum_{h \in \mathcal{H}} (s^{mh}(i+) + r^{mh}(i+) + u^{mh}(i+)) + z^m(i+) \\
& \quad - \sum_{h \in \mathcal{H}} (s^{mh}(-i) + r^{mh}(-i) + z^{mh}(-i)) \\
& \quad \quad - z^m(-i) = 0, \quad \forall m \in \mathcal{M}, i \in \mathcal{V}_P
\end{aligned} \tag{4.7}$$

$$\sum_{m \in \mathcal{M}} (s^{mh}(i+) + r^{mh}(i+)) G^m \leq y^h(i+) PR^h(i+), \quad \forall h \in \mathcal{H}, i \in \mathcal{V} \setminus \mathcal{V}_D \tag{4.8}$$

$$\sum_{m \in \mathcal{M}} u(i,j)^{mh}_O G^m \leq x(i,j)^h_{VOY} CAP^h, \quad \forall h \in \mathcal{H}, (i,j) \in \mathcal{X}^h \tag{4.9}$$

$$\sum_{m \in \mathcal{M}} u(i,j)^{mh}_O G^m \leq (y^h(i+) + w^h(i+)) CAP^h, \quad \forall h \in \mathcal{H}, (i,j) \in \mathcal{U}^{mh},$$

#### 4. LITERATURE REVIEW

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$$port(i) = port(j) \quad (4.10)$$

$$\sum_{c \in \mathcal{H}} (r^{mc}(-i) + z^m(-i) = s^{mh} + z^m(i+), \quad \forall h \in \mathcal{H}, m \in \mathcal{M},$$

$$i \in \mathcal{V}_P \setminus \{B_-^m \cup O_c^m\} \quad (4.11)$$

$$u^{mh}(-i) \geq r^{mh}(i+), \quad \forall h \in \mathcal{H}, m \in \mathcal{M},$$

$$i \in \mathcal{V}_P \quad (4.12)$$

$$s^{mh}(-i)u^{mh}(-i) \geq u^{mh}(i+), \quad \forall h \in \mathcal{H}, m \in \mathcal{M},$$

$$i \in \mathcal{V}_P \quad (4.13)$$

$$\sum_{m \in \mathcal{M}} u(i, j)_O^{mh} G^m \leq x(i, j)_{VOY}^h CAP^h, \quad \forall h \in \mathcal{H}, (i, j) \in \mathcal{X}$$

$$(4.14)$$

$$\sum_{m \in \mathcal{M}} u(j, i)_O^{mh} G^m \leq x(j, i)_{VOY}^h CAP^h, \quad \forall h \in \mathcal{H}, (i, j) \in \mathcal{X}$$

$$(4.15)$$

$$y^h(v_{pt+}) = y^h(v_{p,t+1}), \quad \forall h \in \mathcal{H}, p \in \mathcal{V}_O \cup \mathcal{V}_P,$$

$$\forall t \in \{0, \dots, T-1\} \quad (4.16)$$

$$w^h(v_{pt+}) = w^h(v_{p,t+1}), \quad \forall h \in \mathcal{H}, p \in \mathcal{V}_O \cup \mathcal{V}_P,$$

$$\forall t \in \{0, \dots, T-1\} \quad (4.17)$$

$$u^{mh}(i+) = \sum_{j|(i,j) \in \mathcal{U}} u(i, j)_O^{mh}, \quad \forall m \in \mathcal{M}, h \in \mathcal{H},$$

$$i \in \mathcal{V} \quad (4.18)$$

$$u^{mh}(-i) = \sum_{j|(j,i) \in \mathcal{U}} u(j, i)_O^{mh}, \quad \forall m \in \mathcal{M}, h \in \mathcal{H},$$

$$i \in \mathcal{V} \quad (4.19)$$

$$z^h(v_{pt+}) = z^h(v_{p,t+1}), \quad \forall m \in \mathcal{M}, p \in \mathcal{V}_O \cup \mathcal{V}_P,$$

$$\forall t \in \{1, \dots, T-1\} \quad (4.20)$$

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$$s^{mh}(v_{pt+}) = s^{mh}(v_{p,t+1}), \quad \forall m \in \mathcal{M}, p \in \mathcal{V}_0 \cup \mathcal{V}_P, \\ \forall t \in \{1, \dots, T-1\} \quad (4.21)$$

$$r^{mh}(v_{pt+}) = r^{mh}(v_{p,t+1}), \quad \forall m \in \mathcal{M}, p \in \mathcal{V}_0 \cup \mathcal{V}_P, \\ \forall t \in \{1, \dots, T-1\} \quad (4.22)$$

$$x(i, j)_{VOY}^h \in \{0, 1\} \quad \forall h \in \mathcal{H}, (i, j) \in \mathcal{X}^h \quad (4.23)$$

$$x^h(i+), y^h(i+), w^h(i+) \in \{0, 1\}, \quad \forall h \in \mathcal{H}, i \in \mathcal{V} \quad (4.24)$$

$$0 \leq u(i, j)_O^{mh} \leq 1, \quad \forall m \in \mathcal{M}, h \in \mathcal{H}, \\ (i, j) \in \mathcal{U} \quad (4.25)$$

$$0 \leq u^{mh}(i+) \leq 1, \quad \forall m \in \mathcal{M}, h \in \mathcal{H}, \forall i \in \mathcal{V} \quad (4.26)$$

$$0 \leq z^m(i+) \leq 1, \quad \forall m \in \mathcal{M}, \forall i \in \mathcal{V} \quad (4.27)$$

$$0 \leq s^{mh}(i+) \leq 1, \quad \forall m \in \mathcal{M}, h \in \mathcal{H}, \forall i \in \mathcal{V} \quad (4.28)$$

$$0 \leq r^{mh}(i+) \leq 1, \quad \forall m \in \mathcal{M}, h \in \mathcal{H}, \forall i \in \mathcal{V} \quad (4.29)$$

There are four terms in the objective function. The first term is the fuel cost of sailing the chosen routes and the cost associated with the port calls. The second term is the cost of the vessels staying at berths. The third term is the cost associated with delaying the cargo past the original delivery time. The last term is the cost associated with transshipping cargoes. Constraint 4.2 and constraint 4.5 ensures that each vessel and each cargo enter the planning period exactly once. Through the constraints 4.4, 4.6 and 4.7 the model ensures that both vessels and cargoes sail to its destination port and that there is a connected flow through the arcs. Constraint 4.8 guarantee that cargo is only loaded or discharged from a vessel in port if the ship is really in port. Constraint 4.9 and 4.10 ensure that the amount of cargo onboard a vessel have to be less or equal to the total capacity of the vessel. Constraint 4.10 ensures that a given cargo can only be onboard a vessel between two ports if the vessel is sailing between these ports. Cargo has to be handled in right order; constraint 4.11 ensures that before a cargo is eligible

## 4. LITERATURE REVIEW

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for loading or for waiting in port it must have been discharged from a ship or already waiting in the port. Constraint 4.12 guarantees that a cargo is onboard in the period prior to any attempt of discharging the cargo from the ship. If a cargo is onboard a ship in a given period, constraint 4.13 ensures that the cargo was either onboard the same ship or loaded onto the ship in the previous period. Constraint 4.23 and 4.24 that ensure the variables pertaining to the ships are binary, and constraints 4.25 - 4.29 ensure that the variables pertaining to the cargo are continuous and remain between one and zero (Kjeldsen et al., 2012).

It is possible to solve the mathematic model with a commercial solver. Kjeldsen et al. (2012) developed a heuristic so that they were able to solve the model faster than with the commercial solver. The heuristic they developed was a Large Neighborhood Search (LNS). LNS is a general heuristic search paradigm that was originally proposed by Shaw (1998). It also closely resembles to the Ruin and Recreate heuristic presented by Schrimpf et al. (2000). The purpose of the LNS is to create a new feasible schedule for the ships and new routings for the cargos after one or more disruptions have appeared. Kjeldsen et al.'s heuristic contains two phases, construction and repair, which are repeated until a given computing time is reached. In the construction phase the focus is on constructing a feasible schedule for the ships after there has been a disruption. Starting with the initial solution Kjeldsen et al. try to construct feasible schedules for each ship by advancing delaying and canceling port calls. The heuristic does not allow the amount of time set aside for a port call to be below two time periods, in addition port calls not affected by the disruptions will not be changed. The aim of the repair phase is to repair the cargo routings by changing the schedules which must retain feasibility. In order for the solution to remain feasible, none of the port calls are moved or deleted. Instead the repair phase uses different procedures in an attempt to increase the length of the existing port calls and the possibility of adding new port calls between existing ones.

In order to diversify the search, randomness is included in both the construction and repair phase. Instead of generating a new initial solution, the original schedule is used as the initial solution. This approach was chosen due to the complexity of generating a feasible initial solution and because the original schedule was a good solution at the time of its creation. After a disruption the original schedule is no longer operable, but good alternative solutions closely

## 4.1 Optimization Models

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related to the original schedule are likely to exist, which makes the original schedule a good starting point for the search for good solutions.

The algorithm developed has an 1800 seconds upper time limit. However, the algorithm was tested on 20 different test instances with varying size, and the best objective value for all test instances were found within 152 seconds (Kjeldsen et al., 2012).

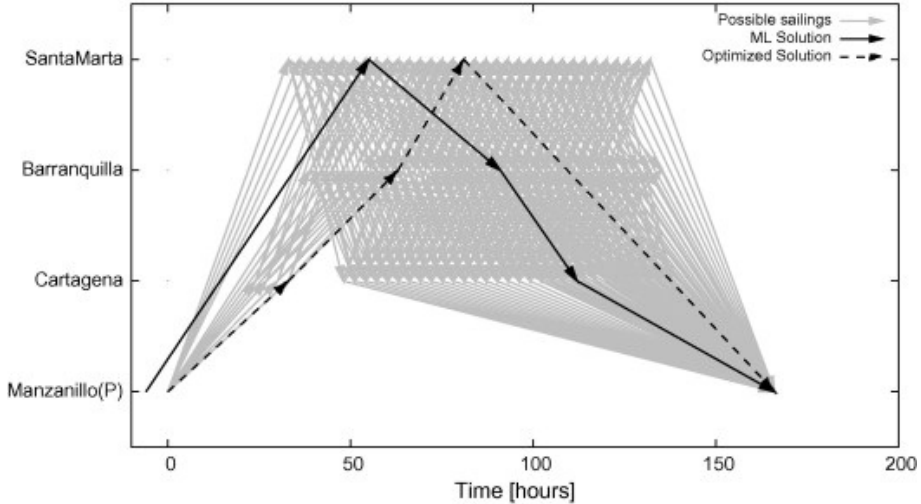
Published in 2013, the second paper on disruption management in liner shipping is *The Vessel Schedule Recovery Problem - A MIP model for handling disruptions in liner shipping* by Brouer et al. (2013). This paper presents and solves the Vessel Schedule Recovery Problem (VSRP) to evaluate a given disruption scenario and to select an appropriate recovery action. The recovery action will balance between increased bunker consumption and the impact on cargo in the remaining network and the customer service level. The model addresses frequently occurring disruption scenarios in the liner shipping industry. Brouer et al. (2013) built their model to fit to a container vessel fleet.

This paper focuses on utilizing the findings in disruption management tools for the airline industry in order to construct a mathematical model of the VSRP to handle disruptions in the context of the liner shipping business. The mathematical model created by Brouer et al. (2013) is particularly based on the work within aircraft recovery with speed-changes by Marla, Vaaben, and Barnhart (2011). Brouer et al. (2013) use a time space graph as the underlying network, but reformulate the model to address the set of available recovery techniques, which are applicable to the VSRP.

Three recovery actions are permitted by Brouer et al. (2013) to get the delayed vessels back on schedule: increase the speed on the delayed vessel, omitting a port, and swap the order in which ports are being visited. Figure 4.1 illustrates the different recovery actions used by Brouer et al. (2013).

Brouer et al. (2013) created a mathematical formulation with a set of vessels,  $V$ , a set of ports,  $P$ , and a time horizon consisting of discrete timeslots,  $t \in T$ . For each vessel  $v \in V$  the current location and a planned schedule consisting of an ordered set of port calls  $H_v \subseteq P$  are known within the recovery horizon. A port call  $A$  can precede a port call  $B$ ,  $A < B$  in  $H_v$ . A set of possible sailings, i.e. directed edges,  $L_h$  are said to cover a port call  $h \in H_v$ . Each  $L_h$  represent a sailing with a different speed. The disruption scenario includes a set of container groups  $C$  with planned transportation scenarios on the schedules of  $V$ . A feasible

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**Figure 4.1: Suggested recovery solutions in the time-space network.** -  
(Brouer et al., 2013)

solution to an instance of the VSRP is to find a sailing for each  $v \in V$  starting at the current position of  $v$  and ending on the planned schedule no later than the time of the recovery horizon (Brouer et al., 2013).

Brouer et al. (2013) define a binary variable  $x_e$  for each edge  $e \in E_s$ . The variables are set to 1 if the edge is sailed and 0 otherwise. A binary variable  $z_h$  is also defined for all port calls  $h \in H$ .  $z_h$  is set to 1 if port call  $h$  is omitted, and 0 otherwise. For each container group  $c \in C$  that are transported there is a binary variable  $o_c$  that indicate whether container group  $c$  is delayed or not. The binary variable  $y_c$  indicates whether container group  $c$  is misconnecting or not.  $O_e^c \in \{0, 1\}$  is a constant, set to 1 if container group  $c$  is delayed when arriving by edge  $e \in L_{T_c}$ .

The cost of a delay to container group  $c$  is denoted  $C_c^d$ , the cost of one or several misconnections to container group  $c$  is denoted  $C_c^m$ , and the cost associated with operating vessel  $v$  on edge  $e$  is denoted  $C_e^v$ .

$B_c$  and  $T_c$  are defined as origin port and destination port for container group  $c \in C$ , while  $I_c$  is defined as intermediate planned transshipment points for container group  $c$ . Brouer et al. (2013) formulate the VSRP as follow:

## 4.1 Optimization Models

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$$\min \sum_{v \in \mathcal{V}} \sum_{h \in \mathcal{H}_v} \sum_{e \in \mathcal{L}_h} C_e^v x_e + \sum_{c \in \mathcal{C}} [C_c^m y_c + C_c^d o_c] \quad (4.30)$$

subject to:

$$\sum_{e \in \mathcal{L}_h} x_e + Z_h = 1 \quad \forall v \in \mathcal{V}, h \in \mathcal{H}_v \quad (4.31)$$

$$\sum_{e \in n^-} x_e + \sum_{e \in n^+} x_e = S_v^n \quad \forall v \in \mathcal{V}, n \in \mathcal{N}_v \quad (4.32)$$

$$y_c \leq o_c \quad \forall c \in \mathcal{C} \quad (4.33)$$

$$\sum_{e \in \mathcal{L}_{T_c}} O_e^c x_e \leq o_c \quad \forall c \in \mathcal{C} \quad (4.34)$$

$$z_h \leq y_c \quad \forall c \in \mathcal{C}, h \in \mathcal{B}_c \cup \mathcal{I}_c \cup \mathcal{T}_c \quad (4.35)$$

$$x_e \sum_{\sigma \in \mathcal{M}_e^c} x_\sigma \leq 1 + y_c \quad \forall c \in \mathcal{C}, e \in \{L_h | h \in \mathcal{B}_c \cup \mathcal{I}_c \cup \mathcal{T}_c\} \quad (4.36)$$

$$x_e \in \{0, 1\} \quad \forall e \in \mathcal{E}_s \quad (4.37)$$

$$z_h \in \mathcal{R}_+ \quad \forall v \in \mathcal{V}, h \in \mathcal{H}_v \quad (4.38)$$

$$y_c, o_c \in \mathcal{R}_+ \quad \forall c \in \mathcal{C} \quad (4.39)$$

The objective function 4.30 aims to minimize the total cost of reschedule after disruption. There are two terms in the objective function. The first term summarizes all costs associated with operating the vessels at the given speeds. The second term summarizes all costs associated with cargo delay and misconnections. Constraint 4.31 ensures that all scheduled port calls are either called by a vessel or omitted. Flow conservation is ensured by constraint 4.32. A misconnection is by definition also a delay of a container group and hence the misconnection penalty is added to the delay penalty. This is expressed in constraint 4.33.

Constraint 4.34 ensures that  $o_c$  takes the value 1 if container group  $c$  is delayed, when arriving by edge  $e$ . Constraint 4.35 provides that if a port call is omitted which had a planned load or unloading of container group  $c$ , the container group is misconnected. Constraint 4.36 is a coherence constraint

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ensuring the detection of container groups' miss-connections due to late arrivals in transshipment ports. Finally constraint 4.37 ensures binarity for  $x_e$ , while constraint 4.38 and constraint 4.39 provides the remaining variables to be non-negative.

When rescheduling, Brouer et al. (2013) only take the delayed vessel into consideration, and look upon alternative schedules for the given vessel. The schedules of the remaining vessels are taken as given.

Brouer et al. (2013) prove that their formulation is **NP**-hard. However, the model is solved using a MIP solver and computational experiments indicate that the model can be solved within ten seconds for instances corresponding to a standard disruption scenario in a global liner shipping network (Brouer et al., 2013).

Not only Kjeldsen et al. (2012) and Brouer et al. (2013) handle disruptions and rescheduling for a liner shipping fleet. Andersen (2010) mentions disruption management in liner shipping in his work, but only in a paragraph. He states that the method developed in his work is able to solve a network recovery problem. However, this is true only if the disruption has already happened when the recovery problem is solved (Kjeldsen et al., 2012). If the rescheduling starts while a disruption is taking place, or in the preparation for a known future disruption Andersen's solution method cannot be used (Kjeldsen et al., 2012). Anderson's solution method is created to solve the network transition problem, which addresses the process of moving assets from operating an existing service network to a new adjusted service network. Andersen describes the problem in the context of liner container shipping, but it also finds applications in other types of service networks. The paper addresses the problem of transitioning a fleet of vessels from operating one liner based service network to being deployed on another service network while meeting the freight obligations during the period of the transition. To solve the problem he developed a general cooperative adaptive neighborhood search framework (Andersen, 2010).

Anderson develops an LNS heuristic to solve the network transition problem. The large neighborhoods allow for the search of broader regions of the solution space thus mitigating some of the difficulties typically associated with tradition local search. To allow for further diversification of the search, Andersen embeds the LNS in a simulated annealing framework.



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The heuristic receives an initial solution as input and proceeds to initialize the local best solution. In the implementation, each thread receives a different initial solution. A new solution is constructed based on the current active solution. The removal algorithm removes a subset of the currently serviced requests and the insertion algorithm subsequently reinserts these requests.

The destruction methods receive a (possibly partial) solution as input and proceeds to remove assigned requests from the routes according to a predefined procedure. Removed requests are inserted into a pool of unserved requests. The heuristic includes three different destruction methods. Common for all of them is that they only remove assigned requests and never change the initial and final visits of the individual routes. The simplest destruction algorithm is random removal which randomly selects and removes requests from an intermediate solution. The second destruction algorithm is related removal. This selection strategy tries to identify requests that are somehow related measured in terms of the constraints imposed on the assignment of requests to vessels. The last destruction algorithm is subsequent removal. The principle behind subsequent removal is to remove a series of requests related in time.

Once requests have been removed from an intermediate solution, the resulting set of unassigned requests is again reinserted using a series of simple insertion algorithms. Infeasible solutions are allowed during the search. The first repair algorithm is greedy insertion. At each iteration the request that increases the objective value least of all is inserted. The second repair algorithm is randomized greedy insertion. This heuristic randomly selects a request from the set of unassigned requests and determines the best insertion position among the available routes and inserts the request into this position if a valid position exists. The last repair algorithm is regret insertion. A problem with greedy insertion algorithms is its tendency to perform short sighted decisions (Andersen, 2010). When inserting a request, the greedy heuristic only evaluates the best position for all the unassigned requests and inserts the best among those. However, when solving the network transition problem situations where delaying the insertion of a request because it is not currently the best will occur. The regret insertion algorithm tries to mitigate this shortcoming by incorporating a look-ahead mechanism into the greedy insertion algorithm. The main idea is to insert the request that has the worst second best insertion cost relative to the cost of the best insertion of that request. Used on a real life case, the algorithm

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developed by Andersen is able to reduce the total distance sailed with more than 10 % for a fleet with 11 vessels compared with the original schedule (Andersen, 2010).

### 4.1.2 Airline Industry Models

Disruption management is a much bigger field in the airline industry than in the liner shipping segment. The airline industry is one of the most successful examples of applying operations research methods and tools for the planning and scheduling of resources (Clausen et al., 2010). Optimization-based decision support systems have proven to be efficient and cost-saving for the scheduling of aircraft and crew, not to mention the short term re-scheduling problems. In short term re-scheduling problems modifications to the initial plans are required before the final schedules can be executed (Clausen et al., 2010). Disruption management research in the airline industry was in 1984 pioneered by Teodorovic and Guberini (1984). In the article *Optimal Dispatching Strategy on an Airline Network After a Schedule Perturbation* they tried to minimize the total passenger delay when one or more planes were unavailable.

In the review article *Disruption Management in the Airline Industry – Concepts, Models and Methods* written by Clausen et al. (2010) many different disruption management strategies are presented. Disruption management in the airline industry is divided into three parts in this review. The first part focuses on crew recovery, the second on aircraft recovery, and the third on integrated and passenger recovery. There are many possible ways to solve these recovery problems. Often it depends on the objective function and how fast the solution is needed.

If the objective is to minimize the number of cancellations and the solution shall be found within three minutes, Løve et al. (2001) recommended a steepest ascent local search (SALS) or a repeated SALS (RSALS). Løve denotes the set of aircraft nodes  $A$  and the set of flights  $F$ .  $r_f$  is the revenue of flight  $f$ ,  $d_{af}$  is the delay incurred if aircraft  $a$  is assigned to flight  $f$ . There are two cost multipliers:  $\alpha_f$  and  $\beta_f$  that are associated with delay cost and cancelling cost for flight  $f$ . The decision variable is:

$$x_{af} = \begin{cases} 1 & \text{if aircraft } a \text{ is assigned to flight } f \\ 0 & \text{otherwise.} \end{cases} \quad (4.40)$$

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The objective function used by Løve et al. includes three terms, and is as follow:

$$\max \sum_{a \in A} \sum_{f \in \mathcal{F}} r_f x_{af} - \sum_{a \in A} \sum_{f \in \mathcal{F} \setminus \mathcal{F}} \alpha_f DF r_f d_{af} x_{af} - \sum_{a \in A} \sum_{f \in \mathcal{F}} \beta_f DF r_f x_{af} \quad (4.41)$$

The first term is maximizing the total revenue, the second term is to minimize the total cost of delay and the third component is minimizing the cost associated with cancellations. A simplified structure of the SALS algorithm can be seen below.

```

procedure Steepest Ascent Local Search (SALS)
   $x_{af} = \text{InitialSolution}$ 
  repeat
     $x'_{af} = \text{LocalSearch}(x_{af})$ 
     $x_{af} = \text{AcceptanceCriterion}(x_{af}, x'_{af})$ 
  until a better solution cannot be found
end SALS

```

**Figure 4.2: Simplified SALS structure** - (Løve et al., 2001)

The initial solution is the original flight schedule. The local search is initiated by a solution  $x_{af}$  in the form of a flight schedule. A best improvement strategy is chosen so that all the neighbors to  $x_{af}$  are evaluated and the best solution among the neighbors is used as a starting point for the next iteration. If the latest local search iteration yields an improved solution it allows the algorithm to continue. RSALS work the same way as SALS, but is repeated for different initial solutions. SALS is a very fast algorithm and works well when local optimums are close to the global optimum (Løve et al., 2001).

An optimization model for aircraft recovery (ARO) that reschedules legs and reroutes aircraft by minimizing an objective function involving rerouting and cancellation costs are presented by Rosenberger, E. L. Johnson, and Nemhauser (2003). The model is set up like a set-packing problem, in which each flight is either exactly one route or cancelled. Consider a set of aircraft  $A$ , a set of disrupted aircraft  $A^* \subseteq A$ , and a time horizon  $(t_0, T)$ . For each  $a \in A$ , let  $r(a)$  be the initial route of aircraft  $a$ , and let  $F = \cup_{a \in A} r(a)$  be the set of all flights

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in the initial routes. For all  $f \in F$ , let  $b_f$  be the cost of canceling flight  $f$ .  $K_f$  is 1 if flight  $f$  is canceled, and 0 otherwise. For each aircraft  $a \in A$ , let  $\mathcal{R}_{(a,F)}$  be the set of maintenance feasible routes of aircraft  $a$  that can be constructed from flights in  $F$ .  $c_r$  is the cost of assigning route  $r$  to aircraft  $a$ .  $x_r$  is 1 if route  $r$  is assigned to aircraft  $a$ , and 0 otherwise. Let  $\mathcal{U}$  be the set of allocated arrival slots, and  $\mathcal{R}_u$  be the set of routes that include a flight that lands in arrival slot  $u$ .  $\mathcal{C}$  is the set of capacity constraints, for each capacity constraint  $c \in \mathcal{C}$  there is a restriction on the number of landings at a station within a time period to capacity  $\alpha_c$ . Finally, let  $\mathcal{R}_c$  be the set of routes that includes flights that land during the time period of capacity constraint  $c$ , and for each route  $r \in \mathcal{R}_c$ , let  $H(r, c)$  be the set of flights in  $r$  that impact constraint  $c$ . The model is then formulated as follows:

$$\min \sum_{a \in A} \sum_{r \in \mathcal{R}_{(a,F)}} c_r x_r + \sum_{f \in \mathcal{F}} b_f K_f \quad (4.42)$$

subject to:

$$\sum_{r \in \mathcal{R}_{(a,F)}} x_r = 1 \quad \forall a \in A \quad (4.43)$$

$$\sum_{r \ni f} x_r + K_f = 1 \quad \forall f \in \mathcal{F} \quad (4.44)$$

$$\sum_{r \in \mathcal{R}_u} x_r \leq 1 \quad \forall u \in \mathcal{U} \quad (4.45)$$

$$\sum_{r \in \mathcal{R}_c} |H(r, c)| x_r \leq \alpha_c \quad \forall c \in \mathcal{C} \quad (4.46)$$

$$x_r \in \{0, 1\} \quad \forall r \in \mathcal{R}_{a,F}, a \in A \quad (4.47)$$

$$K_r \in \{0, 1\} \quad \forall f \in \mathcal{F} \quad (4.48)$$

The objective function 4.42 has two terms, the first is the cost associated with assigning routes to aircrafts, and the second term is the cost of canceling the unassigned legs. In the model constraint 4.43 and constraint 4.44 ensure that each aircraft is assigned to one route and that each flight is either in a route or canceled. Constraint 4.46 ensure that the passenger capacity is not

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violated. Constraint 4.47 and constraint 4.48 require integral solutions. Set-packing problems are **NP**-hard; to overcome this difficulty an aircraft selection heuristic (ASH) that efficiently determines a subset of aircraft to reroute is developed (Rosenberger, E. L. Johnson, and Nemhauser, 2003).

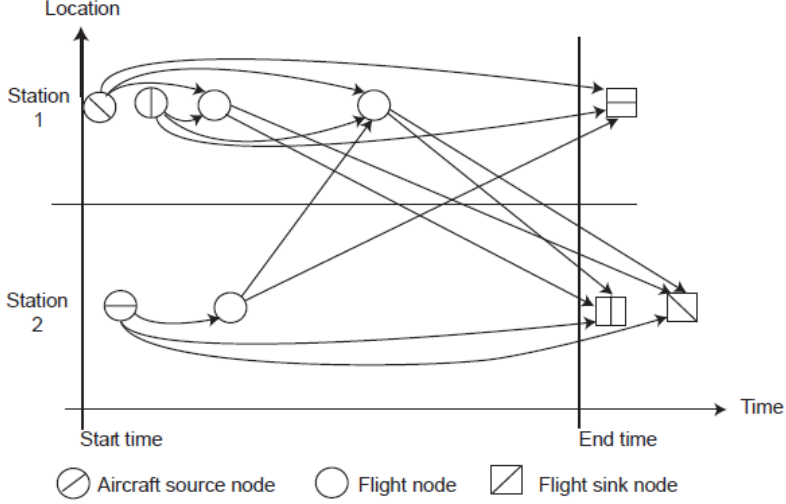
In order to reduce the complexity of ARO, Rosenberger, E. L. Johnson, and Nemhauser (2003) select a subset of aircraft  $A' \subset A$  such that the optimal value of solutions to  $\text{ARO}(A')$  is near optimal value of a solution to  $\text{ARO}(A)$ . For each disrupted aircraft the ASH search for directed cycles with a minimum number of aircrafts. When an efficient number of directed cycles for each disrupted aircraft have been found, ASH returns  $A'$  to ARO.

Andersson and Värbrand (2000) solve the flight perturbation problem. The flight perturbation problem can be briefly stated as: *Minimize the negative consequences of a perturbation that has made it impossible for one or more flights to depart on their scheduled time operated by their originally planned aircraft* (Andersson and Värbrand, 2000). They developed a mixed integer multi-commodity flow model with side constraints. Further, to solve the recovery problem they reformulated the model into a set packing model using the Dantzig-Wolfe decomposition. Their objective was to minimize the number of cancellation and swaps.

Andersson and Värbrand have modeled the network with three different kinds of nodes; aircraft source nodes, flight nodes and flight sink nodes. Every node belongs to a station, in this case an airport. Each aircraft source node represents a specific aircraft and belongs to the airport where the corresponding aircraft is positioned at the start time, or where it will arrive if it is in the air at the start time. All flight nodes and flight sink nodes represent a specific flight, and the position in the network represents the planned departure time and the departure station. In this network the end time often coincides with the end of the day, since there is usually sufficient ground time during the night to cover any delays. The arcs in the network represent feasible connections between sources flights and sinks. When a disruption occurs and a flight arrive late, the source node will appear when the aircraft is available again. A delayed flight departure will cause the associated flight node to appear later in time. To capture and take advance of the network structure, a mixed integer multi-commodity flow formulation is developed by Andersson and Värbrand, and further reformulated into a set packing model.

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**Figure 4.3: Andersson and Värbrand's connection network** - (Andersson and Värbrand, 2000)

Andersson and Värbrand introduce some variables:  $c_{ij}^a$  is the revenue gained if aircraft  $a$  is assigned to flight  $j$  after flight  $i$  and  $c_i$  is the cost per time unit for delaying flight  $i$ . If  $i$  is the correct source node for aircraft  $a$ ,  $s_i^a$  is 1, otherwise it is 0.  $t_i^a$  is 1 if  $i$  is the correct sink node for aircraft  $a$ .  $AD_i$  and  $AA_j$  is respectively the departure and arrival airport for flight  $i$  and  $j$ , while  $TD_i$  and  $TA_j$  is respectively the departure and arrival time for flight  $i$  and  $j$ . Finally  $C^a$  is the capacity of aircraft  $a$ , and  $P_j$  is the number of passengers on flight  $j$ . Two variables are also introduced;  $x_{ij}^a$  is 1 if aircraft  $a$  is assigned to flight  $j$  after the aircraft has operated flight  $i$ , and  $d_i$  that expresses how much the departure of flight  $i$  is delayed. The flight perturbation problem is then formulated as follow:

$$\min \sum_{i \in \mathcal{A} \cup \mathcal{F}} \sum_{j \in \mathcal{A} \cup \mathcal{S}} \sum_{a \in \mathcal{A}} c_{ij}^a x_{ij}^a - \sum_{i \in \mathcal{F}} c_i d_i \quad (4.49)$$

subject to:

$$\sum_{j \in \mathcal{F} \cup \mathcal{S}} x_{ij}^a = S_i^a \quad \forall i \in \mathcal{A}, a \in \mathcal{A} \quad (4.50)$$

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$$\sum_{j \in \mathcal{F} \cup \mathcal{S}} x_{ij}^a - \sum_{j \in \mathcal{A} \cup \mathcal{F}} x_{ij}^a = 0 \quad \forall i \in \mathcal{F}, a \in \mathcal{A} \quad (4.51)$$

$$\sum_{a \in \mathcal{A}} \sum_{j \in \mathcal{F} \cup \mathcal{S}} x_{ij}^a \leq 1 \quad \forall i \in \mathcal{F} \quad (4.52)$$

$$\sum_{j \in \mathcal{A} \cup \mathcal{F}} x_{ij}^a = t_i^a \quad \forall i \in \mathcal{S}, a \in \mathcal{A} \quad (4.53)$$

$$TA_i + TG_{ij}^a + d_i - (TD_j + d_j) + M(x_{ij}^a - 1) \leq 0 \quad \forall i \in \mathcal{A} \cup \mathcal{F}, j \in \mathcal{A} \cup \mathcal{S}, \\ a \in \mathcal{A} \quad (4.54)$$

$$x_{ij}^a (AD_i - AA_j) = 0 \quad \forall i \in \mathcal{A} \cup \mathcal{F}, j \in \mathcal{A} \cup \mathcal{S}, \\ a \in \mathcal{A} \quad (4.55)$$

$$d_i \leq D_i \quad \forall i \in \mathcal{F} \quad (4.56)$$

$$x_{ij}^a P_j \leq C^a \quad \forall i \in \mathcal{A} \cup \mathcal{F}, \forall j \in \mathcal{F}, \forall a \in \mathcal{A} \quad (4.57)$$

$$x_{ij}^k \in \{0, 1\} \quad \forall i, j, a \quad (4.58)$$

$$d_i = 0 \quad \forall i \in \mathcal{A} \cup \mathcal{S} \quad (4.59)$$

$$d_i \geq 0 \quad \forall i \in \mathcal{F} \quad (4.60)$$

The objective function 4.49 in the model has two terms; the first term tries to maximize the revenue, as the second term tries to minimize cost associated with delaying flights. Constraint 4.53 and constraint 4.50 ensure that each airplane starts at the right position and that the aircraft originally assigned to a certain flight sink is the one that will be assigned to it in the solution. There is also a flow conservation constraint(4.51) included in the model. Constraint 4.52 ensures that at most one aircraft can traverse each flight node. If the capacity of the aircraft is less than the number of passengers assigned to a flight the solution is prohibited; this is ensured through constraint 4.57. Constraint 4.54 and 4.55 make sure that the departure time of a given aircraft has to be later than the arrival time plus necessary ground time for the aircraft (Andersson and Värbrand, 2000) .

Further, by using the Dantzig-Wolfe decomposition Andersson and Värbrand reformulate the model into a set-packing model. They define  $R^k$  as the set of feasible solutions for aircraft  $a$  that is not dominated by any other solution,  $r$  is a point in this set.  $b_f^{ar}$  is 1 if flight  $f$  is included in route  $r$  for aircraft  $a$ ,

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otherwise it is zero.  $x^{ar}$  is the binary variable that is one if aircraft  $a$  is assigned to route  $r$ . The revenue parameter  $rev^{ar}$  gives the revenue of assigning aircraft  $a$  to route  $r$ . The set partition model can then be formulated as follow:

$$\max \sum_{a \in \mathcal{A}} \sum_{r \in \mathcal{R}_a} rev^{ar} x^{ar} \quad (4.61)$$

subject to:

$$\sum_{r \in \mathcal{R}_a} x^{ar} = 1 \quad \forall a \in \mathcal{A} \quad (4.62)$$

$$\sum_{a \in \mathcal{A}} \sum_{r \in \mathcal{R}_a} b_f^{ar} x^{ar} \leq 1 \quad \forall f \in \mathcal{F} \quad (4.63)$$

$$x^{ar} \in \{0, 1\} \quad \forall a \in \mathcal{A}, r \in \mathcal{R}^a \quad (4.64)$$

The problem is now represented by a set packing model with a generalized upper bound constraint 4.62, which ensures that each aircraft is assigned to exactly one route. The second constraint 4.63 ensures that each flight is not included in more than one route. The feasible routes in each set  $R^k$  define paths from the aircraft source node to the flight sink node. Each route may include flights that the aircraft was not originally assigned to, and may also include delayed flights. The costs for the swaps and the delays are subtracted from the revenue that the particular route generates. The objective of the model is to pick one route for each aircraft so that the total revenue is maximized (Andersson and Värbrand, 2000).

Andersson and Värbrand solve their SPP model in two different ways. The first approach they are using is branch and bound and thus iteratively solve the LP relaxation of the problem. The second approach they use is to use Lagrangian relaxation and sub-gradient optimization (Andersson and Värbrand, 2000).

In 2009 the French Operational Research and Decision Analysis Society announced a competition to make the best way to re-assign aircraft and passengers simultaneously in case of disruptions, named the Airline Recovery Problem (ARP). The winners were Bisailon and his team. ARP consists in creating a rotation for each aircraft available over the recovery period and in assigning passengers that belong to the itineraries to the scheduled flights. In addition to the flight delays and cancellations forced by the disruptions, one may voluntarily



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delay or cancel additional flights. The assignment of aircraft to flights may be changed and new flights may be created and assigned to available aircraft. All passengers traveling on a flight taking place during the recovery period may be rescheduled on different flights (Bisaillon, Pasin, and Laporte, 2010). Bisaillon et al. developed a large neighborhood search heuristic to solve the ARP. The heuristic alternates between construction, repair and improvement phases. Phase one and two aim to produce an initial solution, while the improvement phase attempts to identify improved solutions (Bisaillon, Pasin, and Laporte, 2010). This large neighborhood heuristic has later been used in rescheduling in liner shipping in events of disruption (Kjeldsen et al., 2012).

There are three types of costs that are considered in the ARP: operating costs, passenger inconvenience costs, and inconsistency costs that are incurred if the positions of the aircraft at the end of the recovery period do not match the planned positions. The objective consists in minimizing a weighted sum of these three types of costs. Two sets of constraints must also be satisfied by any solution: operational constraints related to aircraft assignment and routing, and functional constraints related to passenger assignment. The operational constraints ensure that if an aircraft assigned to a flight is changed, the new aircraft covering the route must belong to the same aircraft family as the one that was originally assigned to the flight. The number of passengers travelling with each aircraft cannot exceed the passenger capacity of the aircraft. Aircraft rotations must ensure that each aircraft visits a specified maintenance station before reaching the maximum allowed number of operation. Rotations must also respect minimum turnaround times and transit times. Finally the operational constraints impose upper bounds on the number of departures and arrivals at each airport. When modifying the passenger itinerary some functional restrictions apply. The new itinerary must have the same final destination as the original one and it cannot start before the planned departure time of the first flight in the original itinerary. Finally, maximum delay at destination cannot exceed a given number of hours (Bisaillon, Pasin, and Laporte, 2010).

The method developed by Bisaillon et al. proceeds in three phases, construction, repair and improvement, which are repeated until a stopping criterion is met. The aim of the first two phases is to produce an initial solution that is feasible with respect to the operational and functional constraints described in the previous section. The third phase then attempts to identify an improved



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step tries to reinsert the sequences that were removed during the construction phase. In the third step the passengers are in focus. The passengers are tried to be accommodated whose itineraries have been cancelled by repeatedly solving shortest path problems. In the improvement phase the solution is tried improved with a simple procedure that considers large changes to the solution. When no further improvements are possible, this phase stops and the algorithm returns to the construction and repair phase to generate new tentative solutions. The improvement phase attempts to delay some flights in the hope of accommodating additional passengers. Again, each aircraft is considered in turn and it is attempted to delay each of its flights by a certain amount of time. The heuristic was to solve the upcoming problems within 10 minutes each. The strength of the algorithm can be explained in part by the fact that it aims to achieve feasibility as quick as possible, and that is executing a very large number of simple and fast moves (Bisaillon, Pasin, and Laporte, 2010).

There are many reasons for rescheduling in the airline industry. One of the most frequent disruptions for airlines is the restriction of maximum number of aircrafts on the ground (MOG) during periods of time at one or more stations. The station capacity that was assumed during the earlier planning phase is no longer available and the airline is forced to reduce the MOG for a particular period of time. This is called the reduced station capacity problem (RSC) (M. Yang, 2007).

M. Yang (2007) aims to solve RSC. He assumes that the following parameters are known: the reduced MOG time period,  $[T_s, T_e]$ , where  $T_s$  is the start time and  $T_e$  is the end time. No more than  $M$  aircrafts are allowed on the ground during the reduced MOG. The time period between the airlines get aware of the MOG,  $T_S$ , and when it is necessary that the original schedule is restored,  $T_E$ , is denoted *recovery window*.

The problem is modeled as a time-space network flow problem with side constraints with two different kinds of arcs; grounding arcs and flight arcs. The grounding arcs start and end at the nodes of the same station indicating the aircraft remaining at the station during the time period. The flight arcs possess start and end nodes at different stations. All arcs are directed downward consistent with the orientation of the time axis. M. Yang (2007) let  $N$  be the set of nodes, where each node  $n$  has an associated station  $s_n$  and time  $t_n$ .  $\sigma_n$  is the flow supply at node  $n$ , and  $\delta_n$  is the flow demand in node  $n$ . The set of

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entering nodes is denoted  $I(n)$ , and the set of leaving nodes is denoted  $O(n)$ .  $S$  is the set of supply nodes,  $D$  is the set of demand nodes and  $R$  is the set of nodes associated with both the reduced MOG time period and the reduced MOG station.  $A$  is the set of arcs, and  $A'$  is the set of arcs associated with recovery window flights.  $C_a$  is the cost of arc  $a$  per unit flow,  $P_a$  is the type of arc  $a$ . Let  $F$  be the set of flights  $f$  and  $F'$  the set of recovery windows flights. The set of flight arcs associated with flight  $f$  is denoted  $G(f)$ .  $\beta_f$  is the cost of cancelling flight  $f$ , while  $\alpha$  is the penalty per aircraft of exceeding MOG. In the mathematical formulation there are three different sets of variables;  $x_a$ , the amount of flow on arc  $a$ ,  $y_f$ , cancellation indicator for flight  $f$  and  $z_n$ , the number of aircraft exceeding the reduced MOG capacity at node  $n \in R$ . The model is formulated as follows:

$$\min \sum_{a \in A'} C_a x_a + \sum_{f \in F'} \beta_f y_f + \sum_{n \in R} \alpha z_n \quad (4.65)$$

subject to:

$$\sum_{a \in O(n)} x_a = \sigma_n \quad \forall n \in S \quad (4.66)$$

$$\sum_{a \in I(n)} x_a = \delta_n \quad \forall n \in D \quad (4.67)$$

$$\sum_{a \in I(n)} x_a = \sum_{a \in O(n)} x_a \quad \forall n \in N \setminus (D \cup S) \quad (4.68)$$

$$\sum_{a \in G(f)} x_a + y_f = 1 \quad \forall f \in F' \quad (4.69)$$

$$\sum_{a \in G(f)} x_a = 1 \quad \forall f \in F \setminus F' \quad (4.70)$$

$$\sum_{a \in I(n)} x_a + \sum_{a \in K(n)} x_a - M \leq z_n \quad \forall n \in R \quad (4.71)$$

$$y_f \in \{0, 1\} \quad \forall f \in F' \quad (4.72)$$

$$x_a \in \{0, 1\} \quad \forall a \in A \quad (4.73)$$

$$z_n \geq 0 \quad \forall n \in R \quad (4.74)$$

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## 4.1 Optimization Models

The objective function (4.65) is to be minimized and has three terms; the first term is the sum of cancellation cost, the second term is sum of delay cost and the last term is the sum of the penalty to the MOG violation. Constraint 4.66 to constraint 4.68 state the flow balance at the supply nodes, demand nodes and the intermediate nodes respectively. Flight coverage is ensured by constraints 4.69 and 4.70. The left hand side of constraint 4.71 consists of three terms, and enforces reduced station capacity. The first term is the sum of flows entering node  $n$ . The second term is the sum of flight arcs entering the nodes which are associated with the same station as node  $n$ , but have times later than node  $n$ , but within the minimum turnaround time. The third term is the reduced station capacity,  $M$ . Constraint 4.72 and constraint 4.73 ensures integer numbers for  $x_a$  and  $y_f$ . Constraint 4.74 ensure that  $z_n$  is greater or equal to zero.

M. Yang (2007) uses a one-pass algorithm to create a route solution from the arc based solution. This solution becomes the initial solution used by a tabu search algorithm. The tabu search algorithm is used to improve the initial solution found (M. Yang, 2007).

In spite of all the research made at the planning level in the airline industry, there has been relatively little work done at the operational level (Petersen et al., 2012). Even though problems at the operational phase are much similar to the problems at planning phase, there are two big differences. The first are the additional operational complexities that arise. For example, suppose an aircraft is approaching its destination but is unable to land because of convective weather. The aircraft may be placed into a holding pattern, requiring additional flying time for the cockpit crew. By the time the aircraft lands, the crew may not be allowed to fly their subsequent leg because they have exceeded their allowed flying time within a 24-hour period, rendering a disruption to the subsequent legs (Petersen et al., 2012).

The second difference is the timing. Most airlines utilize an operations control center (OCC) that provides a centralized decision making environment. Unlike the planning phase in which problems are sometimes made more than a year in advance of operations, OCC coordinators are constrained to making decisions in as close to real-time as possible. Because decisions involving repairing the schedule, aircraft, crew, and passengers are combinatorial in nature, using an optimization-based approach may not be tractable because of the complexity of solving each of these operational problems (Petersen et al., 2012). Petersen

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et al. (2012) define, formulate, solve, and analyze a fully integrated recovery problem in a manner that is amenable to the constraints imposed by an OCC in the paper *An Optimization Approach to Airline Integrated Recovery*. By heuristically reducing the set of disreputable resources that are to be rescheduled, they propose an optimization module that is to reassign the schedule, aircraft, crews, and passengers within a given time horizon.

Petersen et al. (2012) define the *airline recovery problem* to comprise the following four problems:

- *The schedule recovery problem* (SRP) seeks to fly, delay, cancel, or divert flights from their original schedule. We call the solution to this problem the repaired schedule.
- *The aircraft recovery problem* (ARP) assigns individual aircraft routings to accommodate the repaired schedule that are feasible for the constraints imposed by maintenance requirements.
- *The crew recovery problem* (CRP) assigns individual crew members to flights according to the repaired schedule, to satisfy the complex legality requirements.
- *The passenger recovery problem* (PRP) reassigns disrupted passengers to new itineraries that deliver them to their destination.

Instead of a leg-based model, Petersen et al. (2012) utilize flight strings. A flight string is a sequence of flights, with timing decisions, to be operated by the same aircraft.

The size and complexity of the integrated recovery problem most likely precludes the delivery of a globally optimal solution. In order to solve the problem for reasonably large scenarios, careful consideration must be placed on how to limit the size or scope of the problem (Petersen et al., 2012). The goal of Petersen et al. (2012) is to deliver a solution within 30 minutes. There is an inherent tradeoff between solution quality and runtime. A possible method might be to develop a recovery scheme in a two-phased approach that first seeks to recover the schedule, then to recover the other three components taking the repaired schedule as given. Conflicting objectives almost certainly exist between the schedule, crew costs, and passenger delays. Passing a single feasible

schedule is too restrictive with respect to each of the second-stage problems. The approach chosen by Petersen et al. (2012) aims to return a solution that is globally optimal with respect to aggregate passenger delay, meaning passenger assignments are globally optimal over all itineraries and all flight strings.

Because scheduling decisions affect repaired aircraft rotations, crew schedules, and passenger itineraries, a Benders decomposition scheme is employed to decompose the problem. Benders decomposition is a way to split complicated mathematical programming problems into two, and thereby simplifying the solution by solving one master problem and one subproblem. It is commonly used for stochastic two-stage programs with recourse where the problem can be split in the first and second stage problem, but it can be used for deterministic problems too. Originally, Benders decomposition was written to solve integer, non-stochastic programs.

Although the three subproblems are independent of each other, they are solved sequentially. First, the SRP and PRP iterate until the aggregate passenger delay cost is minimal. The ARM is then solved. If the ARP is infeasible, a Benders feasibility cut is added to the rescheduling model. Otherwise, the CRP is then solved. Again, a feasibility cut is added if the CRP is infeasible. Otherwise, a tentative solution is found (Petersen et al., 2012).

### 4.1.3 Railway Models

Other transport segments such as railway and road transportation are also using operational research when dealing with disruption management. The latest review about disruption management in passenger railway transportation is written by Jespersen-Groth, Potthoff, and Clausen (2009). They state that there are many actors belonging to different organizations that play a role in disruption management. The paper describes the different roles and the process they are involved in. In the article the literature discussing disruption management in passenger railway transportation is divided into three main groups. Timetable adjustment is the focus in the first group, the second group focuses on rolling stock, and the last group focuses on crew re-scheduling. There are many different ways to solve disruption management problems in the railway industry.

Huisman (2007) defines and solves the Crew Re-Scheduling Problem (CRSP) for train schedules. This problem aims to repair crew duties because of changes in the underlying timetable and the rolling stock schedule. Huisman (2007) used

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a column generation approach to solve the CRSP. He introduced some terms to be used in his model. A *task* is the smallest amount of work that has to be assigned to a driver, and it has to start and end at a *relief location*. A relief location is a place where a change of driver is allowed. A sequence of tasks on the same rolling stock unit is called a *piece*. A *duty* consists of one or more pieces of work with a minimum connection time between them. Each duty has to follow some rules:

- A duty starts with a sign-on time, which depends on the type of the first task, at the base of the crew member
- A duty ends with a sign-off time at the base of the crew member
- Each piece in a duty should not exceed a maximum length
- A duty should not exceed a maximum length according to the collective labor agreement. This maximum length depends on the start and/or the end time of the duty
- In each duty longer than a certain minimum length, there should be a meal break with a certain minimum length at one of the relief locations with a canteen

The author formulates the problem as a large-scale set covering problem. Let  $N$  be the set of tasks, where  $N^p \subset N$  is the set of passenger tasks, let  $B$  and  $\Delta$  be the set of crew bases and original duties. Furthermore, let  $K^\delta$  be the set of feasible duties which could replace original duties  $\delta \in \Delta$ . The cost of a duty  $k$  corresponds to the original duty  $\delta$  and is denoted  $c_k^\delta$ . The parameter  $b_{ik}^\delta$  is 1 if task  $i$  is a part of the this duty, and 0 otherwise. Finally, the decision variables  $x_k^\delta$  indicate whether duty  $k$  is corresponding to the original duty  $\delta$ . Huisman (2007) formulated the crew re-scheduling problem as follow:

$$\min \sum_{\delta \in \Delta} \sum_{k \in K_\delta} c_k^\delta x_k^\delta \quad (4.75)$$

subject to:

$$\sum_{\delta \in \Delta} \sum_{k \in K_\delta} b_{ik}^\delta x_k^\delta \geq 1 \quad \forall i \in N \setminus N^p \quad (4.76)$$



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## 4.1 Optimization Models

$$\sum_{k \in \mathcal{K}_\delta} x_k^\delta \geq 1 \quad \forall \delta \in \Delta \quad (4.77)$$

$$x_k^\delta \in \{0, 1\} \quad \forall \delta \in \Delta, k \in \mathcal{K}^\delta \quad (4.78)$$

The objective function 4.75 aims to minimize the total cost of all duties. A duty consists of one or more pieces of work for a crew member. Constraint 4.76 in the mathematical model guarantees that every work task is covered by at least one duty. The model also includes constraint 4.77 that ensures that each original duty is replaced by at least one new duty. A column generation based algorithm is used to solve the problem (Huisman, 2007).

The column generation was done in several steps. The first step was to generate duties that looked similar to the original duties, i.e. the alternative duties had to start and end in the same crew bases as the original duties, and the start and end time of the duty should not deviate too much from those of the original duties. The alternative duties were generated by complete enumeration and chosen based on reduced costs. New duties were also found, by solving a pricing problem for the original duties (Huisman, 2007).

When larger disturbances occur in a train or subway network, one of the countermeasures is to take out entire trine lines (Jespersen-Groth and Clausen, 2006). The problem is to decide when the reinsertion shall start on each rolling stock depot in order to resume scheduled service. Each originally scheduled train that is taken out of operation due to disruption must be covered by new train units, and hence reinserted into operation according to schedule. It must also be decided from which depot the train should be reinserted from and when the reinsertion should take place. As the process of resuming service is regulated by a number of constraints, the task of calculation a reinsertion plan becomes complex (Jespersen-Groth and Clausen, 2006). A mixed integer programming model was developed by Jespersen-Groth and Clausen (2006) to minimize the latest time to reinsertion. Each originally scheduled train has to be covered with train units and hence reinserted in operation according to schedule. The variables representing which train to be inserted from which and when are binary.

$$x_{ijk} = \begin{cases} 1 & \text{if train } i \text{ is inserted in time slot } t \text{ from depot } k \\ 0 & \text{otherwise.} \end{cases} \quad (4.79)$$

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Jespersen-Groth et al. introduce  $I$  the set of train that must be inserted,  $K$  as the set of depots they can be inserted from and  $J$  as the set of available slot for reinsertion. The model decides which trains will run, but it does not consider which train units to use to cover the trains. It is assumed that the information of distribution of train units across depots,  $D_k$ ,  $k \in K$  is provided as input and thereby sufficient in number to cover the trains. Terminal depots are denoted  $K_T$  and intermediate depots are denoted  $K_I$ . The intermediate depots are constructed by sets of two depots together denoting one intermediate depot where reinsertion can be carried out in  $l$  where  $l \in L$  is the set of directions. To assure that each train is inserted only once, it is necessary to take into consideration the train sequences of each train describing in which time slot each train is at the different depots. To handle this the constant  $in_{ijk}$  is introduced. To model the order within stations two sets of integer variables are introduced:  $start_k$  and  $end_k$ . Finally, the constant  $c_k$  indicates how many trains has been scheduled at depot  $k$ . The model for optimal reinsertion of cancelled train lines is then formulated as follows:

*min* latest time to reinsertion

subject to:

$$\sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}} x_{ijk} = 1 \quad \forall i \in \mathcal{I} \quad (4.80)$$

$$\sum_i x_{ijk} \leq 1 \quad \forall j \in \mathcal{J}, k \in \mathcal{K} \quad (4.81)$$

$$\sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} x_{ijk} = D_k \quad \forall k \in \mathcal{K}^T \quad (4.82)$$

$$\sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}} x_{ijk} = \sum_{k \in \mathcal{K}} D_k \quad \forall l \in \mathcal{L}, k \in K_l^I \quad (4.83)$$

$$\sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} x_{ijk} = D_k^I \quad \forall k \in \mathcal{K}^I \quad (4.84)$$

$$D_k^I \geq \lfloor \frac{D_k}{2} \rfloor \quad \forall k \in \mathcal{K}^I \quad (4.85)$$

$$D_k^I \leq \lceil \frac{D_k}{2} \rceil \quad \forall k \in \mathcal{K}^I \quad (4.86)$$

## 4.1 Optimization Models

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$$x_{ijk} \leq in_{ijk} \quad \forall i \in \mathcal{J}, j \in \mathcal{J}, k \in \mathcal{K} \quad (4.87)$$

$$start_k + \sum_{i \in \mathcal{J}} \sum_{j \in \mathcal{J}} x_{ijk} - 1 = end_k \quad \forall k \in \mathcal{K} \quad (4.88)$$

$$start_k \geq C_k + 1 \quad \forall k \in \mathcal{K} \quad (4.89)$$

$$start_k \leq j + M(1 - x_{ijk}) \quad \forall i \in \mathcal{J}, j \in \mathcal{J}, k \in \mathcal{K} \quad (4.90)$$

$$end_k \geq j - M(1 - x_{ijk}) \quad \forall i \in \mathcal{J}, j \in \mathcal{J}, k \in \mathcal{K} \quad (4.91)$$

All the trains must be covered exactly once, this is guaranteed by partitioning constraint 4.80. In each depot there are only a given number of available trains; the model ensures through constraint 4.81 that not more than the given number of available trains are inserted from each depot. Constraint 4.89 assures that reinsertion can not begin before a train driver can arrive from the crew depot. Constraint 4.87 ensures that the trains are inserted in a correct time slot, it is necessary to take into consideration the train sequences of each train describing in which time slot each train is at the different depots. Constraint 4.88 connects the end and start variables. When a reinsertion has begun on a depot, constraint 4.90 and 4.91 ensure that it is continuously in adjustment time slots (Jespersen-Groth and Clausen, 2006).

If a disruption occurs, the train driver's schedule needs to recover. To solve this, Rezanova and Ryan (2010) have developed a set partition model. Their solution method is based on solving the LP relaxation of a set partition problem with a dynamic column generation approach with the limited subsequence strategy and an expanding disruption neighborhood (Rezanova and Ryan, 2010). Rezanova and Ryan denote the set of train drivers involved in the recovery  $K$  and the set of trains belonging to the drivers  $N$ .  $P^k$  is the set of feasible recovery duties for a driver  $k \in K$ . Each recovery duty  $p \in P^k$  contains either a subset of train tasks in  $N$  or does not contain any tasks. The cost  $c_p^k$  reflects the unattractiveness of the recovery duty  $p$  for the driver  $k$ . If duty  $p$  is included in driver  $k$ 's recovery schedule the binary decision variable  $x_p^k$  is 1, otherwise it is 0. A binary parameter  $b_{ip}^k$  is used to define whether or not task  $i$  is covered by duty  $p$ . The train driver problem can then be formulated as follows:

$$\min \sum_{k \in \mathcal{K}} \sum_{p \in \mathcal{P}_k} c_p^k x_p^k \quad (4.92)$$

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subject to:

$$\sum_{p \in \mathcal{P}_k} x_p^k = 1 \quad \forall k \in \mathcal{K} \quad (4.93)$$

$$\sum_{k \in \mathcal{K}} \sum_{p \in \mathcal{P}_k} b_{ip}^k x_p^k = 1 \quad \forall i \in \mathcal{N} \quad (4.94)$$

$$x_p^k \in \{0, 1\} \quad \forall p \in \mathcal{P}^k, k \in \mathcal{K} \quad (4.95)$$

The objective function 4.92 aims to minimize the total cost of the recovery solution. In the model constraint 4.93 ensures that each train driver is assigned to exactly one recovery duty in the schedule. Constraint 4.94 provides that each train task is covered exactly once in the recovery schedule (Rezanova and Ryan, 2010).

Rezanova and Ryan solve their problem with branch & price. Branch & price is a method for solving large integer programming problems, where the LP-relaxation of the IP problem is solved with column generation at each node of the branch & bound tree (Rezanova and Ryan, 2010).

### 4.1.4 Other Models

Operational research is also used to solve the vehicle rescheduling problems (VRSP). When a vehicle breaks down on a scheduled trip, one or more vehicles need to be rescheduled to serve that trip and other service trips originally scheduled for the disabled vehicle. Li, Mirchandani, and Borenstein (2009) used a Lagrangean relaxation based insertion heuristic to solve the VRSP (Li, Mirchandani, and Borenstein, 2009).

Mu et al. (2010) use a heuristic with a neighborhood search to solve the vehicle disruption management problem.

Disruption management is also used outside the transportation business. Hall and Potts (2004) are handling disruption management in their article *Rescheduling for New Orders*, that is about machine scheduling. This article considers scheduling problems where a set of original jobs has been scheduled to minimize an objective, when a new set of jobs arrives and creates a disruption. The new jobs have to be inserted into the existing schedule without excessively disrupting it. Two different ways to solve the problem is suggested. The first way to solve the problem is to minimize the scheduling cost of all the jobs, subject to a limit

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## 4.1 Optimization Models

on the disruption caused on the original schedule. It is also possible to solve the problem by introducing and minimizing a total cost objective, which includes both the original cost measure, and the cost of disruption (Hall and Potts, 2004).

Disruption management studies can also be found in project scheduling (Eden et al. (2002) and Zhu, J F Bard, and G Yu (2004)), production planning (J. Yang, Qi, and Gang Yu, 2005) and supply chain coordination ( Xia et al. (2004), Qi, Jonathan F. Bard, and Gang Yu (2004) and Xiao et al. (2005)).

### 4.1.5 Heuristics, Search Methods and Column Generation

When solving optimization problems modeled as networks there are many different heuristics and search methods to use. Some of them are simulated annealing, threshold accepting, the great deluge algorithm, and related Monte Carlo-type optimization algorithms. These heuristics apply ideas of statistical physics and applied mathematics to find near-to-optimum solutions for combinatorial optimization problems. These are all iterative improvement algorithms. They start with an initial configuration and proceed by small exchanges in the actual or current solution to get a tentative new solution. The tentative new solution is evaluated, i.e., its objective function, e.g., its total cost, is computed. Decision rules whether we should accept the rebuilt structure or rather keep the original one should be included. There are also many different decision rules that can be applied. In a random walk every new solution is accepted. The greedy acceptance accepts every solution which is better than the current solution. Simulated annealing procedures accept every better solution and, with a certain probability, also solutions being worse than the current solution. Threshold accepting accepts every solution which is not much worse than the current solution, where “not much” is defined by a threshold. The great deluge algorithm rejects all solutions below a required quality level. It is decided if the tentative new solution is kept as the current solution; in case of acceptance the new solution is taken as the new current solution (Schrimpf et al., 2000).

Simulated annealing and related techniques have in common that a new configuration is generated based on the actual one. No information about former configurations is used (Schrimpf et al., 2000).

Genetic algorithms mostly use different kinds of crossover operators generating children from parent configurations, while evolution strategies concentrate

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on mutations altering a member of the population (Schönenburg, Heinzmann, and Feddersen, 1994)

Tabu search is a memory based search strategy to guide the system being optimized away from parts of the solution space which were already explored. This can be achieved either by forbidding solutions already visited or structures some former solutions had in common, which are stored in a tabu list. This list is updated after each mutation according to some proposed rules, which have to guarantee that the optimization run never reaches a solution which was visited before (Reinelt, Rinaldi, and Michael, 1994).

Searching for backbones compares results of independent optimization runs for equal parts. These parts are supposed to be optimal, i.e. to be parts of the optimum solution. This information is considered in the next series of optimization runs in which these parts remain unchanged. The new solutions are supposed to be better than the previous ones because the optimization could concentrate on parts which are more difficult to solve optimally. This algorithm is repeated iteratively until all optimization runs produce the same solution (Schneider et al., 1996).

In the article *Record Breaking Optimization Result Using the Ruin and Recreate Principle* by Schrimpf et al. (2000) they are introducing a search method called ruin and recreate. The basic element of Schrimpf et al.'s idea is to obtain new optimization solutions by a considerable obstruction of an existing solution and a following rebuilding procedure. According to Schrimpf et al. (2000) it is important to think about the kind and size of the disintegration steps and how to recreate ruined parts. The ruin and recreate method proposes using well-known concepts from simulated annealing and threshold accepting with bold, large moves instead of smaller ones. For “simple structured” problems like the traveling salesman problem there is no real need to use large moves. This because algorithms usually deliver near-to-optimum solutions with very small moves already. Dealing with more complex problems, however, Schrimpf et al encountered in their research difficulties using these classical algorithms. If they were considering wide area networks, or very complex vehicle routing tasks, they faced troubles (Schrimpf et al., 2000).

Complex problems often can be seen as discontinuous: Taking only one step from a solution to a neighbor solution, the heights or qualities of these solutions can be dramatically different, i.e., the landscapes in these problem areas can

## 4.1 Optimization Models

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be very “uneven”. Solutions of complex problems often have to meet many constraints, and it is often even hard to get just allowed solutions. neighbor solutions of complex schedules are usually inadmissible solutions, and it may be very hard to walk in such a complex landscape from one allowed solution to another neighbored allowed solution. Many forms of the classical algorithms try to avoid the admissibility problem by modeling artificial penalty functions, but they can get stuck in solutions which might not be allowed (Schrimpf et al., 2000).

The ruin and recreate principle first ruins a quite large fraction of the solution and then it tries to restore the solution as best as possible. The method shows an important advantage; if a large part of the previous solution is disintegrated, a lot of freedom to build a new solution is created. In this large space of solutions it may be possible to find an improved solution (Schrimpf et al., 2000).

Large Neighborhood Search (LNS) developed by Shaw (1998) is another search method. It works much in the same way as the ruin and recreate method by Schrimpf et al. (2000). LNS is based upon a process of continual relaxation and re-optimization. Shaw demonstrates LNS by solving VRP. Two factors can affect the way in which the search operates: how the set of customer visits are chosen for removal, and the process used to re-insert the visits. Shaw believes in a general strategy for choosing visits to remove by choosing related visits. One criterion for related visits are that the visits that are geographically close to one another will be more related than visits that are more distanced. If visits close to one another are removed from the routing plan together, there is opportunity for interchange of positions and so on. No more customer visits than necessary should be removed from the routing plan, as the re-insertion process is more expensive for larger numbers of visits. Related visits might also have similar allowable visiting hours, or be visited at similar times in the current routing plan. For efficiency, one wants to remove the smallest set that will yield an improvement in the cost when the visits are re-inserted. The main advantage of using LNS is that the addition of side constraints can be handled better than in other methods. A difficulty with problems with many side constraints is that many of the simple move operations will be illegal due to violation of the side constraints. Increasing numbers of side constraints constantly reduce the number of feasible moves. This can make the search difficult, as the search space can become pitted with local minima or even

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disconnected. LNS alleviates this problem somewhat by providing more powerful far-reaching move operators that allow the search to move over barriers in the search space created by numerous side constraints. Evaluation of cost differences can be a time consuming phenomenon in local search techniques. This type of search is very naturally suited to constraint programming technology, which allows very general models of combinatorial problems to be specified (Shaw, 1998).

LNS is used by Kjeldsen et al. (2012), Andersen (2010) and Bisailon, Pasin, and Laporte (2010)

The main aim of an optimization algorithm can either be to achieve a new best solution or to be used in practice. In the latter case a small variance in the (good) results is even more important than the average quality or the best solution that can be found by an algorithm (Schrimpf et al., 2000).

When solving disruption management problems it is important to know if the problem should be solved to optimality, or that the best approach is to find a good solution in a short time. There is a clear trade-off between the solution quality and the computing time (Mu et al., 2010). It is also important to consider the robustness of the model. If the optimization should be a knife-edge solution optimal for one scenario only, or one should optimize on thoughts of several scenarios. The solution will then be a good solution even if some changes occur. Stochastic optimization gives a solution that has the highest possibility to succeed, but not necessary best solution in any scenario (Nowak, 2012).

According to, among others Wilhelm (2002) and Lubbecke and Desrosiers (2005), column generation has proven to be one of the most successful approaches for solving large-scale integer programs.

As shown in section 4.1.2 and section 4.1.3, a much used method to solve disruption management models is the set partition approach with column generation. When using this approach the mathematical model itself becomes small and simple. The set partition model is much simpler to solve than the original problem. The problem gets a simple structure and the LP solution is much closer to the IP solution than for the original problem, this results in a smaller branch and bound tree. With an SPP approach for a transport problem there is a large flexibility in how to generate the routes. It is easier to include restrictions in the route generation than in a mathematical formulation. The route generation and the problem can be fitted together to perform as desired. The drawback with



the SPP method is the complex route generation. To ensure an optimal solution all possible columns have to be generated. In large problems it may be hard to generate all the good routes.

It is almost five decades since Ford and Fulkerson (1958) suggested dealing only implicitly with the variables of a multicommodity flow. This fundamental idea was pioneered by Dantzig and Wolfe (1960). They developed a strategy to extend a linear program column-wise as needed in the solution process.

Wilhelm (2002) describes Type I, II and III column generation approaches. Type I column generation involves using an auxiliary model to generate columns and a restricted master problem (RMP) to prescribe the optimal subset of generated columns. Type II comprises a more sophisticated approach in which the RMP interacts with a priceout problem to select the entering variable at each iteration of the Simplex method. Type III is based on Dantzig–Wolfe decomposition in which one or more subproblems (SPs) are used to generate improving columns for the RMP (Wilhelm, 2002).

In 2005 the review article *Selected Topics in Column Generation* by Lubbecke and Desrosiers (2005) was published. This paper is a survey on column generation biased toward solving integer programs. The paper is divided in two parts. The first part covers the theory that is needed to expose integer programming column generation algorithms. i.e. classical decomposition principles and convexification and discretization approaches for extending the decomposition principle to handle integrality constraints. While the second part is the algorithmic counterpart of the first part. For more about these topics see the review article.

## 4.2 Simulation

One way to verify disruption management plans is to use a simulation model.

Modeling is a constructed representation of a system, or as discussed by Fu et al. (2009), *A scientific model can be defined as an abstraction of some real system, an abstraction that can be used for prediction and control.*

Regarding Anu Maria (1997), a simulation of a system is the operation of a model of the system. Simulation is a widely used power tool that requires a computer to be executed. During the last decades, the rapid development of the computer technology has increased the use of simulation. Currently, there are a multiple number of simulation softwares, but regular script languages such as

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Python, JavaScript may also be applied to develop a simulation (Anu Maria, 1997).

Simulation may be used as a tool to analyze the current or future performance of a proposed or existing system. Instead of executing and observing a real life system, a simulation may be a more feasible and inexpensive solution. One of the drawbacks with a simulation is that the mathematical model may not take into account all the aspects of the reality. A validation of the result may be executed to ensure the model reflects the reality.

A simulation model is a way to examine how a system is handling uncertainty. In a simulation, the system is modeled as if the parameters are known. Then for each uncertain parameter, a value is drawn from its probability distribution. Under that regime, it is possible to analyze how a solution handles uncertainty by collecting statistical data after running a large number of simulations (E.E. Halvorsen-Weare, 2012).

During the development of a mathematical simulation model, one has to classify the model (Angeloudis and Bell, 2011). There are a number of classifications that may be applied, each focusing on different aspects.

*Static or dynamic:* Static models simulate the state of the system independent of time, e.g. a simulation of a structure with a certain load. A dynamic model is dependent of the time, and usually the system is continuously changing over time, e.g. seaport simulation. (Angeloudis and Bell, 2011)

*Timing:* A simulation may be or not be time dependent. There are also some distinctions regarding the time aspect: continuous, discrete time or discrete event (Angeloudis and Bell, 2011). Continuous models simulate the state of a system at any point in time. To calculate this, differential equations with rates of change may be used. In opposite of a continuous model, the evolution of the state of the system in a discrete model happens discretely, time or event driven (Angeloudis and Bell, 2011).

*Deterministic or stochastic:* A simulation may be based on given or stochastic parameters. McCabe (2003) discusses the development of a probabilistic model. The paper is claiming that experts are comfortable estimating the most likely values, but rather uncomfortable estimating the lower and upper limits. McCabe (2003) believes that Monte Carlo Simulations can provide valuable information. The lack of common knowledge about the technique is a major barrier when using the Monte Carlo Simulation (McCabe, 2003).

## 4.2 Simulation

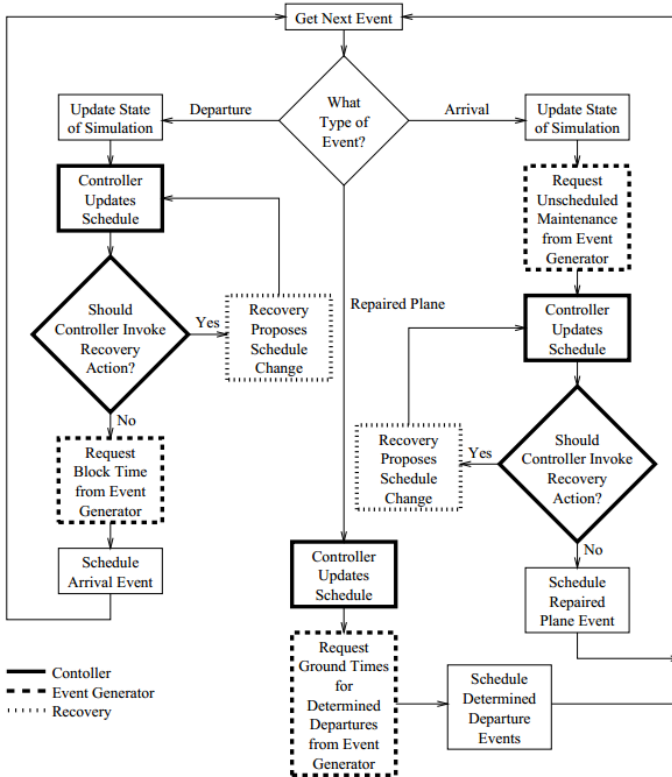
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During a simulation, one has at least one performance measure to calculate the performance of the modeled problem, e.g. factories' profits over a period of time. Most of the simulation optimizations do only have one performance measure, but research for simulation optimizations with multiple performance measures have been done. Rosen, Harmonosky, and Traband (2008) surveys multiple performance measures methodologies and discuss strengths and weaknesses of each.

The airline industry is often using simulation models to verify their optimization models. One of these simulation models, SimAir, was developed and described by Rosenberger, E. L. Johnson, Schaefer, et al. (2002) in the article *A Stochastic Model of Airline Operations* (2002). SimAir is a modular airline simulation that simulates the daily operations of a domestic airline. Its primary purpose is to evaluate plans and recovery policies. SimAir does not explicitly consider the sources for the delays that occur; it is then not necessary to simulate them individually. There is a significant amount of randomness due to mechanical failure and bad weather within airline transportation systems.

SimAir was developed in a flexible modular environment, and consists of three modules. The *Controller Module* determines when a disruption prevents the flights from flying as scheduled. When this occurs, the Controller Module activates the *Recovery Module*. Then the Recovery Module proposes a revised schedule, and the Controller Module can either accept the revisions or request a different recovery proposal. The *Event Generator Module* generates random ground time delays, additional block time delays, and unscheduled maintenance delays. SimAir does not explicitly consider the sources of the delays, it is then unnecessary to simulate them individually. Instead, the Event Generator uses aggregate distributions for additional block time and ground time. The Event Generator generates two random variables for unscheduled maintenance for an aircraft. The first random variable determines whether there is a maintenance delay. If there is a delay, then a second random variable is generated which determines the length of the delay. Both random variables may depend on the aircraft. When a flight is delayed, the Recovery Module need to find a recovery action to respond to the delay. The Recovery Module may use a simple routine which waits for the scheduled planes and crews regardless of their tardiness (Rosenberger, E. L. Johnson, Schaefer, et al., 2002). The structure of the simulation model is presented i figure 4.5.

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**Figure 4.5: Structure of SimAir** - (Rosenberger, E. L. Johnson, Schaefer, et al., 2002)

Simulation has several other applications, e.g. in the recycling industry (Hirsch, Kuhlmann, and Schumacher, 1998), railway industry (Sayarshad and Ghoseiri, 2009), vehicle routing (Tavakkoli-Moghaddam et al., 2011), taxicabs (Grant et al., 1987), fisheries (Hilborn, 1987), and aircraft maintenance (A. P. Johnson and Fernandes, 1978).

Terzi and Cavalieri (2004) have written a survey about simulation in the supply chain. The authors have reviewed over 80 papers. The reviewed papers differs broadly in scope, objectives, processes and morphology.

Gurning and Cahoon (2011) do a simulation of a wheat supply chain be-

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## 4.2 Simulation

tween Australia and Indonesia with extra focus on maritime disruptions. To do the analysis, the Markov chain process is used. A Markov chain contains a set of *states* and *steps* which represents the movement between the same (no movement) or two different states. Each step has a given *transition probability*.

The study by Gurning and Cahoon (2011) assesses four major mitigation strategies (inventory and sourcing mitigation, contingency rerouting, recovery planning and business continuity planning) to determine their suitability for managing potential disruptions in the wheat supply chain. During the period when wheat supply chain plans are in effect, changes in supply chain performance may be identified beyond the assumptions predicted in the planning stage. An objective of the study by Gurning and Cahoon (2011), is to provide a mitigation framework for the maritime service operators when responding to various maritime disruptive events along wheat supply chains. The goal is to alleviate the consequences of disruptions and risks, and then to increase the robustness of a wheat supply chain through the maritime leg.

The Markov chain methodology has been found to be a general tool for modeling network and dynamic maritime disruption systems. This due to its ability to predict precedence, and concurrent and asynchronous events on a mathematical basis. Gurning and Cahoon (2011) creates a four-stage continuous time period Markov chain. This application allows measurement and prediction of supply chain costs and time functions in relation to disruptive events affecting the transportation and distribution processes of millers, wholesalers, and retailers. The four different mitigation approaches (inventory and sourcing, contingency rerouting, business continuity plan and recovery planning) are implemented in the simulation model. The Markov mitigation process by Gurning and Cahoon (2011) works in three steps. First, the event sequence begins with the initial risk state to a disruptive state that may come from one or more potential disruptive events. Secondly, the probabilities of internal stages for each risk event are further approached by using four different stages. The final stage is to obtain the initial probability vector, which represents the possibility of each disruption-state when a mitigating plan is implemented.

By analysing data collected from a maritime disruption survey, the initial probability vector is calculated using formula 4.96 satisfied by the condition in formula 4.97. The overall likelihood of each outcome is determined by multiplying conditional probabilities, the risk level is aggregated along potential

## 4. LITERATURE REVIEW

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consequences as shown in formula 4.96.  $V_{j,i}$  is the mitigation value index for disruptive event type  $j$ , related to scenario  $i$ .  $P_i$  is the probability of scenario  $i$ .  $DM_{j,i}$  is the  $j$ -type mitigated consequences related to the  $i$ -scenario. The potential consequence of selected mitigation  $DP_{j,i,m}$  is determined by comparing the impact areas  $i$ -th to supply chain links.

$$V_{j,i} = P_i DM_{j,i} \quad (4.96)$$

$$DM_{j,i} = \sum_m (DP_{j,i,m} V_{j,i,m}) \quad (4.97)$$

The Markovian-based methodology allows the issues to be addressed in relation to multi-mitigation analysis. The integration and the comparison of each scenario were obtained by considering the effects of each single scenario on different sensitive targets. This is performed by defining a mitigation model and related indicators for assessing the impacts.

In the maritime industry, simulation is used for several different problems. Fagerholt (1999) developed a simulation model to design flexible cargo holds in small sized bulk ships. The purpose of the model is to find the optimal cargo hold configuration. The simulation study was performed with background from a real ship planning problem faced by a major company engaged in production and distribution of various dry bulk products. The company receives cargo requests from their customers. Each cargo request consists of a designated quantity of a particular product to be delivered to a given harbour within a specified time interval.

Because of the characteristics of the various bulk products to be transported, two different cargos cannot be mixed in the same cargo hold. The ships in the fleet are equipped with moveable bulkheads which can be placed in a given number of positions in the cargo hold. In this way, the ships' cargo holds can be partitioned into several smaller holds with flexible sizes so that several cargos can be transported simultaneously by the same ship. A simulation model was developed to find the optimal cargo hold configuration. The simulation algorithm consists of two main steps. The first step is to generate a large number of different cargo sets. The next step of the simulation procedure is to make an optimal location of the moveable bulkheads. i.e. an optimal allocation of the cargos of each set to the nominal compartments for the given cargo

## 4.2 Simulation

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hold configuration. The optimal location of the bulkheads or cargo allocation is defined as the one which maximizes the total tonnage transported by the ship. This procedure is performed for a given number of predefined cargo hold configurations to find the configuration which on average gives the best results. Simulations for nine different cargo hold configurations was performed. 10 000 cargo sets consisting of three cargos and 10 000 sets consisting of five cargos are generated with two different distributions.

Due to great variations on cargo quantities, an optimal cargo configuration may increase the profit. Fagerholt (1999) and his model prove that the potential savings are significant. The results also strongly indicate that configurations with equal-sized nominal compartments give poor results.

Cheng and Duran (2004) simulated the logistics for the global crude oil transportation. To do this, they developed a discrete-event simulator which used the Markov chain queueing process. This model is described more in detail in section 4.3.

There has been done a lot of research on simulation of seaport operations (Angeloudis and Bell, 2011), (Hayuth, Pollatschek, and Roll, 1994), (Yi, S. H. Kim, and N. H. Kim, 2002), (Gambardella, Rizzoli, and Zaffalon, 1998), (Nevins, Macal, and Joines, 1998), (Thiers and Janssens, 1998), (Merkurjevs, 2006). Most of them are developed in the intention of being used as a decision support system during both the tactic and strategic operations of the port. The simulation technology is now considered as an important asset by the operators of the ports. Industrial research is therefore often graded as confidential (Angeloudis and Bell, 2011). Thiers and Janssens (1998) have written a paper that describes the development of a port simulator. The paper describes a simulation which is modeled as a traffic simulation model. In other words, the vessel navigating is treated in the terms of the time required for certain activities. The time perspective is given in discrete time slots, hence, the simulation runs in discrete time. Thiers and Janssens (1998) evaluate different boundaries of the model, both controllable and uncontrollable, which are included in the model. But they simplify their simulation model to be deterministic, apart from the generation of the input data, e.g. harbor time, have stochastic elements. For the harbor time, lognormal and gamma distributions are used, depending on the size and type of the vessels.

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Yi, S. H. Kim, and N. H. Kim (2002) present a paper that describes a method for modeling the dynamic behavior of harbor supply chains. This method may also evaluate strategic and operational policies of the proposed harbor supply chain by applying multi-agent systems and simulation. Multi-agent systems is a collection of computational entities, that have their own problem-solving capabilities and which are able to interact in order to reach an overall goal. The simulation model that is developed is to determine which strategic and operational policies are the most effective in smoothing the variations in the supply chain. The simulation model is developed for berth allocation and crane assignment policies. The berth allocation policies simulate the movement of the ship to the berth and assignment of the ship to the berth. The crane assignment policies simulate the assignment of the cranes to the ship at the berth.

A supply chain is composed of several business entities, they can be viewed as agents. Each business entity has its capability and capacity and can be assigned to or take certain types of tasks. Also these capabilities, capacities and organizational roles can be modeled as agents. Multi-agent systems focus on the coordination and the communication among agents to collaboratively accomplish tasks. Every agent is responsible for one or more activities interacting with other in agents the supply chain, and each agent in the planning executetheir responsibilities.

The multi-agent model contains two kinds of agents: physical agents and logical agents. A physical agent represents objects, such as ships and cranes. A logical agent represents a logical object with a information function, such as scheduling agents and resource agents. The interaction of these agents enables the flow of materials and information within an entity and to other entities that are immediately adjacent to it in the supply chain.

To optimize performance, the supply chain must operate in a coordinated manner and coordinate the revision of plans or schedules across the supply chain. Using Markov decision's recursive relationship, the solution procedure moves backwards period by period until it finds the optimal policy in a given number of iterations.

Yi, S. H. Kim, and N. H. Kim (2002) have studied a harbor supply chain with ten ships, eight berths and sixteen cranes for import and export berth operations. Based on the type of ship, the priority assignment for berth allocation was implemented in order to improve the operations within the studied port. Priority



### 4.3 Simulation and Optimization

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assigned to the ships results in ship turnaround time. The ships that arrive at the port are handled at the appropriate berths. Each berth was allowed at most an allocation of three cranes. The cranes were located in serial order, and were not allowed to cross or overtake each other. The assignment of the cranes to the ship at the berth was based on three different constraints. The first constraint is a fixed crane assignment based on the given priority. The second constraint is a sharing crane assignment. When the ship is berthing, sharing of cranes is allowed only between two berths adjacent to each other. For every ship, at least one crane is available for the loading and unloading activities to begin. The third rule is an available crane assignment based on the adjacent to other berth for loading or unloading.

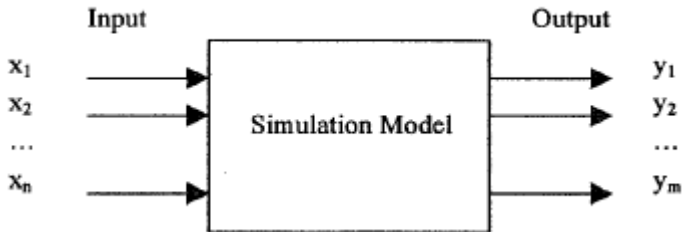
Yi, S. H. Kim, and N. H. Kim (2002) make use of fill rate and on-time delivery for output performance measure, volume and delivery performance measure, flexibility and inventory for flexibility level for resource performance measure.

### 4.3 Simulation and Optimization

April et al. (2003) stated that since the last years of the previous millennium the research on merging optimization and simulation has grown rapidly. The increase of computer processing power is one of the main reasons for this growth, as simulation and optimization both requires huge amounts of calculations (April et al., 2003). April et al. (2003) wrote an article that gives the reader a practical introduction to simulation optimization. They describe optimization of simulation models as “the situation in which the analyst would like to find which of possible many sets of model specifications (i.e. input parameters and/or structural assumptions) lead to optimal performance.” The input parameters and structural assumptions of the simulation model are called factors. The outputs of a simulation model are called responses. The goal of simulation optimization is to find the combination of factors that maximize or minimize the response, often subject to various constraints. Y. Carson and A Maria (1997) define simulation optimization as *the process of finding the best input variable values from among all possibilities without explicitly evaluating each possibility*. They further explain that when the mathematical model of a system is studied using simulation, it is called a simulation model.

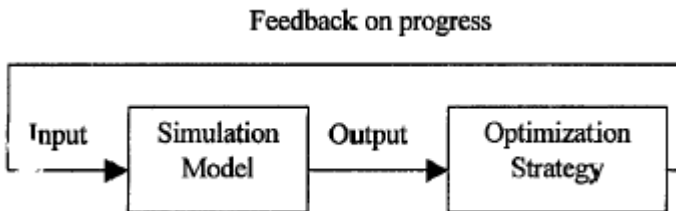
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**Figure 4.6: Simulation model** - (Y. Carson and A Maria, 1997)

Simulation optimization is the process of finding the optimal input variables, i.e.  $x_1 \dots x_n$ , which optimizes the output variables  $y_1 \dots y_m$ . A simulation optimization model is shown in figure 4.7 below. The simulation is run with a first set of input variables. The output is then used by an optimization strategy to provide feedback on the progress of the search for the optimal solution. This in turn guides further input to the simulation model (Y. Carson and A Maria, 1997).



**Figure 4.7: Simulation optimization model** - (Y. Carson and A Maria, 1997)

Fu (2002) distinguishes between simulation for optimization and optimization for simulation. Simulation for optimization refers to a stochastic programming approach where a Monte Carlo scenario generator is an add-on. This Monte Carlo add-on generates scenarios for the mathematical programming formulation. Optimization for simulation refers to a situation where an optimization subroutine is an add-on that generates candidate solutions to a discrete-event simulator.

### 4.3 Simulation and Optimization

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Simulation and optimization together is used in many different areas of research. Zeng and Z. Yang (2009) are using simulation and optimization to schedule loading and unloading of containers in container terminals. The paper *Integrating simulation and optimization to schedule loading in container terminals* (Zeng and Z. Yang, 2009) states that operation of container terminals are a too complex problem to be solved analytically and by a mathematical program alone. Instead of an analytical solution method the authors combine simulation and optimization. The main disadvantage in simulation optimization modulating is that running the simulation model is computationally expensive (Zeng and Z. Yang, 2009). To increase the computation efficiency the authors design a surrogate model to filter out obvious bad solutions.

The supply vessel planning problem consists of determining the optimal fleet size and mix of supply vessels and the corresponding weekly voyages and schedules. E Halvorsen-Weare and Fagerholt (2011) used simulation and optimization to address the problem of creating robust schedules to the supply vessel planning problem. The study is done on a real planning problem faced by Statoil, who with their current supply service is highly affected by weather conditions. Operators of offshore oil and gas installations need to have a reliable supply service. Temporarily shut-downs may in worst case be the result of interruptions of such services, which again will result in lost income.

The objective of Halvorsen-Weare and Fagerholt's study is to create more robust solutions to the supply vessel planning problem. Robustness is here the capability for a voyage or schedule to allow for unforeseen events during execution. To solve the supply vessel planning problem, Halvorsen-Weare and Fagerholt use a mathematical formulation for the voyage based solution method developed in *Fleet size and mix and period routing of offshore supply vessels* (E. E. Halvorsen-Weare et al., 2010). Several constraints are implemented to take into account the weather impact and robustness of the solutions. The prevailing weather conditions will affect the supply vessels' sailing speed and the unloading and loading operations at the offshore installations. This again may have severe consequences for the offshore supply service, especially in the North Sea during the winter season. The critical factor is the significant wave height (E Halvorsen-Weare and Fagerholt, 2011).

E Halvorsen-Weare and Fagerholt (2011) let  $V$  be the set containing the supply vessels available for time charter, and let  $N$  be the set of offshore instal-

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lations.  $R_v$  is defined as the set of pre-generated voyages that vessel  $v \in V$  may sail.  $T$  is the set of days in the planning horizon, and  $L$  is the set containing all possible voyage duration in days.  $H$  is the set with all possible visit frequency values. Then set  $R_{vl}$  contains all candidate voyages of duration  $l \in L$  that vessel  $v$  may sail, and set  $N_k$  contains all offshore installations that require  $k \in H$  visits per week. There are some costs related to sailing and operational the vessels. The weekly time charter cost for vessel  $v$ ,  $C_v^{TC}$ , and the sailing cost for vessel  $v$  sailing voyage  $r \in R_v$ ,  $C_{vr}^{TC}$ .  $D_{vr}$  is the duration of voyage  $r$  sailed by vessel  $v$ .  $S_i$  is the required weekly visit frequency to offshore installation  $i$ . Further, Halvorsen-Weare and Fagerholt let  $F_v$  be the number of days vessel  $v$  can be used during a week, nad  $B_t$  be the number of supply vessels that may be serviced at the onshore supply depot on day  $t \in T$ . The binary parameter  $A_{vir}$  is 1 if vessel  $v$  visits offshore installation  $i$  on voyage  $r$ , and 0 otherwise.  $G_k \in [0, |T|]$  is a number representing the length of a sub-horizon for the offshore installations with visit frequency  $k$ .  $\underline{P}_k$  and  $\overline{P}_k$  are lower and upper bounds on the number of visits during the sub-horizon of length  $G_k$  an offshore installation with visit frequency  $k$  should receive. Finally, there are two binary variables. First,  $x_{vrt}$  that equals 1 if vessel  $v$  sails voyage  $r$  on day  $t$ , and 0 otherwise. Second,  $\delta_v$  that equals 1 if supply vessel  $v$  is chosen for time charter. The supply vessel planning problem can then be formulated as follows.

$$\min \sum_{v \in \mathcal{V}} C_v^{TC} \delta_v + \sum_{v \in \mathcal{V}} \sum_{r \in \mathcal{R}_v} \sum_{t \in \mathcal{T}} C_{vr}^S x_{vrt} \quad (4.98)$$

subject to:

$$\sum_{v \in \mathcal{V}} \sum_{r \in \mathcal{R}_v} \sum_{t \in \mathcal{T}} A_{vir} x_{vrt} \leq S_i \quad \forall i \in \mathcal{N} \quad (4.99)$$

$$\sum_{r \in \mathcal{R}_v} \sum_{t \in \mathcal{T}} D_{vr} x_{vrt} - F_v \delta_v \leq 0 \quad \forall v \in \mathcal{V} \quad (4.100)$$

$$\sum_{v \in \mathcal{V}} \sum_{r \in \mathcal{R}_v} x_{vrt} \leq B_t \quad \forall t \in \mathcal{T} \quad (4.101)$$

$$\sum_{r \in \mathcal{R}_{vl}} x_{vrt} + \sum_{r \in \mathcal{R}_v} \sum_{v=1}^{l-1} x_{vr,((t+v) \bmod |\mathcal{T}|)} \leq 1 \quad \forall v \in \mathcal{V}, t \in \mathcal{T}, l \in \mathcal{L} \quad (4.102)$$

### 4.3 Simulation and Optimization

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$$\underline{P}_k \leq \sum_{v \in \mathcal{V}} \sum_{r \in \mathcal{R}_v} \sum_{v=0}^{G_k} A_{vir} x_{vr, ((t+v) \bmod |\mathcal{T}|)} \leq \bar{P}_k \quad \forall k \in \mathcal{H}, i \in \mathcal{N}_k, t \in \mathcal{T} \quad (4.103)$$

$$\delta_v \in \{0, 1\} \quad \forall v \in \mathcal{V} \quad (4.104)$$

$$x_{vrt} \in \{0, 1\} \quad \forall v \in \mathcal{V}, r \in \mathcal{R}_v, t \in \mathcal{T} \quad (4.105)$$

The objective function 4.98 has two terms, and minimizes the sum of time charter cost and the sailing cost. Constraint 4.99 ensures that all offshore installations get the required number of visits each week. Constraint 4.100 ensures that a vessel is not in service more than it is available during the week. Constraint 4.99 and constraint 4.100 together ensure that  $\delta_v$  equals 1 if a vessel is in service. The number of vessels to be serviced at the onshore depot on a given week day is limited by constraint 4.101. Constraint 4.102 ensures that a vessel does not start a voyage before it has returned to the onshore supply depot. Constraint 4.103 spread the visits to the offshore installations evenly throughout the week. Constraint 4.104 and constraint 4.105 ensures the binary requirements for the variables.

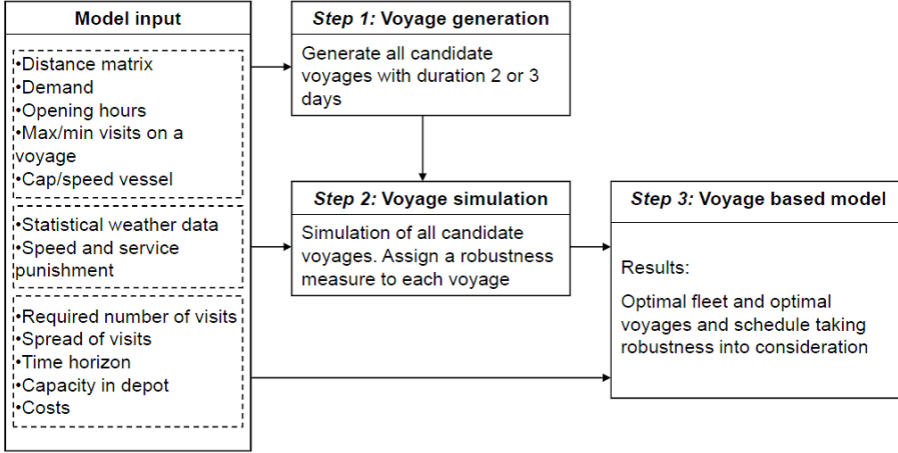
The solution method developed combines optimization and simulation to provide robust schedules to the supply vessel planning problem. It is a three-step model that uses voyage generation and voyage simulation to return an optimal fleet and optimal voyages and schedules. First all candidate voyages are generated, then in the second step each candidate voyage are simulated and a robustness measure is assigned. In the final step, the voyage based model with robustness measures assigned to each voyage is solved. The model is presented in figure 4.8.

Statistical data about the uncertain elements of the problem, e.g. weather data, is used in the second step to calculate a robustness measure for each candidate voyage. The robustness measure used is not delivered volume. This is then used to create a robust weekly schedule for the supply vessel planning problem by giving it a cost in the objective function in the voyage based model. Figure 4.9 shows a flow chart of the simulation procedure.

For each simulation, a set of consecutive weather states are drawn from their respective probability distributions. Each weather state has a given start state probability. The next weather state will be dependent only on the current weather state, a random process recognized as a Markov chain. When the

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**Figure 4.8: Robust supply vessel planning** - (E Halvorsen-Weare and Fagerholt, 2011)

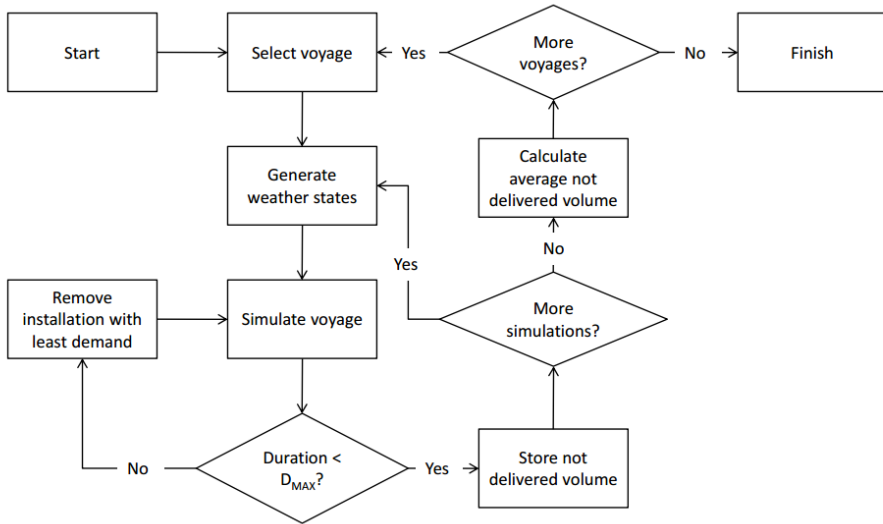
weather states are drawn, a voyage is simulated according to the necessary reduction in sailing speed and increase in service times the prevailing weather state demands. If the voyage cannot be completed within the maximum duration of that voyage, the offshore installation with the least demand is removed from the voyage. This process continues until the voyage can be completed. Then the total cargo volume not delivered, calculated as the sum of the cargo volume from the removed offshore installations, is stored and a new simulation is started. The average cargo volume not delivered over all simulations for each voyage is the output from the simulation procedure (E Halvorsen-Weare and Fagerholt, 2011).

The objective function 4.98 is then replaced with:

$$\min \sum_{v \in \mathcal{V}} C_v^{TC} \delta_v + \sum_{v \in \mathcal{V}} \sum_{r \in \mathcal{R}_v} \sum_{t \in \mathcal{T}} C_{vr}^S x_{vrt} + \sum_{v \in \mathcal{V}} \sum_{r \in \mathcal{R}_v} \sum_{t \in \mathcal{T}} C^P E_{vr} x_{vrt} \quad (4.106)$$

$E_{vr}$  is the average demand not delivered for voyage  $r$  sailed by vessel  $v$ , and  $C^P$  is the penalty cost for each square meter cargo not delivered. The penalty cost is estimated based on the real cost of not delivered volume: This volume

### 4.3 Simulation and Optimization



**Figure 4.9: Flow chart of the simulation procedure - (E Halvorsen-Weare and Fagerholt, 2011)**

has to be delivered at a later time. Either by one of the vessels in the fleet, a vessel that are to be chartered in on short term at a higher costs, or by helicopter at a much higher cost. Based on the simulation procedure described above, a schedule simulation model was developed to test the different schedules after using various solution approaches. In the schedule simulation model, a sequence of weather states for the whole time period of a schedule is drawn. Then every voyage sailed in the schedule is simulated. Extra slack, in form of idle days for supply vessels, is added to the voyage sailed before such an idle day, giving the voyage 24 hours (or more) of extra slack. The overall average square meters of cargo not delivered is then calculated and multiplied by the penalty cost (E Halvorsen-Weare and Fagerholt, 2011).

Cheng and Duran (2004) addressed the design and control of the inventory/transportation system in a global crude supply chain in the oil industry, and proposed a decision support system based on simulation and optimization. A unifying simulation framework that integrates the simulation model and the controller is constructed to simulate the controlled inventory/transportation

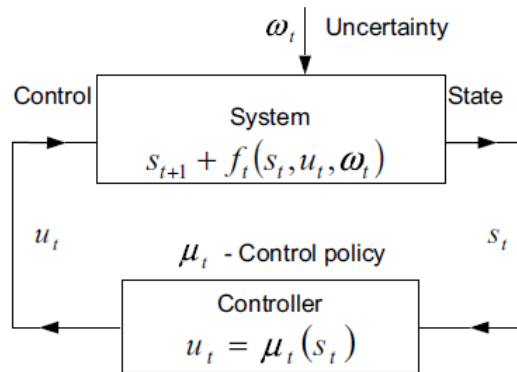
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system. It provides the decision makers valuable insights into the behavior of the dynamic and stochastic system. It is also a powerful tool used to evaluate various strategies for the design and operation of the system. The decision support system was based on the integration of discrete event simulation and stochastic optimal control of the inventory/transportation problem. They identified two crucial characteristics of the combined inventory and transportation system:

- The system was *dynamic* as the state of the system changes over time
- The system was *stochastic* as there were so many uncertainties in some elements in the system, e.g. crude prices and demand

In their studies only crude demand and tanker travel time was considered uncertain. They considered only one central supply location and four major demand regions around the world. There were one or more routes from the supply location to the different demand locations. Cheng and Duran formulated a simulation model that described the complexity of a real problem. The simulation model could then be used to study *what if...* scenarios. The main parts of their simulation model are shown below.



**Figure 4.10: Simulation model of logistics for world-wide crude oil transportation using discrete event simulation - (Cheng and Duran, 2004)**

At a specified point in time the controller observes the state of the system. Based on this state, the controller chooses a control action. The action then



### 4.3 Simulation and Optimization

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results in either a reward or a cost, and the system evolves into a new state, which then again requires a new control action. A typical action could be to charter in an extra ship. The optimal problem is then to find a sequence of control actions such that total expected cost is minimized.

Because of the system's complexity, the number of all possible configurations would be around  $2.58 * 10^{520}$ . In order to solve the problem to optimality, the cost of each possible state has to be calculated. The large amount of computing resources required renders the control problem not possible to solve within a reasonable amount of time. Cheng and Duran therefore proposed an approximation architecture to approximate the expected total cost. The approximation architecture was similar to the one developed by Kleywegt (2002). This was a two-stage method, first decomposing the whole system into several subsystems, and then approximating the cost of each sub problem using a linear function approximator.

To compute the simulation model, they first implemented the approximation algorithm in MATLAB. They found that MATLAB did not calculate efficiently enough for the model to be used on an industrial sized problem, and further work on the computational platform and/or approximate schemes was still required.

(Crary, Nozick, and Whitaker, 2002) have produced a paper that aims to find the optimal fleet size and mix for the US destroyer fleet. The authors have used analytical hierarchy process (AHP) to gather expert opinions and then created distributions used in a simulation.

A possible war has been divided in five missions,  $m$ , and four phases,  $p$ . Given this structure the probability to win the war is defined as:

$$P(\text{winning the war}) = \sum_{p,m} W_p C_{mp} X_{mp} \quad (4.107)$$

$W_p$  is the importance of phase  $p$ ,  $C_{mp}$  is the importance of mission  $m$  in phase  $p$  and  $X_{mp}$  denotes the effectiveness of the fleet at mission  $m$  during phase  $p$ .

15 senior officers in the Navy and Air Force have compared each mission pairwise against the other missions in terms of importance for winning the war. The result for the AHP is used to create a Dirichlet distribution that is a multivariate generalization of the Beta distribution. Crary, Nozick, and

#### 4. LITERATURE REVIEW

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Whitaker (2002) then use this distribution to simulate different scenarios of importance.

An optimization model (MIP) is then developed and solved multiple times, each time with different scenario of importance, and with a fixed fleet size and mix to find the probability to win the war. The probability for each size and mix are then compared and the best configuration is found.

## 5

# Maritime Transport

Maritime transport is the major channel of international trade. Measured by weight, more than 80 % of world trade is carried by seagoing vessels. There has almost been a doubling in transport volume since 1990 (IMO et al., 2009). The shipping industry almost has monopoly on transportation of large volumes of cargo among the continents. The only competitor is pipelines, but they can only move fluids (Christiansen, Fagerholt, Nygreen, et al., 2007).

Compared with the other transport modes maritime transport is a low speed, high volume transport. The characteristics that differ from the other transport modes are continuous voyages with no general brakes, long roundtrip times, repositioning take a considerable amount of time, large costs in ports and port facilities (Nowak, 2012).

Other features that are characteristic for maritime transport are that ships do not return to an origin or a hub, that ships can transport multiple products at the same time, vessel-port compatibility may depend on the load due to the draft and a larger operational uncertainty (Christiansen, Fagerholt, and Ronen, 2004). Sea transport is probably the least regulated mode of transportation because the vessels usually operate in international water, and few international treaties cover their operations (Christiansen, Fagerholt, Nygreen, et al., 2007).

There are three basic modes of operations of commercial shipping; tramp, industrial and liner shipping (Lawrence, 1972). A vessel is engaged in the tramp trade if it does not have a fixed schedule or published ports of calls. Tramp ships are trading on the spot market; they follow the available cargoes, much similar

## 5. MARITIME TRANSPORT

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to taxies. Tramp ships often engage in contracts of affreightment. Contracts of affreightment are contracts where specified quantities of cargo have to be transported within specified time windows for an agreed payment. Typical tramp vessels are tankers and dry bulk carriers. Freight rates are influenced by supply and demand. Ship owners that own tramp vessels try to maximize the profit per time unit (Christiansen, Fagerholt, Nygreen, et al., 2007). In industrial shipping the cargo owner also own the ships that transport the cargo. Industrial operators try to minimize the cost of shipping their cargoes. Industrial operators are usually more risk averse than average (Christiansen, Fagerholt, Nygreen, et al., 2007).

### 5.1 Liner Shipping

Liner shipping is based on fixed and published schedules, and is often operated on cyclic routes. Liner shipping is operated similar to a bus line. Within the class of liner shipping there is a distinction between short sea and deep sea operations. Short sea vessels often service both intra-region freight and provide feeder service for the deep sea vessels. Deep sea vessels handle the main haul, typically over a longer distance. Liner shipping operators usually control container vessels and general cargo vessels. (Andersen, 2010).

Liner shipping vessels carry about 60 % of all goods measured by value moved internationally by sea every year. Around 80 % of liner vessels are container vessels (Worldshipping, 2012).

Schedules for the coming period are published by the liner shipping companies; they specify every voyage on the routes. A voyage includes a time window in which a vessel starts its voyage from a given port. All voyages have an estimated duration until it reaches the last port call. The estimated duration includes both the sailing time and the time spent in the ports (Fagerholt, Johnsen, and Lindstad, 2009).

Liner services involve higher fixed costs and administrative overhead than tramp and industrial shipping. This is because liner vessels depart on fixed schedules regardless of whether the ship is fully loaded or not. Tramp ships may wait in port until they are fully loaded. In liner shipping, given a set of ports, a fleet of ships, and a set of cargo to be delivered, the service network is designed by creating the ship routes, i.e., the sequence of port visits by the given

## 5.1 Liner Shipping

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fleet of ships. In general, it is assumed that the ships move in cycles, referred to as service routes, from one port to another following the same port rotation for the entire planning horizon. The service network is utilized to deliver the profit-maximizing cargo. Carriers decide which cargo to accept or reject for servicing and which paths to use to deliver the selected cargo. The cargo is allowed to travel on ships on several routes before reaching its final destination (Agarwal and Ergun, 2010).

Liner shipping expanded from transporting 5,1 % in 1980 to 25,4 % in 2008 of the world's dry cargo transported by sea. This is mainly a result of a huge growth in volume of container carriers in liner shipping. Transported volume has increased by 600 % the last 20 years (UNCTAD, 2011).

### 5.1.1 RoRo Vessels

Roll-on/roll-off (RoRo) ships are designed to transport wheeled cargo. Typical cargos are cars, trucks, buses, construction equipment, railway wagons and heavy machinery driven on board on their own wheels. RoRo vessels have built-in ramps which allow the cargo to be efficiently driven on and off the vessels. The ramps can be placed in the bow, in the stern or at the side and a vessel may have more than one ramp to make the loading and unloading more efficient. There are many different types of RoRo vessels; ferries, cargo ships and barges. New build cars are usually transported on pure car carriers (PCC) and pure car truck carrier (PCTC) that are large RoRo vessels. The PCTCs have adjustable decks to increase vertical clearance and decks that are designed to withstand heavy cargo. Wilh. Wilhelmsen's MV Tønsberg is a ship in the new Mark V class, which is the largest RoRo class ever built, with a capacity of 8 000 cars.

Within the RoRo segment of the liner shipping industry, routes are not required to be closed loops. Vessels do not have to operate on the same route all the time, as it is usual for container vessels (Kjeldsen et al., 2012). For companies involved in the RoRo business, it is often desired to secure long term contracts with manufacturers that produce cars, trucks, rolling equipment and other cargo that can be transported.

Höegh Autoliners, NYK line, Mitsui O.S.K Lines, EUKOR Car Carriers and WWL are examples of companies operating in the RoRo segment.

Below is the world's RoRo fleet presented in table 5.1. From the table it is possible to see that most RoRo vessels are small. However, the vessels that are

## 5. MARITIME TRANSPORT

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**Figure 5.1: Sideview of the Mark V class - Wilh. Wilhelmsen (2013)**

larger than 25 000 dwt have a total capacity that exceed the capacity of the small vessels.

Cars and other wheeled cargo can be containerized and transported with container vessels. The RoRo vessel industry must improve continuously to maintain its position as the dominating transport mode for rolling cargo (Øvstebø, Hvattum, and Fagerholt, 2011b). Both RoRo vessels and container ships are operated in the liner shipping segment. Container vessels often operate on routes that are closed loops, in contrast to RoRo vessels. The world's container ship fleet is twice as big as the RoRo fleet measured in number of ships, and measured in dwt the container fleet is five times larger (Lindstad, Asbjørnslett, and Pedersen, 2012). This difference in fleet size is a threat for the RoRo industry; the container shipping segment can obtain a more efficient short sea feeder traffic out and in of the ports. Most research in the liner shipping segment has been done with respect to container vessels due to the large share of cargo transported by container ships.

One major difference between a RoRo vessel and a container ship is the loading and unloading process and the port facilities needed. RoRo vessels are equipped with one or more ramps which most of the cargo can use to load and unload; there is no need for advanced and expensive port facilities. Container

## 5.2 Maritime Transport vs. Air, Road and Railway Transport

Vessel size [1 000 dwt]	Number of ships	Average dwt	Average net pay load capacity [ton]	Average distance per voyage [nm]	Average speed [knot]	Days per voyage
35 -	20	44 603	38 000	8 500	18	31
25 -35	49	28 403	24 000	4 000	19	18
15 -25	360	18 565	15 600	1 500	19	10
5 -15	678	9 844	8 100	700	18	6
0 - 5	1 303	1 292	1 000	300	12	3

**Table 5.1: The world's RoRo fleet (Lindstad, Asbjørnslett, and Pedersen, 2012)**

ships need large specialized cranes, and equipment to move the containers in the port.

## 5.2 Maritime Transport vs. Air, Road and Railway Transport

There are many differences and similarities between the maritime transport segment and other transport modes.

Compared with maritime transport, air transport is organized as a liner service. For high speed intercontinental transport, air transport is the mode of choice, but the limited capacity and high cost means it is mostly used to carry low volume and time sensitive cargo, like packages and mail. However, airplanes mostly carry passengers. The usual network configuration is the hub and spoke where each destination is served by a flight from and to the hub. Daily routes take the form of a shuttle service. Fixed charter routes and non-daily routes are scheduled end-to-end. In the airline industry all is happening much faster than in the maritime transport industry, and the airline companies have usually some spare planes to replace delayed or broken down planes. Usually there is a time of the day where most airplanes are not used. Due to these facts and due to the

## 5. MARITIME TRANSPORT

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high speed, the repositioning can be done within hours (Nowak, 2012). Both airplanes and ships require large capital investments, they both pay port fees, and need port facilities (Kjeldsen et al., 2012).

Road transportation is organized the same way as tramp or industrial shipping. Trucks are flexible, relatively fast, and can reach most locations, but they have limited capacity and are relatively costly (Andersen, 2010). Compared with maritime, air and railway transportation the investment costs are low, but the operating and labor costs are high. The main advantage for road transport is the possibility for door to door service. Time windows mainly exist for ferry services, and pick-up and delivery. For the drivers there are limitations on work hours. The road transport is divided into two main groups; long hauls and local distribution (Nowak, 2012).

Railway transport operates in the same way as liner shipping or industrial shipping companies. Railway transport competes with long haul road transport with respect to general cargo, but the railway transport needs road-based in- and out haul. Trains can carry large volumes of cargo, but suffer from rigid, limited infrastructure and slow service, and it is limited to operating on the same continent. This transportation mode requires less moving personnel, but need additional personnel operating the infrastructure. The infrastructure is limited and access to it is given on a schedule basis. The trains have their own dedicated right of way, and cannot pass each other except for at specific locations. Like in the maritime transportation, there are usually no breaks in the railway cargo transportation (Nowak, 2012).

One major difference between the transportation at sea and transport by trains is that for trains the power unit is not an integral part of the transportation unit. In addition, by adding rail cars the transportation unit size for trains can be enlarged which is not possible for ships (Kjeldsen et al., 2012).

The differences between the transport modes are presented in table 5.2 below, provided by Christiansen, Fagerholt, and Ronen (2004).



## 5.2 Maritime Transport vs. Air, Road and Railway Transport

Operation characteristic	Sea transport	Air transport	Road transport	Railway transport
Fleet variety	Large	Small	Small	Small
Power unit is an integrated part of the transport unit	Yes	Yes	Often	No
Transportation unit size	Fixed	Fixed	Usually fixed	Variable
Operating around the clock	Usually	Seldom	Seldom	Usually
Voyage length	Days or weeks	Hours or days	Hours or days	Days
Operational uncertainty	Larger	Larger	Smaller	Smaller
Right of way	Shared	Shared	Shared	Dedicated
Port fees	Yes	Yes	No	No
Route tolls	Possible	None	Possible	Possible
Destination change while underway	Possible	No	No	No
Port period spans multiple operational time windows	Yes	No	No	Yes
Vessel-port compatibility depends on load weights	Yes	Seldom	No	No
Multiple products shipped together	Yes	No	Yes	Yes
Returns to origin	No	No	Yes	No

**Table 5.2: Comparison of operational characteristics of freight transport nodes (Christiansen, Fagerholt, and Ronen, 2004)**

## 5. MARITIME TRANSPORT

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## 6

# Optimization Research in Maritime Transport Industry

The maritime business environment has changed in the last decades, the industry has been more globalized and there is tougher competition from other transport segments. Despite for this the business methods of many shipping companies are not changing. As mentioned in the introduction, shipping companies are often conservative, low risk family businesses. As a result, several companies still rely on intuition and experience when doing strategic, tactical and operational planning (Christiansen, Fagerholt, Nygreen, et al. (2007), Ronen (1983)).

Christiansen, Fagerholt, Nygreen, et al. (2007) state four reasons for the low attention drawn in the literature by maritime transportation planning problems. The first reason is the low visibility. In most areas people see aircrafts, vehicles and trains, but not ships. Furthermore, research is often financed by large organizations. The majority of these organizations operate fleets of vehicles, but few operate ships. The second reason is that maritime transportation planning problems are often less structured than for the other transport segments. In maritime transportation planning, there is a much larger variety in problem structure and operation environment than in other transport segments. This makes the decision support systems more expensive because they need to be more customized. Over the last years more attention has been drawn to more complex problems in transportation planning in general, this is also demonstrated by the

## 6. OPTIMIZATION RESEARCH IN MARITIME TRANSPORT INDUSTRY

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maritime transportation. The third reason is that there is a high degree of uncertainty in maritime operations. Ships may be delayed due to among others bad weather condition, mechanical problems or increased port time. Due to the high cost, minimal slack is built into the schedules. This results in a frequent need of rescheduling. Compared to vehicles, ships usually have a long life time, typically up to 30 years, which is contributing to an increase in uncertainty. The final reason is that the shipping industry has a long tradition and is fragmented. Ships have been around for thousands of years, and therefore the industry may be conservative and not to open for new ideas. In addition, due to low barriers to entry there are many small family owned shipping companies; small companies may not have the capital to implement large and expensive operational research systems.

### 6.1 Fleet Size and Mix

The article *A Survey on Maritime Fleet Size and Mix Problems* (Pantuso, Fagerholt, and Hvattum, 2013) analyzes and summarizes the available literature on fleet size and mix problems in the maritime transportation. The authors states several aspects that make maritime fleet size and mix problems (MFSMP) different to fleet size and mix problems in other transportation contexts.

The high level of uncertainty in the planning process is the first reason mentioned in the article. In strategic planning much of the uncertainty comes from the long lifetime of the vessels. Due to the long lifetime, investments in ships require taking a long term view of the shipping company's predictions for the future market situation. The second aspect that are different from other types of fleet size and mix problems, are the high amount of capital involved. New vessels can cost hundreds of millions USDs. This is increasing the relevance of the financing of the investment compared with other transport segments. Several financing alternatives are often available, and the chosen one will influence the capital cost of the vessel. According to Stopford (2009) the financing cost can amount up to 42 % of the total running costs for a ten year old ship. Underlying routing features also make the MFSMP different from other fleet size and mix problems. Some of the differences in routing are listed by Ronen (1983) and Christiansen, Fagerholt, and Ronen (2004): The diversity of capacities, speeds and costs are much greater for ships than for other transport segments. Ships do

not usually return to a hub, and there is more uncertainty present due to high dependency on weather conditions. Finally, the vessel's value function makes the MFSMP different from other fleet size and mix problems. Vehicle's value is often modeled as a function of whose value decreases with increasing age and mileage. A vessel's value is a more complex parameter to model. Ådland and Koebakker (2007) claim that the second-hand value of a given type of ship can be described as a non-linear function of three parameters; age, size and the state of the freight market.

In their review Pantuso, Fagerholt, and Hvattum (2013) have 41 references. Currently there is a clear trend towards increasing research in the field. Most papers about MFSMPs are written in the 2000's followed by the 1990's. Most of the reviewed papers assume that there is no existing fleet. Only one fifth of the papers assume that there is an initial fleet that should be adjusted by including or excluding vessels (Pantuso, Fagerholt, and Hvattum, 2013). According to Fagerholt, Christiansen, et al. (2010), it happens rarely in real life that a completely new fleet has to be determined. In their review, Pantuso, Fagerholt, and Hvattum (2013) present four different points of discussion for future research in MFSMPs:

- The appropriate level of detail in modeling the underlying routing of the ships.
- The number of scenarios to use and the appropriate description of the uncertain elements in the scenarios.
- The difference between different methodologies meant to handle uncertainty.
- The comparison and eventual integration of stochastic and deterministic models to achieve efficient solution algorithms.

Despite that there is a high level of uncertainty in the strategic planning; methods for planning in a deterministic context have been proposed in most of the reviewed papers (Pantuso, Fagerholt, and Hvattum, 2013).

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### 6.2 Tactical Planning

In spite of the reasons for the low attention drawn in the literature by maritime transportation planning problems mentioned above, there is a considerable growth of research in maritime transportation. In 1983, the first article reviewing operations research in the maritime transportation was written by Ronen. He traced papers back to the 1950s, and has almost forty references (Ronen, 1983). Ronen also wrote the second review in 1993. This review has about the same number of references, mostly of them are written during the decade since the first review (Ronen, 1993). The last review was written by Christiansen, Fagerholt, and Ronen (2004). This review has almost 80 references for the last decade. These three reviews all focus on scheduling and ship routing problems, but they also discuss problems on the tactical level and the operational level.

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Review	Ronen 1983	Ronen 1993	Christiansen et al. 2003
References from	1950 – 1983	1983 - 1993	1993 - 2003
Number of references	Almost 40	Almost 40	Almost 80

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**Table 6.1: Review of routing and scheduling in maritime transport**

When studying *Ship Routing and Scheduling: Status and Perspectives* by (Christiansen, Fagerholt, and Ronen, 2004) some trends in the tactical planning in the maritime transport can be observed. Most research has been done in the industrial shipping segment, and remarkably less in the liner shipping segment, despite the increase in container traffic and the large number of merges in container shipping industry. However, there is an increasing amount of research in how to operate container terminals (Crainic and K. H. Kim, 2007). There is also an increasing focus on supply chains, both regarding design and how to operate maritime supply chains. It is worth mentioning that a large share of research in maritime transport planning is based on real applications. In other transport segments, the problems discussed are not based on real cases but on artificially generated data (Christiansen, Fagerholt, Nygreen, et al., 2007).

### 6.3 Operational Planning

Compared with strategic and tactical planning, there have been few studies in optimization research in operational planning. In addition to disruption management and rescheduling, which are the focus in this project thesis, there are several areas where operational planning can be used. Operational planning can be used in environmental routing, speed selection and booking of single orders. In several of these topics there have not been published any scientific papers (Christiansen, Fagerholt, Nygreen, et al., 2007).

Vessels navigate in bodies of water and are exposed to currents, waves, tides and winds. When a vessel sails between the ports, it has to decide which route it should take. It can either sail the shortest distance, straight forward, sail around an upcoming storm, or take benefit from a current. Environmental routing is complicated because of the complexity of the continuous dynamic environment in which it takes place, and because of the lack of the necessary timely reliable data (Christiansen, Fagerholt, Nygreen, et al., 2007).

Under various operational situations the planners have to assign the available fleet of vessels to transport a given amount of cargo between different ports. An inherent part of the fleet scheduling is cruising speed decisions. Cruising speed decisions affect both the capacity of the fleet and the operating cost (Christiansen, Fagerholt, Nygreen, et al., 2007).

Vessels need to be loaded in a safe manner in order to prevent damage on the ship or the cargo. During unloading and loading of cargo and during transit the vessel needs to maintain stability. Not only the stability of the vessel has to be assured, also the efficiency of cargo handling operations in the current and following ports must be taken into account (Christiansen, Fagerholt, Nygreen, et al., 2007).

The container stowage planning problem is a very complex problem. Researchers are far from finding an optimal solution. This problem is discussed in depth by Crainic and K. H. Kim (2007). Cargo stowage planning problems are also hard in the RoRo shipping segment. Øvstebø, Hvattum, and Fagerholt (2011a) are introducing and solving the RoRo ship stowage problem. In this problem it has to be decided which cargo to carry, how much of each cargo to carry, and how to stow each cargo onboard a RoRo vessel during a voyage. The ships follow a predefined route, time usage is ignored and all cargo quantities are fixed (Øvstebø, Hvattum, and Fagerholt, 2011a). The RoRo ship stowage

## 6. OPTIMIZATION RESEARCH IN MARITIME TRANSPORT INDUSTRY

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problem has later been extended to a single-vessel RoRo ship routing and stowage problem, where routing and scheduling decisions and the ability to select cargo quantities are included. It is possible to formulate this problem as a MIP. A tabu search can be developed to handle the routing and scheduling problem, and the stowage part can be handled by a local search and squeaky wheel optimization (Øvstebø, Hvattum, and Fagerholt, 2011b).

Optimization research can be used to decide if a ship owner should accept a single booking order of a cargo. In liner shipping, a single cargo is often a small fraction of the vessel capacity. It is normal to accept a cargo if there is space available or suggest another departure time for the cargo if not. However, it may sometimes be more beneficial to reject the cargo as there may appear a better request later on. In tramp shipping a cargo is usually a bigger fraction of the vessel capacity. As for liner shipping, sometimes it may be better to reject a cargo as there may appear a better cargo request later on the route (Christiansen, Fagerholt, Nygreen, et al., 2007).

### 6.4 Perspective

Optimization based decision support systems will probably be more accepted in the future. There will probably also be a greater benefit from optimization research and an increased need for it (Christiansen, Fagerholt, Nygreen, et al., 2007).

Reasons for increased attention to optimization research in maritime transport are various and complex. One reason is the increased profit margin for shipping companies. During the last decades there has been a consolidation in the manufacturing sector, resulting in bigger actors on the demand side for maritime transport services. This has given the shippers an increased market power compared with the shipping companies. As a result of bigger actors many shipping companies have merged over the past decade. It is harder to determine a fleet schedule and the right fleet size when dealing with a larger fleet and more trades.

Traditionally planners and decision makers in maritime transport have often been experienced people using pen and paper when planning. However, in recent years shipping companies have started employing planners with less practical background, but more academic background. These new planners are often more



open to new ideas, such as using optimization research in planning of maritime transport.

A rapid technological development in computer power and a significant algorithm development are also increasing the attention towards optimization research in maritime transport. It is possible to find good solutions to hard problems in a reasonable amount of time. A trend towards an increased emphasis on integrating maritime transport into the supply chain will also increase the attention towards optimization research (Christiansen, Fagerholt, Nygreen, et al., 2007).

## **6. OPTIMIZATION RESEARCH IN MARITIME TRANSPORT INDUSTRY**

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# 7

## Potential Incidents Causing Delays

There are many incidents which can cause delays for a vessel, and thereby create uncertainty in the planning. These incidents may be caused by the weather, political issues, human errors or mechanical problems.

The main reason for developing the simulation model in this project thesis is to validate the deployment model in the MARFLIX project. The simulation is intended to model the daily operation of a fleet, included disruptions. The possible incidents and the following consequences will be discussed in this section.

Which incidents that can occur are dependent on the ship's situation. A ship may have a large number of different statuses, but in this thesis we have defined four operation statuses:

- At sea
- Arrival in port
- Departure from port
- Alongside

In the shipping business, a planned dry-docking is usually done every fifth year for a ship and may be detected as a status. To keep the simulation model

## 7. POTENTIAL INCIDENTS CAUSING DELAYS

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simple, the docking process is neglected. There are several different incidents which can cause a delay in each operating status. The consequences after an incident is in this model:

- Reduced speed
- Delayed
- Changed resistance
- Off-hire

Reduced speed means the ship has to sail with reduced speed due to safety and reliability issues. E.g. the engine has some mechanical problems and the ship must sail with reduced speed until the problems are fixed. Weather may also cause that the ship has to sail with reduced speed. Delayed means the incident causes a delay in the ship's schedule. At WWL, a ship is defined as off-hire once the ship is unavailable for WWL (Foyen, 2012). In this thesis, off-hire means the ship is out of service for several days due to dry-docking etc. If a ship is off-hire, we assume it cannot be affected by more incidents until the ship is on-hire. Some incidents can cause major damages on the ship and the cost of repairing will be too high. The ship owner will then scrap the ship, those extreme conditions are not included in this thesis. Responses to the incidents in respect to the schedule are discussed in chapter 9, *Probability of Incidents and Impacts*. To develop the simulation model further, and based on Vernimmen, Dullaert, and Engelen (2007) possible incidents were found and connected with an operation status and a consequence. The results may be found in Appendix A. These incidents and their consequences are applied later on in the simulation model.

Weather is the main cause of delays during transit mode at sea, but there are still some other incidents that can cause delays, both incidents on board and in the surroundings. During arrival and departure of ports, the main incidents which can cause disruptions are collisions, late arrival of tugs and pilots, and even the tide water. During port stay, the ship is exposed to authorities and stevedores. These are factors that may cause the ship to be delayed.

### 7.1 Several Incidents in a Row

One incident may cause another incident to be rendered impossible, e.g. when a ship experience headwind, it cannot experience tailwind at the same time. This was implemented in the model by the use of matrices that specify what incidents are not allowed to occur simultaneously. These matrices may be found in Appendix B.

## **7. POTENTIAL INCIDENTS CAUSING DELAYS**

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## 8

# Dealing with Delays

Disruptions and delays in liner shipping networks will cascade through the network and influence other ports and ships. This is given by the nature of many liner shipping networks (Theo Notteboom and Rodrigue, 2008). Maritime liner based service networks are an example of a transport mode that operate around the clock. In addition, the ships are almost never empty at any points, and freight forwarding obligations must be met during the recovery period. These facts make it hard to get a delayed vessel back on schedule; it can take days, or even weeks (Andersen, 2010).

There are many different ways to deal with delays that occur. The possibilities presented below are described by T Notteboom (2006) and Kjeldsen et al. (2012).

The first way to deal with delays is to increase the speed of the vessel. Increasing the speed of the vessel leads to higher fuel costs, as vessels use more fuel per distance if they increase the speed. Vessels are often designed to maintain a service speed at sea. Usually the service speed is some knots lower than the vessels maximum speed, and is more fuel efficient. In modern container ship design there is a trend towards an increasing speed margin (T Notteboom, 2006) i.e. a bigger difference between the service speed and the maximum speed, this to maintain a sailing schedule with good dependability. The dependability is better for a vessel with a high speed margin than for a vessel with a lower speed margin as the vessel with the high speed margin can increase the speed more if a delay has occurred. It can then catch up with the delay more easily.

## 8. DEALING WITH DELAYS

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A shipping line is able to cancel one or more port calls to reduce port and sailing time to get the vessel back on schedule. Omitting a port call can have a huge impact on the pattern and cost of land transport. If a vessel cancels a port call the cargo that was intended for that port ends up in another port. Ship owners then have to arrange and pay for transport of the cargo so it ends up in the right place. Cargo that was to be picked up in the omitted port has also to be picked up later or at another place. Trains and trucks are quite often used for this purpose in Europe, due to the relatively small distances. During the 2002 US West Coast lockout of longshoremen, cargo was discharged in Mexico for intermodal transport to the US (Kjeldsen et al., 2012). Canceling port calls might decrease customer satisfaction. A frequent canceling of port calls often means that changes should be made in the schedule (Kjeldsen et al., 2012).

It is also possible to use the cut and run principle. This can be an option when loading and unloading in a tide dependent port. The cut and run principle is based on that the loading or unloading is ended before all of the cargo are handled. Cargo that is left in the port has to wait for the next vessel to arrive, or it has to be transported to the next port. A reason for the cut and run principle can be to avoid unproductive port time caused by a low tide situation. The vessel does not have to wait for next high tide to leave the port. As an example, Maersk Sealand vessels sometimes leave Antwerp before they finished loading cargo to benefit from favorable tidal windows (T Notteboom, 2006).

If a delay has occurred for a vessel, ship owners can deploy other vessels to take its place. To compensate for a delay the ship owner can use a vessel that is not in service for recovering the schedule. The delayed vessel is then to be taken out of service and it is deployed again on demand. This policy is causing periods where one or more vessels are out of service. It is also possible to charter in a ship that can cover parts of a published schedule. Space chartering, when the ship owner is chartering space on a vessel for one load of cargo is also an opportunity.

One other way to handle a delay is to reshuffle the order of port of calls. In some cases, this coincides with discharging more import cargo at the first port of call combined with the transfer of cargo over land to destinations near ports that will be called at a much later time than initially planned (T Notteboom, 2006). It is also possible to increase the port productivity to recover from delays. This possibility can only recover small amounts of time and it is a possibility only in a



few ports worldwide (Kjeldsen et al., 2012). To increase the port productivity it is possible to extend the hours of operation e.g. work at night instead of taking the night off and it is possible to load and unload with double shifts (Le-Griffin and Murphy, 2006).

As mentioned in the Literature Review, in their article Brouer et al. (2013) increase the speed on the delayed vessel, omit ports, and swap the order in which ports are being visited to get the delayed vessels back on schedule. Figure 8.1 from Brouer et al. (2013) illustrates different recovery actions in a time-space network environment.

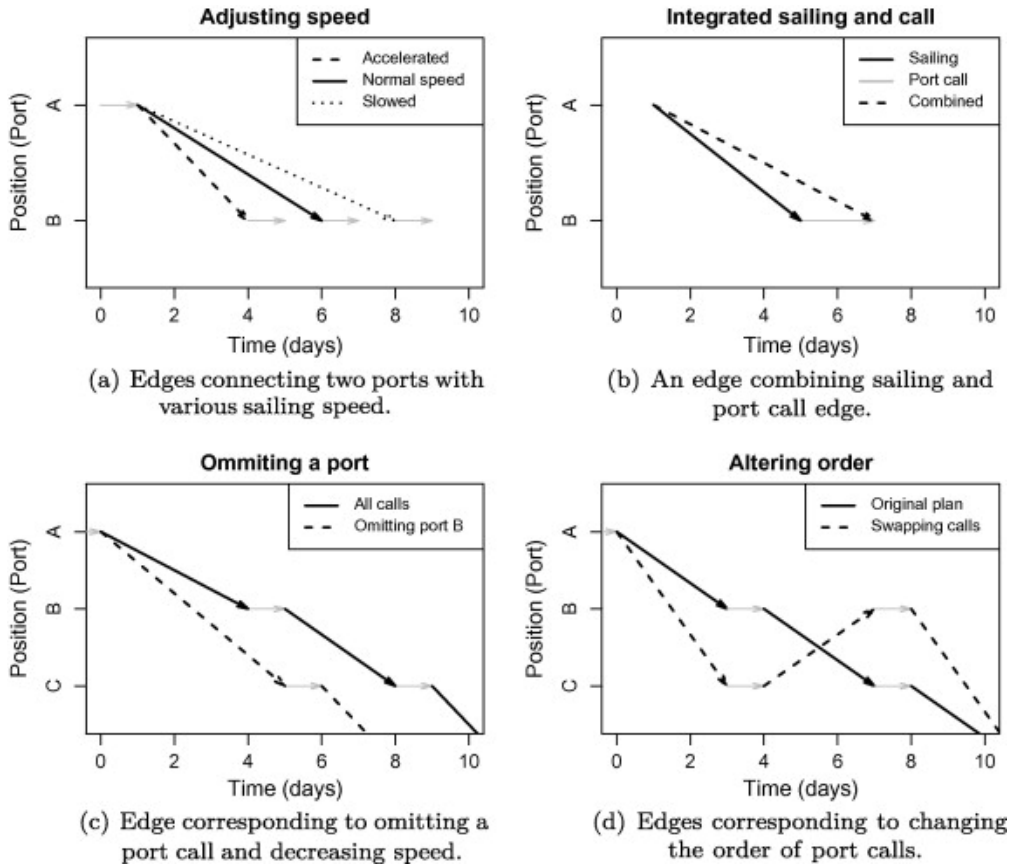


Figure 8.1: Possible recovery actions in a time-space network - (Brouer et al., 2013)

## 8. DEALING WITH DELAYS

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When a ship needs to recover from a delay, the cost associated with each of the different recovery strategies has to be found. The amount of time that can be saved for each of the strategies also needs to be known. Additional cost and time saved associated with a speed increase and increased port productivity are easy to find. The cost incurred while sailing is closely related to the speed, as the fuel consumption is strongly dependent on the speed (Perakis and Jeramillo, 1991). Costs associated with an increase in port productivity are depending on which actions are taken to increase the productivity. It is harder to find the costs associated with canceling a call of port, the cut and run strategy and the port reshuffling strategy. With these strategies, the recovery costs are dependent of the cost associated with transporting the cargo over land or by sea, so that it ends up in the right port. Costs associated with land transport and sea transport need to be found. It may be more cost efficient to not move the cargo and instead just wait for the next vessel on the route. To implement this into the model the cost associated with the cargo delay need to be found. The easiest way to find the cost associated with space chartering and chartering in a ship is to create a function where the cost is depending on the distance the cargo needs to be transported and the amount of cargo that is to be transported.

Which ports that have the possibility to increase their productivity need to be known, this also applies to which ports that are typical cut and run ports due to tides. When our rescheduling model is searching for the best recovery strategy it has not only to check all the different strategies, but also combinations of them. A combination can be that a delayed vessel increases the speed and then calls a port that increases its productivity. If a ship is ten hours delayed it can increase the speed so that the delay is reduced with eight hours and then the increased port productivity will handle the remaining two hours. It is also possible to combine the cut and run strategy with space chartering. A ship will then leave the port before it has loaded all the cargo, and the ship owner can then charter space at another ship that will transport the remaining cargo. A model also needs to calculate if it is best to cover the delay as fast as possible or if it should be handled over a greater amount of time. A ship that is delayed can either increase the speed on a leg and call next port on time, or it can adjust the cruising speed on the two next legs so that she calls the next port with a smaller delay, and calls port number two on time.

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The customer satisfaction may also be included in the rescheduling mode. If the customers get to unsatisfied they may want to use another company. Some of the recovery strategies might decrease the customer satisfaction a great deal. It is possible to add a customer dissatisfaction fee to the objective function if the strategy is lowering the customer satisfaction. The fee may be the same each time or it may be raised for each time a recovery strategy is lowering the customer satisfaction. The extra cost can also be set as a function since the last recovery strategy was lowering the customer satisfaction. Different costumers may have different dissatisfaction fees as they respond differently to delays and unforeseen events, but it is easier to use the same strategy for all customers. A typical recovery strategy that might decrease the customer satisfaction is cancel port calls. If a ship is going to call a port that have tide windows the recovery heuristic may check if the ship should increase the speed or decrease the speed so it do not have to wait for entering the port, or it have to cut and run.

Commitments may have been made regarding time for start of servicing, and a specific ship may have been nominated for transporting given cargoes in the deployment model. In planning problems with a rolling horizon the planners are interested in that the new rescheduled solutions are close to the current solution (Fagerholt, Korsvik, and Løkketangen, 2009). In *Ship Routing and Scheduling with Persistence and Distance Objectives* (2009) Fagerholt et al. present a method to achieve solutions that is close to the baseline solution. They introduce a persistence penalty function to penalize solutions deviating from the baseline solution. The authors describe two kinds of penalties, a cargo-ship penalty and a cargo-time penalty. A cargo-ship penalty is a penalty for transporting cargo with a different ship in the new solution, and the cargo-time function is a penalty per time unit difference in service start at a port. The authors are doing this for a planning problem with a rolling horizon, but it may also be included in our recovery heuristic. This is a method that can be used if it is important that the rescheduled solutions are close to the baseline solutions.

A cost is associated with the recovery actions after a delay has occurred. Figliozzi and Zhang (2009) have written a paper where they focused on estimating and understanding the costs and causes of transport related supply chain disruptions. Under normal operating conditions, on average and per TEU, logistic and supply chain managers are willing to pay \$33 for a one day reduction in transit time, and \$198 for a 1% increase in on-time reliability. If a disruption

## 8. DEALING WITH DELAYS

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takes place, the willingness to pay changes significantly for transit time, the managers are willing to pay \$180 for a one day reduction in transit time and \$383 for a 1% increase in on-time reliability. For the managers it is worth expediting at least part of the shipment to mitigate stock-out costs and other disruption costs. The article indicates that disruption costs include lost sales, expediting costs, intangibles such as loss of reputation, and financial impacts on the cash flows.

## 9

# Probability of Incidents and their Impacts

Incidents may have different impacts on different ships and in different situations. A simulation model is deterministic if all input variables are known, and stochastic if one or more of the input variables are randomly generated (Banks and J. S. Carson, 1984). The incidents and their impacts are in our simulation model randomly generated, hence the simulation model is stochastic. Calculations of the random input variables are found by using probability theory. The calculations used to find the probability of disruption are presented in this section.

Some assumptions about the incidents regarding the probability distributions were made:

All incidents, with some exceptions, are independent. This means:

$$P(A | B) = P(A),$$

where  $A$  and  $B$  are incidents.

The exceptions are the cases where another incident is blocking some incidents to occur, as discussed in section 7.1, *Several Incidents in a Row*. It is also assumed that the model is memory less, which results:

## 9. PROBABILITY OF INCIDENTS AND THEIR IMPACTS

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$$P(A; t) = P(A; t + t_R),$$

where  $A$  is an incident  $t$  is time  $t_R$  is time needed to recover if incident  $A$  occurs.

### 9.1 Stochastic Distributions

The possible consequences have different stochastic distributions. The incidents' impacts are divided into four different outcome categories:

- Reduced speed
- Delayed
- Changed resistance
- Off-hire

To find the probability of disruptions and their impacts, two different stochastic distributions were applied.

#### 9.1.1 Exponential distribution

The exponential distribution density function is given as:

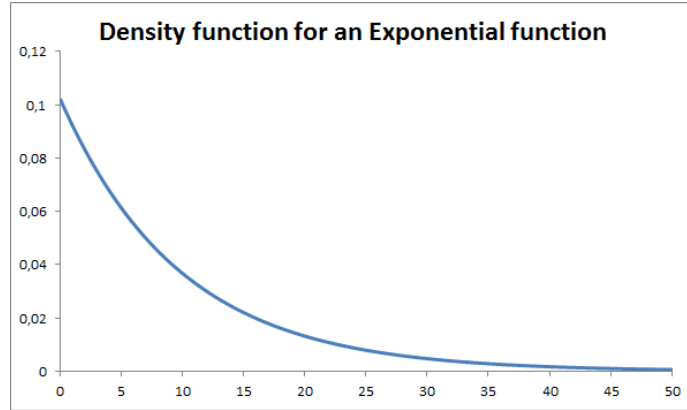
$$f(x, \mu) = \begin{cases} \frac{1}{\mu} e^{-\frac{x}{\mu}} & \text{if } x > 0 \\ 0 & \text{elsewhere} \end{cases}$$

where  $\mu > 0$ ,  $\mu$  is the mean of the exponential distribution, and  $x$  is time impact (Walpole et al., 2007).

An example of an exponential density function with  $\mu = 0, 1$  can be found below in figure 9.1.

The exponential distribution is applied for the following consequences:

- Reduced speed
- Delayed
- Off-hire



**Figure 9.1: Exponential density function with  $\mu = 9,77$  -**

The x-value of the distribution represents the duration of the consequence, while the kind of impact depends on the consequence. For *Reduced speed* the x-value represents the amount of time the ship has to sail at a reduced speed. The reduced speed is given. The x-value for *Delayed* and *Off-hire* is the amount of time the ship is delayed.

For all three consequences, it is habitual that the majority of the incidents lasts for a shorter time and a smaller amount of the incidents lasts for a longer time. Therefore an exponential distribution is applied for these consequences.

### 9.1.2 Weibull-distributions

The Weibull distribution density function is given as:

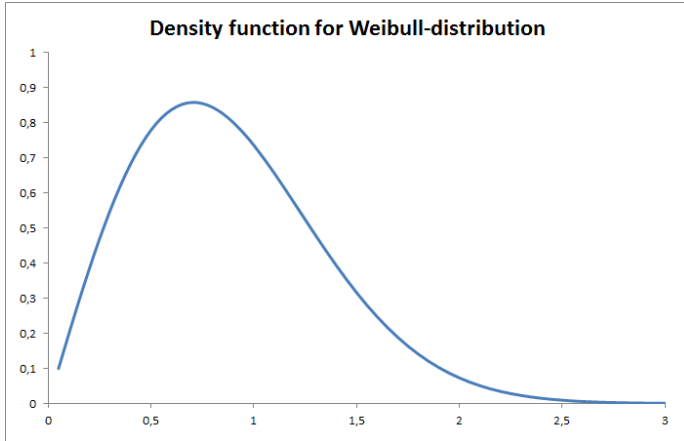
$$f(x, \alpha, \beta) = \begin{cases} \alpha\beta x^{\beta-1} e^{-\alpha x^\beta} & \text{if } x > 0 \\ 0 & \text{elsewhere} \end{cases}$$

where  $\alpha > 0$  and  $\beta > 0$ , the  $\alpha$  represents a scale factor, and  $\beta$  represents a shape factor (Walpole et al., 2007).

As an example a Weibull distribution with  $\alpha = 3$  and  $\beta = 2$  may be found in figure 9.2.

## 9. PROBABILITY OF INCIDENTS AND THEIR IMPACTS

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**Figure 9.2: Example of a Weibull distribution -**

Some incidents may cause the resistance of the ship to change. The Weibull-distribution is applied for changed resistance-consequences in the simulation model.

The changed resistance factor is by default set to 1, and is defined as the maximum value of  $f(x, \alpha, \beta)$  as shown below:

When  $f'(x, \alpha, \beta) = 0$  and  $f''(x, \alpha, \beta) < 0$ , then

Default changed resistance factor =  $x$

Due to the nature of ship resistance, the hull speed and the impact of the weather, the average resistance factor over a long time will always be greater than default. For given  $\alpha$ 's and  $\beta$ 's, the graphs

$f(x, \alpha, \beta)$  for  $x <$  Default changed resistance factor

and

$f(x, \alpha, \beta)$  for  $x >$  Default changed resistance factor

will be asymmetric around  $x=1$ . This makes the Weibull-distribution a good fit for this consequence.



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## 9.2 Monte Carlo Simulation Approach

Weibull-distributions have in addition a rather simple cumulative function, which is beneficial when performing a Monte Carlo Simulation, as mentioned later on in this section.

An issue regarding both the Weibull and the exponential distributions is the tail effects. The probability for a very large and unnatural impact will be small in these distributions, but may occur during the simulation. This thesis looks into the daily operation of the ships, where extreme situations with major time impacts are neglected. To avoid simulations with major delays, the tail effects are excluded. The distributions therefore have upper limits on the impact.

## 9.2 Monte Carlo Simulation Approach

The cumulative distribution can be calculated based on the probability density function. The cumulative probability function  $F(x)$  of a continuous random variable  $X$  with a density function  $f(x)$  is:

$$F(x) = P(X \leq x) = \int_{-\infty}^{\infty} f(x)dx, \text{ for } -\infty < x < \infty$$

According to Ross (2003) one may approximate the expected value  $E[g(x)]$  of the impact of a consequence  $g(x)$  by applying the Monte Carlo Simulation. The algorithm is described by the following terms:

- Generate an independent and random variable  $x_i$  between 0 and 1
- Find the value of the impact of a consequence,  $g(x_i)$
- Repeat step 1 and 2  $n$  number of times
- Proven by the strong law of large numbers, the expected value  $E[F(x)]$  can be found by

$$\lim_{n \rightarrow \infty} \frac{g(x_i) + \dots +}{n} = E[g(x)]$$

The Monte Carlo Simulation is implemented in our model by generating a random variable between 0 and 1. This is done for each incident and each ship for every time interval  $\text{deltat}$ . Since a large number of time intervals are included

## 9. PROBABILITY OF INCIDENTS AND THEIR IMPACTS

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in each simulation run ( $> 700$  for simulation of operation for six months), the number of occurred disruptions should be similar to the expected value of the probability functions.

### 9.2.1 Monte Carlo Applied on Continuous Distributions

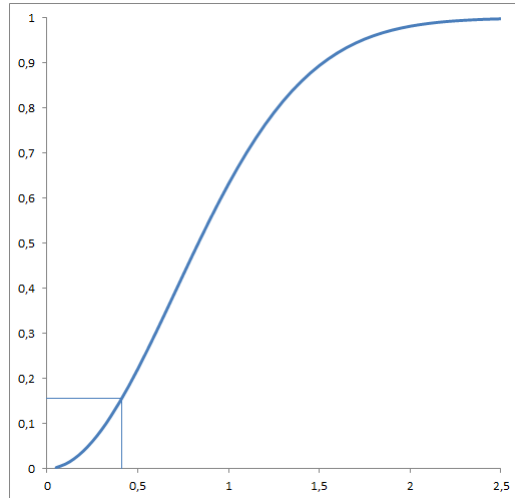
Given a probability density function, the Monte Carlo Simulation approach may be used. A Weibull distribution is used here, but the method is applicable for all given probability functions. The Weibull probability density function is given as:

$$f(x, \alpha, \beta) = \begin{cases} \alpha\beta x^{\beta-1} e^{-\alpha x^\beta} & \text{if } x > 0 \\ 0 & \text{elsewhere} \end{cases}$$

where  $\alpha > 0$

where  $x$  is the time unit.

The cumulative function  $F(x)$  with  $\alpha = 1$  and  $\beta = 2$  is shown in figure 9.3 below:



**Figure 9.3:** Cumulative function  $F(x)$

The algorithm used in this thesis to calculate the delay is:

## 9.2 Monte Carlo Simulation Approach

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- Generate a random variable  $r - j$  between 0 and 1, e.g.  $r_j = 0.1576$
- Calculate  $x$  when the cumulative function  $F(x) = r_j = 0.1576$
- The delay is calculated to be  $x = 0.4141$  for this incident

An illustration of the calculation may be found in figure 9.3, where  $F(x)$  is represented on the vertical axis and  $x$  is represented on the horizontal axis.

During each simulation run, this algorithm will run significantly many times and will therefore be valid due to the strong law of large numbers.

By applying this method, the model will calculate a delay for each incident for each ship in each time slot. This results in a great number of minor delays which have no relative impact on the schedule. To avoid neglectable delays, a lower limit of the disruptions is applied.

## **9. PROBABILITY OF INCIDENTS AND THEIR IMPACTS**

# 10

## Development of the Optimization Model

The aim of the optimization model is to reschedule vessels and cargos in a liner fleet in event of disruptions and delays. The models by Kjeldsen et al. (2012) and Brouer et al. (2013) have been important sources of inspiration for our model, and have showed how it is possible to solve disruption management problems in the liner shipping segment. Also disruption management studies from the airline industry and the railway industry have been used as guidance. The model has to meet some key requirements, these are listed below:

- Deliver all cargos to the correct port
- Deliver all cargos on time or with as little delay as possible
- Get the vessels back on schedule
- Minimize the costs related to the rescheduling

The purpose of a shipping company is to transport cargo from its origin port to its destination port. A liner shipping company often has contractual cargos that must be transported, usually on a monthly basis. If it is not possible to transport the contractual cargos with the vessels available, the cargos have to be transported with chartered vessels or by trains or trucks. There are

## 10. DEVELOPMENT OF THE OPTIMIZATION MODEL

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considerable costs associated with transporting cargo on chartered vessels, trains and trucks. If the cargos are not transported to the destination port on time, the shipping company may get paid less and the costumer may be dissatisfied. The vessels should be back on the original schedule within a short time period after a disruption has ocured. This is because the original schedule, found by the deployment model, is the optimal schedule considering the fleet available and the cargos to be transported. By not following the original schedule, there will be a lot of extra work for the shipping company; they must among other things cancel and reorder berth and make new schedules for crew members. The optimization model ensures that the freight forwarding obligations are met during the recovery period, and that the vessels get back on schedule with as little additional expenses as possible.

From the Literature Review two main approaches that are used to solve large and complex rerouting problems can be found. The first approach is to create a time-space network and solve the problem with different types of heuristics and search methods. The second approach is to model the problem as a set partition problem and use different algorithms for generating columns.

Our model has to satisfy some constraints regardless of which approach we choose to use. All the vessels and all the cargos have to enter the model once. The vessels can only perform one activity at a time, i.e. either be at sea, waiting in port or under operation in port. The cargos can also only perform one activity at any given time i.e. on board a vessel, loaded onto a vessel, unloaded from a vessel or waiting in port. It is not possible to load the vessel with more cargo than its capacity. There has to be a constant connected flow of actions for each vessel and each cargo. The cargos can only be discharged from a vessel if the cargo is on board the vessel, and only be loaded on vessel if the vessel is in port. The cargos also have to be waiting in the port to be able to be loaded onto a vessel. Cargos can only be on board a vessel between two ports if the vessel is sailing between these two ports.

## **10.1 Other Models**

### **10.1.1 Time-Space Network Models**

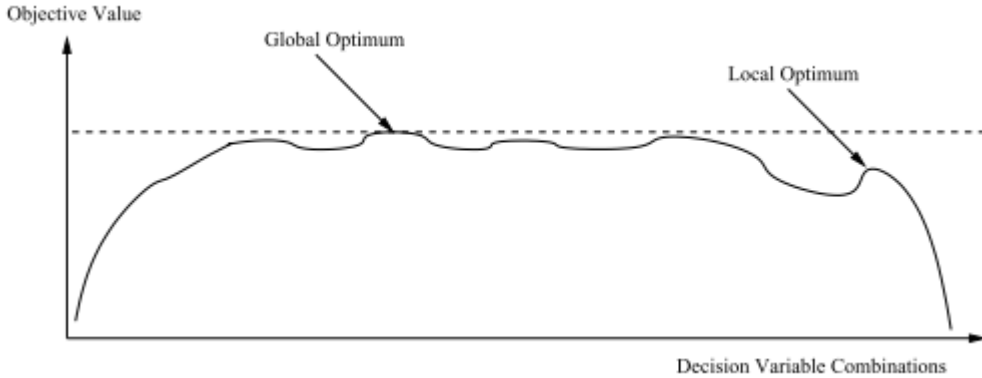
From the Literature Review it is possible to see that Kjeldsen et al. (2012), Andersen (2010), Bisailon, Pasin, and Laporte (2010), M. Yang (2007) and Løve et al. (2001) model their problems as time-space networks and use heuristics and search methods to solve the problems. It may be possible to solve these problems without the use of heuristics as Brouer et al. (2013) do, but the computing time required drops drastically when heuristics are used. Kjeldsen et al. (2012), Andersen (2010) and Bisailon, Pasin, and Laporte (2010) all use large neighborhood search (LNS), while Løve et al. (2001) use steepest ascent local search (SASL) and repeated SALS (RSALS). M. Yang (2007) uses a limited tabu search.

As mentioned in the Literature Review, LNS is a general heuristic search paradigm that was first proposed by Shaw (1998). LNS also has many similarities to the ruin and recreate heuristic presented by Schrimpf et al. (2000). Both LNS and the ruin and recreate heuristics perform well in complex problems. An advantage with these two methods is that when a large part of the initial solution is removed, there is much freedom to build a new and improved solution. Another advantage is the handling of the side constraints that occur. As mentioned in the Literature Review; a weakness with many side constraints is that many of the simple move operations will be illegal due to violation of the side constraints. This can make the search difficult, as the search space can become pitted with local minima or even disconnected. LNS and the ruin and recreate heuristics handle side constraints better than other methods. They alleviate the problem by providing more powerful and far-reaching move operators. The far-reaching move operators allow the search to move over barriers in the search space created by numerous side constraints. Shaw (1998) claims that this type of search is very naturally suited to constraint programming technology, which allows very general models of combinatorial problems to be specified. This type of search method thus seems ideal for models involving complex real-world constraints (Shaw, 1998).

If the solution space structure looks like the one in figure 10.1, where the local optimums are close to the global optima, other search methods will perform good. However, the problem solved in this case is non-linear.

## 10. DEVELOPMENT OF THE OPTIMIZATION MODEL

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**Figure 10.1:** Geometric fitness landscape as a function of all combinations of values assigned to decision variables - (Løve et al., 2001)

Løve et al. (2001) use SALS and RSALS to solve their problems when values in the local optimums are close to the global optimum. Local search methods like SALS are very rapid.

Also Mu et al. (2010) and Li, Mirchandani, and Borenstein (2009) solve their problem with heuristics. Mu et al. (2010) use a heuristic with a neighborhood search, while Li, Mirchandani, and Borenstein (2009) use a Lagrangean relaxation based insertion heuristic.

One benefit with formulating the problem as a time-space network is that the heuristic and the search method used to solve the problem can be fitted together to perform as desired. If the solution has to be calculated within a short time period a simple heuristic can be used. If there is more time available a more complex heuristic can be chosen. It is also possible to choose different heuristics depending on the solution space structure. If the problem is solvable to optimality with a commercial solver it is easy to find the goodness of the heuristic solution.

The mathematical formulation when using the time-space network approach can become highly complex. As an example, the mathematical formulation by Kjeldsen et al. (2012) has 28 sets of constraints. Problems that are comprehensive and difficult to solve can be formulated this way. Both hard and soft constraints can be included into a time-space network.



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## 10.1 Other Models

From the Literature Review it is possible to see that there are some differences in how to formulate disruption management models. The model in Kjeldsen et al. (2012) is highly complex, while the mathematical time-space network models in Brouer et al. (2013), Andersson and Värbrand (2000) and M. Yang (2007) are less comprehensive. This shows that to reschedule a liner fleet after one or more disruptions is a highly complex problem. A reason for the complexity in reschedule a liner fleet is that the ships are almost never empty at any points and freight forwarding obligations must be met during the recovery period.

Kjeldsen et al. (2012) and Brouer et al. (2013) both aim to reschedule a liner fleet after a disruption, but choose two different approaches. As mentioned, Kjeldsen et al. (2012) use the LNS to solve their problem and Brouer et al. (2013) use a commercial MIP solver. Kjeldsen et al. (2012) take the whole fleet of vessels into consideration when rescheduling after a disruption, while Brouer et al. (2013) only change the schedule for the vessel that is disrupted. With the approach used by Kjeldsen et al. (2012) the fleet of vessels will be better utilized than in the approach used by Brouer et al. (2013). In the real world, shipping companies may change the schedule for more than the disrupted vessel to recover from the delay. In this area the model by Brouer et al. (2013) is a simplification of the model made by Kjeldsen et al. (2012).

In section 8, several recovery actions were presented. Brouer et al. (2013) allow their vessels to increase speed, omit port calls and swap port calls to recover from a disruption. In the model by Kjeldsen et al. (2012) vessels can speed up to recover from a disruption and cargo can be transhipped by a different vessel than originally intended. Omitting port calls and swapping port calls are also possible recovery actions in the model by Kjeldsen et al. (2012). The model from Brouer et al. (2013) does not allow transshipment as a recovery action. It is the recovery actions that allow Kjeldsen et al. (2012) to take more than one vessel into consideration when rescheduling after a disruption, while Brouer et al. (2013) only change the schedule for the vessel that is disrupted. In section 8, a cut and run recovery action is described, but neither Kjeldsen et al. (2012) nor Brouer et al. (2013) use this strategy.

The model developed by Kjeldsen et al. (2012) is larger and more complex than the model developed by Brouer et al. (2013). One reason for that is the fact that Kjeldsen et al. (2012) allow more than the delayed vessel to take part

## 10. DEVELOPMENT OF THE OPTIMIZATION MODEL

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in the recovery. Another reason is that Kjeldsen et al. (2012) allow more than one disruption for each problem, while Brouer et al. (2013) only solve problems with one disruption. The model by Kjeldsen et al. (2012) finds the best value within three minutes, while the model by Brouer et al. (2013) finds the optimal value within 10 seconds. This is caused partly by the extra complexity due to the recovery strategies, and partly because the problems solved by Kjeldsen et al. (2012) are larger than the problems in Brouer et al. (2013). The largest problem solved by Kjeldsen et al. (2012) contained 400 different cargos, 9 vessels, 16 different ports and 3 disruptions, while the largest problem solved by Brouer et al. (2013) had 33 different cargos and 10 different ports.

Not only the recovery strategies and the size of the problem distinguishes the two models. Both the solution approach and the mathematical formulation differentiate the two models. The problems Brouer et al. (2013) solve are so small that a commercial solver is sufficient, while Kjeldsen et al. (2012) deal with problems that are larger and where an LNS heuristic is needed to solve their problems.

The major difference in the mathematical formulations come from the choice of set of variables. Brouer et al. (2013) have developed a model with four sets of binary variables. The first variable,  $x_e$ , is set to 1 if edge  $e$  is sailed, and 0 otherwise. If port call  $h$  is omitted the variable  $z_h$  is set to 1, and 0 otherwise.  $y_c$  indicates if container group  $c$  is misconnected or not. Finally,  $o_c$  is set to 1 if container group  $c$  is delayed, and 0 otherwise. In the model by Kjeldsen et al. (2012) the sets of variables are divided into two groups, one vessel group and one cargo group. There are three sets of binary variables in the vessel group. These constraints indicate if the vessels are in port, waiting or at sea. Five sets of continuous constraints with the value between 0 and 1 form the cargo group. As for the vessels, these constraints indicate whether the cargo is waiting in port, loading, unloading or transported by a vessel.

The objective functions in the two models are very similar, in Kjeldsen et al. (2012) an extra term for the transshipment cost is added compared to the objective function in Brouer et al. (2013). There are many differences in the constraints in the two mathematical formulations. The only constraints that can be directly compared are constraint 4.4 and constraint 4.7 in Kjeldsen et al. (2012) and constraint 4.32 in Brouer et al. (2013). These constraints ensure a flow conservation. Kjeldsen et al. (2012) have included one flow conservation

## 10.1 Other Models

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constraint for the vessels and one for the cargos, while Brouer et al. (2013) only have one flow conservation constraint for the vessels. Many of the constraints in the model in Kjeldsen et al. (2012) are included because of the high number of variables and their interaction. This applies to constraint 4.2 to and including constraint 4.7, and from constraint 4.11 to and including constraint 4.21 in Kjeldsen et al. (2012). These constraints are therefore not needed in the model in Brouer et al. (2013).

The mixed multicommodity flow model in Andersson and Värbrand (2000) differs some from the models in Kjeldsen et al. (2012) and Brouer et al. (2013). Andersson and Värbrand (2000) try to maximize the revenue when rescheduling a fleet of airplanes after a disruption. This causes the problem to be a maximization problem rather than a minimization problem as in Kjeldsen et al. (2012) and Brouer et al. (2013). Otherwise the objective function 4.49 is quite similar.

Andersson and Värbrand (2000) do not pay any attention to the crew or the passengers. The goal is to get the aircrafts back on schedule. This differs some from the problems in Kjeldsen et al. (2012) and Brouer et al. (2013), where they are trying to get the vessels back on schedule and at the same time deliver the cargo on time.

Andersson and Värbrand (2000) allow aircraft swapping, flight cancellation and the use of a spare aircraft to recover from a disruption. This implies that the schedules of all the aircrafts in the fleet are evaluated, as in Brouer et al. (2013). The model handles problems with more than one disruption at the time, this is also similar to Brouer et al. (2013).

Constraint 4.50 and constraint 4.53 in Andersson and Värbrand (2000) correspond to constraint 4.2 and constraint 4.3 in Kjeldsen et al. (2012). These constraints initiate a flow of one unit from each aircraft/vessel source node, and ensure that each aircraft/vessel gets to its destination on time. No such constraints are found in the mathematical formulation in Brouer et al. (2013). Constraint 4.56 and constraint 4.57 ensure that the delay does not exceed the maximum allowed delay and that the number of passengers do not exceed the capacity on the plane. There are no equivalent constraints in Kjeldsen et al. (2012) or Brouer et al. (2013). The mixed multicommodity flow model by Andersson and Värbrand (2000) is later reformulated as an SPP problem.

M. Yang (2007) aims to solve the reduced station capacity problem (RSC). To solve this problem he developed a time-space network model. It is possible for the

## 10. DEVELOPMENT OF THE OPTIMIZATION MODEL

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whole fleet of airplanes to take part in the recovery. M. Yang (2007) allows flights to be cancelled and delayed to get the airplanes back on schedule. As Andersson and Värbrand (2000), M. Yang (2007) is only focusing on the airplanes when he solving his problems. When the restriction of maximum number of aircrafts on the ground (MOG) occur on an airport, this will inflict more than just one flight and one aircraft. The model in M. Yang (2007) has to be able to handle multiple disruptions at the time.

The mathematical formulation in M. Yang (2007) is not very complicated. The objective function has the same structure as Kjeldsen et al. (2012) and Brouer et al. (2013). M. Yang (2007) aims to minimize the cost associated with the rescheduling. As in the mathematical formulation in Andersson and Värbrand (2000) and Kjeldsen et al. (2012), M. Yang (2007) has included a set of constraints in his model that initiate a flow of one unit from each aircraft/vessel source node. There is also one set of constraints that ensures that each aircraft/vessel gets to its destination on time. Constraint 4.67 in M. Yang (2007) is equivalent to constraint 4.32 in Brouer et al. (2013). These constraints ensure the flow conservation. Constraint 4.71, which is the reduced station capacity constraint, is unique for the model in M. Yang (2007),

The mathematical formulations in Kjeldsen et al. (2012), Brouer et al. (2013), Andersson and Värbrand (2000) and M. Yang (2007) show that rescheduling both vessels/aircrafts and "content", i.e. cargos or passengers, is much harder than rescheduling only the vessels/aircrafts. The models get larger and more complicated when the "content" is considered.

### 10.1.2 SPP Models

Set partition models are widely used to solve disruption management problems in the airline industry and in the railway industry. Rosenberger, E. L. Johnson, and Nemhauser (2003), Andersson and Värbrand (2000), Huisman (2007) and Rezanova and Ryan (2010) all model their disruption management problems as set partition problems (SPP). As mentioned in section 4.1.5, when using this approach the mathematical model itself gets small and simple. The set partition model is much simpler to solve than the original problem, e.g. there will be one variable per route instead of one variable per leg. The problem gets a much better structure and the LP solution is much closer to the IP solution than for the original problem, which result in a smaller branch and bound tree. With

an SPP approach there is a large flexibility in how to generate the routes. It is easier to include restrictions in the route generator than in a mathematical formulation. Similar to the heuristic approach, the route generation and the problem can be fitted together to perform as desired. A simple route generation algorithm provides a solution within a short time, while a more complex route generation algorithm provides a better solution within a longer time.

In Andersson and Värbrand (2000), the difference in complexity between the mathematical formulation for an original problem and an SPP is clear. Andersson and Värbrand (2000) first model their problem as a mixed integer multicommodity flow model before they reformulate the problem as an SPP model. With its 11 sets of constraints, the original model is much more complex than the SPP formulation which only has three sets. The number of variables is also much higher for the original formulation. In the original model there are two different sets of variables ( $x_{ij}^k$  and  $d_i$ ), while there is just one set of variable in the SPP model ( $x^{ar}$ ). Objective function 4.49 in the original formulation contains two terms, while objective function 4.61 in the SPP formulation only contains one term. The original mathematical formulation has to handle much more information. The information is at the same time not structured in the same simple way as in the SPP formulation.

As discussed in section 4.1.5, the drawback with the SPP method is the complex route generation. To ensure an optimal solution all possible routes have to be generated. The routes have to be generated before the model can be solved, which leads to a two-step solution approach. In complex problems where all routes are not generated it may be hard to generate good routes.

The mathematical formulation in Andersson and Värbrand (2000), Huisman (2007) and Rezanova and Ryan (2010) have many similarities. There are two small differences; the first is that Andersson and Värbrand (2000) aim to maximize the revenue while Huisman (2007) and Rezanova and Ryan (2010) aim to minimize the cost. The second difference is that the model by Huisman (2007) is a set covering model instead of a set partition model. Huisman (2007) demands that each original duty is replaced by at least one new duty. The models by Andersson and Värbrand (2000) and Rezanova and Ryan (2010) are modeled as set partition models. They demand respectively that each train driver is assigned to exactly one recovery duty and that each aircraft is included in exactly one route. All three models contain a set of binary constraints for

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the decision variables. A set of binary parameters is also included in all three models. The characteristic of these three mathematical formulations is that they are all simple and only contain a few simple sets of constraints.

The mathematical formulation in Rosenberger, E. L. Johnson, and Nemhauser (2003) differs slightly from the mathematical formulation in Andersson and Värbrand (2000), Huisman (2007) and Rezanova and Ryan (2010). The model developed in Rosenberger, E. L. Johnson, and Nemhauser (2003) has two sets of binary decision variables; one that decides which aircraft shall cover which route, and one that decides which routes will be cancelled. The results of this are two terms in the objective function instead of one and two more sets of constraints. These extra sets of constraints are constraint 4.44 and constraint 4.48. In addition there is a set of constraints that ensures that the passenger capacity is not exceeded. The formulation is still simple and contains only simple sets of constraints.

Although there are major similarities in the mathematical formulations in Rosenberger, E. L. Johnson, and Nemhauser (2003), Andersson and Värbrand (2000), Huisman (2007) and Rezanova and Ryan (2010), there are differences in how they solve their problems. Rosenberger, E. L. Johnson, and Nemhauser (2003) search for directed cycles with a minimum of aircrafts. Andersson and Värbrand (2000) solve their models with two different approaches; branch and bound and thus iteratively solve the LP relaxation of the problem, and Lagrangian relaxation and then sub-gradient optimization. Huisman (2007) generates new duties that are similar to the original duties by complete enumeration and chooses columns based on reduced cost. Then new duties are found by solving a pricing problem for the original duties. A branch and price approach is used by Rezanova and Ryan (2010).

Reasons for the different solution methods are the difference in size of the problems and the difference in the computing time available. As an example Andersson and Värbrand (2000) solve their models in 5 - 60 seconds. They solve a problem with 32 airports, 30 aircrafts and 215 flights and where 4 flights are delayed. Huisman (2007) solves his problem within 15 hours, which contains more than 8 500 tasks and 770 duties where around 800 tasks have to be rescheduled due to disruptions.

### 10.1.3 Other Methods

Petersen et al. (2012) propose a two-stage method to solve the airline integrated recovery problem in the article *An Optimization Approach to Airline Integrated Recovery*. Petersen et al. (2012) aim to repair the flight schedule, aircraft rotations, crew schedule, and passenger itineraries in a tractable manner after a disruption. This is not very different from our thesis, which seeks to repair the vessel routes, the vessel schedules and the cargo schedules after one or more disruptions have occurred.

The solution method proposed by Petersen et al. (2012) first seeks to recover the schedule, then to recover the other three components taking the repaired schedule as given. As mentioned in the Literature Review, a Benders decomposition scheme is employed to decompose the problem. The two-stage method makes the problem much easier to solve. It divides the problem into several manageable sections, and adds a Benders feasibility cut to the rescheduling model if the problem gets infeasible. Another benefit with this approach is that it is possible to focus on different parts when solving the problem. Petersen et al. (2012) have chosen to focus on the passenger recovery. The model considers a problem with a fleet that has 800 daily flights. A disruption in the hub that leads to a one hour closure is solved within 18 minutes. A drawback with this approach is that there can be many Benders feasibility cuts included in the model before a solution is found.

## 10.2 Model Proposals

Our problem can either be formulated as a time-space network or as an SPP model. In this section some alternative formulations are proposed and the drawbacks and advantages are discussed. In addition to the SPP and time-space network models, a model based on the two-stage method with Benders feasibility cuts in Petersen et al. (2012) is proposed.

### 10.2.1 Time-Space Network Models

One way to solve our problem is to use the mathematical formulation from Kjeldsen et al. (2012). The model used by Kjeldsen et al. (2012) is based on

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the model developed by Bisailon, Pasin, and Laporte (2010). The model by Kjeldsen et al. (2012) reschedules vessels and cargos after a disruption.

This model has already proven its qualities; a problem with 8 vessels, 16 ports, 449 cargos to transport and 2 disruptions was solved within two minutes. There is one big difference from our problem to the problem solved by Kjeldsen et al. (2012). As mentioned in the Literature Review, Kjeldsen et al. (2012) model their problem as a multicommodity flow problem with side constraints based on a time-space network. The model was developed for the simultaneous rescheduling of ships and cargos in liner shipping in the event of disruptions. They reschedule a given number of disruptions and minimize the operation cost for the planning period, but no disruptions can occur during the planning period. The cut and run recovery strategy described in section 8 is not included in the model in Kjeldsen et al. (2012). The mathematical formulation needs some changes if this recovery action should be included in the model.

Both Kjeldsen et al. (2012) and Bisailon, Pasin, and Laporte (2010) use LNS, which was first developed by Shaw (1998). To perform optimal for our problem the heuristic approach may be changed. Either the LNS itself can be changed or another heuristic may be used. However, LNS seems to be a good heuristic approach to solve big and complex time-space network problems. Andersen (2010) is also using an LNS heuristic to solve the network transition problem. LNS is handling side constraints better than many other heuristics. As mentioned in the Literature Review, LNS alleviates the problem with many side constraints by providing a powerful far-reaching move operator that allows the search to move over barriers in the search space.

Another way to solve our problem is to use the mathematical model in Brouer et al. (2013) as a starting point. Brouer et al. (2013) evaluate a given disruption scenario and select a recovery action balancing the trade off between increased fuel consumption and the impact on cargo in the remaining network and the customer service level. Also this model has proven its qualities.

Some changes have to be done in the model if it should be used. In Brouer et al. (2013) only the disrupted vessel are rescheduled after a delay. To utilize the fleet in a better way our model also has the possibility to change the schedule on more than the affected vessel. This change will makes model more complex and the computing time required will increase. Depending on the problem size a heuristic might have to be implemented to solve the model faster than with a



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commercial solver. Brouer et al. (2013) permit only one disruption per problem. In our model it is possible that more than one disruption occurs during each time period. Only three recovery actions are included in the model in Brouer et al. (2013), other strategies are included in our model (see section 10.4). If new recovery strategies are included, the mathematical formulation of Brouer et al. (2013) has to be changed and adjusted.

It is possible to add an extra penalty term in the objective function in these models. For an example can routes that differ too much from the original vessel route be penalized. This extra term can be formulated as below in 10.1.

$$\sum_{v \in \mathcal{V}} C_v^P p_v \quad \forall v \in \mathcal{V} \quad (10.1)$$

$C_v^P$  is the penalty cost for vessel  $v$ .  $p_v$  is a parameter that indicates if there should be added a penalty cost for vessel  $v$ . This parameter can be binary and take the value 1 if vessel  $v$  exceeds some penalty limit, and take the value 0 otherwise. The parameter can also be a function, linear or non-linear, that adds a higher cost if the changes are comprehensive.

### 10.2.2 SPP Models

If the problem is to be formulated as an SPP, there will be some different formulations that are suitable. The first formulation is based on the models by Andersson and Värbrand (2000), Huisman (2007) and Rezanova and Ryan (2010), while the second and third formulations are based on the model by Rosenberger, E. L. Johnson, and Nemhauser (2003).

In the first formulation, which is based on Andersson and Värbrand (2000), Huisman (2007) and Rezanova and Ryan (2010), let  $V$  be the set of vessels and  $R^v$  the set of routes for each vessel  $v \in V$ . The cost  $c_v^r$  reflects all the costs for vessel  $v$  when assigned to route  $r$ . A binary decision variable  $x_v^r$  equals 1 if vessel  $v$  is assigned to route  $r$ , and 0 otherwise. A binary parameter  $b_{vi}^r$  is used to define whether or not the cargo  $i \in N$  is transported on vessel  $v$  on route  $r$ .

$$\min \sum_{v \in \mathcal{V}} \sum_{r \in \mathcal{R}^v} c_v^r x_v^r \quad (10.2)$$

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subject to:

$$\sum_{r \in \mathcal{R}_v} x_v^r = 1 \quad \forall v \in \mathcal{V} \quad (10.3)$$

$$\sum_{v \in \mathcal{V}} \sum_{r \in \mathcal{R}_v} b_{vi}^r x_v^r = 1 \quad \forall i \in \mathcal{N} \quad (10.4)$$

$$x_v^r \in \{0, 1\} \quad \forall r \in \mathcal{R}^v, v \in \mathcal{V} \quad (10.5)$$

The objective function 10.2 aims to minimize the total cost. Constraint 10.3 ensures that each vessel is assigned to exactly one route. Constraint 10.4 ensures that all the cargos are transported. Finally, constraint 10.5 ensures an integer solution.

All costs associated with the rescheduling process, both the vessel specific costs and the cargo specific costs, should be included in the cost parameter. The cost parameter includes fuel costs, port fees, transshipment costs if the cargo is not transported with the vessels available, and the costs associated with late pickup and delivery. The binary parameter  $b_{vi}^r$  together with constraint 10.4 ensure that all cargo is transported from the origin port to the destination port and that the cargo is transported by exactly one vessel. The vessel cargo capacity is considered in the column generator. The route generation connected to this model is hard to construct, since the column generator has to be able to generate routes where some cargos are transported by a chartered ship and some are transported by train or truck.

Andersson and Värbrand (2000) use two different column generation approaches that may be appropriate for our SPP model. The size of their problem is similar to the problem we want to solve, and they solve their problem relatively fast, which is the goal for our model. Andersson and Värbrand (2000) use a branch and bound approach that iteratively solves the LP relaxation of the problem, and a Lagrangian relaxation approach that then solves with sub-gradient optimization. Both of these approaches may be implemented in our SPP model to see which one performs best for our problem. Also other column generation approaches may be used.

An advantage with an SPP formulation is the simple and comprehensible mathematical formulation. As most SPP models the mathematical formulation itself is easy to solve. There is a large flexibility in how to generate columns that do not violate the constraints.

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In the second SPP formulation, which is based on the model developed by Rosenberger, E. L. Johnson, and Nemhauser (2003), let  $V$  be the set of vessels and  $R^v$  the set of routes for each vessel  $v \in V$ . The cost  $c_v^r$  reflects the costs for vessel  $v$  when signed to route  $r$ . The cost  $f_i^v$  reflects the cost associated with transporting cargo  $i$  on vessel  $v$ . All costs associated with the vessels, as fuel costs and port fees are included in  $c_v^r$ .  $f_i^v$  includes costs like the costs related with late pickup and delivery and the transshipment costs. A binary decision variable  $x_v^r$  equals 1 if vessel  $v$  is assigned to route  $r$ , and 0 otherwise. Another decision variable  $y_{it}^v$  equals 1 if cargo  $i$  is transported on vessel  $v$  in time  $t \in T$ , and 0 otherwise. The time  $t$  is included in  $y_{it}^v$  because of the limited cargo capacity for each vessel. For each vessel  $v \in V$  there is a limit on how much cargo it can transport  $CAP_v$ . Each cargo  $i \in N$  has a given size  $s_i$ .

$$\min \sum_{v \in \mathcal{V}} \sum_{r \in \mathcal{R}^v} c_v^r x_v^r + \sum_{v \in \mathcal{V}} \sum_{i \in \mathcal{N}} f_i^v y_{it}^v \quad (10.6)$$

subject to:

$$\sum_{r \in \mathcal{R}^v} x_v^r = 1 \quad \forall v \in \mathcal{V} \quad (10.7)$$

$$\sum_{v \in \mathcal{V}} y_{it}^v \leq 1 \quad \forall t \in \mathcal{T}, i \in \mathcal{N} \quad (10.8)$$

$$\sum_{i \in \mathcal{N}} \sum_{t \in \mathcal{T}} y_{it}^v s_i \leq CAP_v \quad \forall v \in \mathcal{V} \quad (10.9)$$

$$x_v^r \in \{0, 1\} \quad \forall r \in \mathcal{R}^v, v \in \mathcal{V} \quad (10.10)$$

$$y_{it}^v \in \{0, 1\} \quad \forall v \in \mathcal{V}, i \in \mathcal{N}, t \in \mathcal{T} \quad (10.11)$$

The objective function 10.6 aims to minimize the total cost. There are two terms in the objective function; the first term aims to minimize the cost associated with the vessels, while the second term aims to minimize the cost associated with the cargo. Constraint 10.7 ensures that each vessel is assigned to exactly one route, just like constraint 10.3 in the first formulation. Constraint 10.8 ensures that each cargo is not transported on more than one vessel at any time. Constraint 10.9 ensures that each vessel does not transport more than the its capacity. This is in contrast to the previous model where the capacity of the

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vessels are considered in the column generation. The two last constraints ensure an integer solution.

There is no link between the two sets of variables in the model,  $x_v^r$  and  $y_{it}^v$ , except for in the objective function. The model has two separate parts; one part that takes care of the vessels and one part that takes care of the cargos. The model could have been divided into two models.

A column generator has to be created also for this model. As the formulation has been based on the model by Rosenberger, E. L. Johnson, and Nemhauser (2003), it is also natural to use the column generation from Rosenberger, E. L. Johnson, and Nemhauser (2003) as a starting point. Rosenberger, E. L. Johnson, and Nemhauser (2003) use a column generation approach where they search for directed cycles with a minimum number of aircrafts. The model by Rosenberger, E. L. Johnson, and Nemhauser (2003) solves a much bigger problem than our model solves. Rosenberger, E. L. Johnson, and Nemhauser (2003) allow their model to run for many hours before returning a solution. Considering the problem size and computing time the column generation probably has to be altered to fit for our problem. Other column generation approaches should also be considered if this SPP should be chosen.

Similar to the first SPP proposal this SPP formulation also has a simple and comprehensive mathematical formulation. The first SPP proposal is a bit more simple than the second one, but the column generation should be easier in the second proposal because it is divided into two parts.

A third SPP proposal is also constructed. This SPP formulation is based on the SPP model in Rosenberger, E. L. Johnson, and Nemhauser (2003). In this formulation, let  $V$  be the set of vessels  $v$ , and  $r$  be the routes the vessels  $v \in V$  can be assigned to. The cost associated with assigning vessel  $v$  to route  $r$  is denoted  $C_{vr}$ .  $I$  is the set of cargos  $i$  that are to be transported. In this model all cargos with the same index  $i$  have the same departure port and arrival port.  $C_i$  is the cost associated with transport cargo  $i$  with a chartered vessel.  $T$  is the set of time periods  $t$  the model shall run.  $b_{irv}^t$  is the number of times cargo  $i$  is transported in route  $r$  in time period  $t$  multiplied by the cargo capacity of vessel  $v$ , while  $D_i^t$  is the amount of cargo  $i$  that has to be transported in time period  $t$ . As in the model in Rosenberger, E. L. Johnson, and Nemhauser (2003), this formulation proposal has two sets of variables. This formulation includes one set of binary variables and one set of non-negative variables instead

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of two sets of binary variables.  $x_v^r$  is equal to 1 if vessel  $v$  is assigned to route  $r$ , and 0 otherwise, while  $\delta_i^t$  is equal to the amount of cargo  $i$  in time period  $t$  is transported with a chartered vessel.

$$\min \sum_{v \in \mathcal{V}} \sum_{r \in \mathcal{R}} C_{vr} x_v^r + \sum_{i \in \mathcal{J}} \sum_{t \in \mathcal{T}} C_i \delta_i^t \quad (10.12)$$

subject to:

$$\sum_{r \in \mathcal{R}} x_v^r = 1 \quad \forall v \in \mathcal{V} \quad (10.13)$$

$$\sum_{v \in \mathcal{V}} \sum_{r \in \mathcal{R}} b_{irv}^t x_v^r + \delta_i^t = D_i^t \quad \forall t \in \mathcal{T}, i \in \mathcal{J} \quad (10.14)$$

$$x_v^r \in \{0, 1\} \quad \forall v \in \mathcal{V}, r \in \mathcal{R} \quad (10.15)$$

$$\delta_i^t \geq 0 \quad \forall i \in \mathcal{J}, t \in \mathcal{T} \quad (10.16)$$

The objective function 10.12 aims to minimize the total cost. There are two terms in the objective function. The first term aims to minimize the cost associated with the route assigning for all the vessels, while the second term aims to minimize the cost associated with transporting cargo on chartered vessels. All costs except for transshipment costs and cost associated with chartering vessels are included in the first term. Constraint 10.13 ensures that all vessels  $v$  are assigned to a route  $r$ . This constraint is similar to constraint 10.3 and constraint 10.7 in SPP proposal one and two respectively. Constraint 10.14 ensures that all cargos  $i$  that should be transported in time period  $t$ , are transported either by a vessel in our fleet or by a chartered vessel. Constraint 10.15 ensures binarity for the variables  $x_v^r$ . Finally, constraint 10.16 ensures that  $\delta_i^t$  is non-negative.

As mentioned above this set partition formulation is based on the mathematical formulation in Rosenberger, E. L. Johnson, and Nemhauser (2003) The objective functions 4.42 and 10.12 both contain two terms and try to minimize the cost associated with the rescheduling process. The first term in both of the objective functions aims to minimize the cost associated with assigning routes to the vessels. The second term in Rosenberger, E. L. Johnson, and Nemhauser (2003) aims to minimize the cost of canceling the unassigned legs, while the second term in our model aims to minimize the cost associated with transporting cargo on chartered vessels. This makes the two objective

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functions almost identical. Constraint 4.43 and constraint 10.13 both ensure that all aircrafts/vessels are assigned to a route. Constraint 4.46 ensures that the passenger capacity is not violated. Constraint 10.14 ensures that all cargos are transported, either on a vessel in the fleet or a chartered vessel. Constraints 4.46 and 10.14 ensure that operational constraints are covered by the mathematical formulation instead of by the column generation. The rest of the operational constraints are in both cases covered by the column generation.

A column generator has to be created for this formulation. The column generation method depends on the size of the problem and the solving time. Complete enumeration, Lagrangian relaxation and branch & bound may all be considered. The column generation model in Rosenberger, E. L. Johnson, and Nemhauser (2003), which searches for directed cycles with a minimum number of aircrafts, may also be used as a starting point.

The third SPP proposal is also a simple and comprehensible mathematical formulation. It is a little bit more complex than the first SPP proposal because of the two sets of variables. However, the extra complexity will make the column generation easier. It is a trade off between extra complexity in the mathematical formulation and in the column generation. In the third SPP proposal, the mathematical formulation takes care of transshipment and chartered vessels, while in the two first SPP proposals this is done in the column generation.

For many transport problems modeled as an SPP the assignment constraint is usually relaxed. If this approach is chosen the formulation will then be a set covering model instead of a set partition model, like the model by Huisman (2007). A relaxation of a problem is easier to solve than the original problem. For the three SPP proposals above the assignment constraint would then look like this:

$$\sum_{r \in \mathcal{R}_v} x_v^r \geq 1 \quad \forall v \in \mathcal{V} \quad (10.17)$$

Constraint 10.17 ensures that each vessel is assigned to at least one route, instead of exactly one route. This constraint will therefore relax respectively constraint 10.3, 10.7 and 10.13 in the three SPP proposals. However, for our problem this is not a good approach. The vessels are to be assigned to only one new route each before they are back on the original schedule. By choosing more

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than one route for a vessel it will take a longer time to get the vessels back on their original schedules.

The three different SPP proposals have many similarities. However, there are some vital differences in the composition and structure of the different proposals. One of the most obvious differences is the number of variables. The first SPP proposal contains only one set of binary variables, while the other two proposals contain two sets of variables. This leads to a simpler mathematical model for the first SPP proposal.

In the first SPP proposal the mathematical formulation assigns the vessels to different routes and ensures that all cargo is transported from the origin port to the destination port. In the second SPP proposal the mathematical formulation also assign the vessels to different routes and makes sure that all cargo is transported. Additionally the mathematical formulation ensures that the vessel capacity is not violated. Also the mathematical formulation in the third SPP proposal assigns the vessels to different routes and makes sure that all cargo is transported, but the vessel capacity is handled in the column generation. In addition this model takes care of the transshipment and chartered vessels in the mathematical formulation.

All the models have to execute the same tasks. Constraints have to be considered either in the mathematical formulation or in the column generation. As an example; the column generation for the first two SPP proposals has to be constructed so that it is possible to charter in vessels, while this is handled in the mathematical formulation in the third SPP proposal.

The cargos are treated in two different ways in the model proposals. In the first two SPP proposals each cargo is given a unique index and each cargo has an origin port, a destination port, a pick up time and a delivery time. In the third SPP proposal the cargos are not given a unique index; instead all cargos that have the same departure port and arrival port are given the same index. The cargos do not have a specified pick up time and a specified delivery time, but there is a required number of cargos to be transported each month.

The cargo assigning to the vessels are solved differently in all of the three SPP proposals. In the first SPP proposal the binary parameter  $b_{vi}^r$  is used to indicate whether or not a given cargo is transported with a given vessel. Together with constraint 10.4, this parameter ensures that all cargo is transported. In the second SPP proposal the binary variable  $y_{it}^v$  is 1 if a given cargo is transported

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on a given vessel, and 0 otherwise. Constraint 10.8 ensures that all cargos are transported. The third SPP proposal solves this problem in a different way. The parameter in the third SPP proposal takes the value of the cargo capacity of the vessel in question if the chosen route transports the cargo in question. Constraint 10.14 then ensures that all cargo types are transported the required number of times.

For all three SPP proposals it is possible to add an extra penalty term as in the time-space network models. This penalty term can be formulated in the same way as for the time-space network models:

$$\sum_{v \in \mathcal{V}} C_v^P p_v \quad \forall v \in \mathcal{V} \quad (10.18)$$

### 10.2.3 Other Methods

The model approach developed by Petersen et al. (2012) is also a possible way to solve our problem. As mentioned earlier the problem solved by Petersen et al. (2012) and our problem do not differ all to much. If our problem is solved by this approach there will be one master problem and two sub-problems: repairing the vessel routes and then repairing the vessel schedules and the cargo schedules. The model will first recover the vessel routes and then assign vessels and cargos to the routes. When using the approach from Petersen et al. (2012) there will be two ways to solve the model. Either first assign vessels to the routes and then the cargos to the vessels, or first assign cargos to the routes and then vessels to the cargos. The Benders decomposition will in the first case allow vessel routes and assign vessels so that the cargo will be transported. In the second case Benders decomposition will allow vessel routes and cargo schedules so that the vessel can be assigned the routes. In our problem it will probably be more appropriate to create the vessel routes and vessel schedules first, and then assign the cargos to the vessels.

The master problem can then be formulated as follow: let  $V$  be the set of vessels and  $R^v$  the sets of routes for each vessel  $v \in V$ . The cost  $c_v^r$  reflects all the costs for vessel  $v$  when signed to route  $r$ . A binary decision variable  $x_v^r$  equals 1 if vessel  $v$  is assigned to route  $r$ , and 0 otherwise.



### 10.3 Applied Optimization Model

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$$\min \sum_{v \in \mathcal{V}} \sum_{r \in \mathcal{R}^v} c_v^r x_v^r \quad (10.19)$$

subject to:

$$\sum_{r \in \mathcal{R}^v} x_v^r = 1 \quad \forall v \in \mathcal{V} \quad (10.20)$$

$$x_v^r \in \{0, 1\} \quad \forall r \in \mathcal{R}^v, v \in \mathcal{V} \quad (10.21)$$

The objective function 10.19 is the same as constraint 10.2 in the first SPP proposal, and tries to minimize the total cost associated with the vessel rescheduling. Constraint 10.20 ensures that each vessel is assigned to exactly one route. The last constraint 10.21 ensures an integer solution. The model is similar to the first SPP proposal; the difference lies in constraint 10.4 that assigns cargos to the vessels.

The problem will then be solved by finding the solution when assigning cargos to the vessels. Benders feasibility cuts will be included in the master problem each time an infeasible solution is found.

For our problem this approach is quite similar to a "regular" SPP approach. Adding Benders feasibility cuts will complicate the model, and not attain the same simple structure as an SPP model without Benders decomposition. The problem solved by Petersen et al. (2012) is so divided that a Benders decomposition has relevance. Our problem is not that divided, and the Benders decomposition will make more trouble than gain.

### 10.3 Applied Optimization Model

As shown in the preceding sections there are several different ways to formulate and solve our problem. There are advantages and drawbacks with all of the proposals above.

One way to formulate our problem is to use a known time-space network model. Both of the models in Kjeldsen et al. (2012) and Brouer et al. (2013) have solved problems that are similar to our problem. The solution methods have proven their qualities on disruption management problems in the liner shipping segment. Both models are based on solution methods from the airline industry.

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Kjeldsen et al. (2012) are based on the model developed in Bisailon, Pasin, and Laporte (2010), while the model in Brouer et al. (2013) is particularly based on the work within aircraft recovery with speed-changes by Marla, Vaaben, and Barnhart (2011).

Set partition models are also widely used to solve disruption management problems in the airline industry. These kind of models are also used in the railway industry. In section 10.2.2 we have proposed three different set partition models. The first SPP proposal is based on models developed in Andersson and Värbrand (2000), Huisman (2007) and Rezanova and Ryan (2010). The second and third SPP proposals are based on a model developed in Rosenberger, E. L. Johnson, and Nemhauser (2003).

A third and final strategy to solve our problem is to use the model developed in section 10.2.3. This model is based on the work by Petersen et al. (2012). This model divides the problem in subproblems and makes use of Benders decomposition to solve the problem. As discussed in section 10.2.3 the model based on Petersen et al. (2012) is quite similar to a "regular" SPP approach. Instead of making the model easier, the Benders feasibility cuts will complicate the model.

As mentioned before, both the models developed in Kjeldsen et al. (2012) and Brouer et al. (2013) are customized to solve disruption management problems in the liner shipping segment. If we are to use one of these models as a starting point we know that the model will perform well even if we are to make some changes. The disruption management problem in the liner shipping segment is a large and complex problem to solve. Models formulated as time-space networks with side constraints are well suited to solve such problems. A heuristics may be implemented if the problem is to be solved as a time-space network model. It is possible to adjust the heuristic and the search method used to solve the problem. As mentioned in section 10.1.1, a simple heuristic can be used if the solution has to be found within a short period of time. A more complex heuristic can be chosen if there is sufficient time available, and the solution should then be better. It will also be possible to choose different heuristics depending on the solution space structure. It is easy to find the goodness of the heuristic solution if it is possible to solve the problem to optimality with a commercial solver. One problem with many side constraints is that many of the simple move operations will be illegal due to violation of the side constraints. A large number of side

### 10.3 Applied Optimization Model

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constraints constantly reduces the number of feasible moves, making a search difficult. In section 4.1.5 LNS is described. LNS is a search method that handles side constraints better than many other methods. LNS alleviates the problem with many side constraints by providing a powerful far-reaching move operator that allows the search to move over barriers in the search space. With the right heuristic a time-space network model can be very efficient and give a good result.

The mathematical model can become large and complex when the problem is solved as a time-space network model. As an example, there is a big difference in size and complexity between the mathematical formulation in Kjeldsen et al. (2012) and an SPP model. With a large and complex mathematical formulation it may be hard to get a clear overview of the model. If some new operating constraints or recovery actions are to be included in the model, there has to be made some changes in the mathematical formulation. There is often a high number of sets of variables in a such model. In a transport problem the structure can be simple and comprehensive. A time-space model does not fully take advantage of the simplicity in the structure.

However, if the problem is modeled as an SPP the model makes use of the simple structure. The mathematical formulation becomes simple and small, and there is often a low number of sets of variables. As a result, disruption management problems are often modeled as SPPs in the airline industry and railway industry. As for the heuristics in the time-space networks models, the SPP models need the column generation algorithms to be adjusted to fit the problem. Solving time and solution quality have to be decided when creating the column generator. For an SPP the column generation handles the operational constraints and the recovery actions. It can often be easier to include restrictions in the route generation than in the mathematical formulation. It will therefore not be necessary to do any changes in the mathematical formulation if any operational constraints or recovery actions are added to the problem. There is a large flexibility in how to generate the columns. As mentioned in section 4.1.5, to ensure an optimal solution all possible columns have to be generated. If all columns are generated the goodness of the chosen column generator can be found.

It can prove difficult to produce a good column generator. Often it is hard to find a way to be able to know for certain that all good columns are produced. Most of the good columns may be easy to find, but the last percentage of good

## 10. DEVELOPMENT OF THE OPTIMIZATION MODEL

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columns may be hard to locate and can therefore easily be left out by a heuristic column generator.

Both the time-space network approach and the SPP approach seem to be methods that will work good for our problem. Both methods have been used to solve similar problems in the liner shipping segment, the airline industry and in the railway industry. Although the time-space network approach has been used to solve disruption management problems before, we chose to formulate our problem as an SPP. This method is chosen so that the model can utilize the simple structure that occurs in a transportation problem. The mathematical formulation will then be small and easy to solve. Any changes in the operational constraints will be considered in the column generator, allowing the mathematical formulation to remain unchanged. One of the most important reasons to model the problem as a set partition model is that this approach can take advantage of the simulation model. The column generation and the simulation model will be closely linked together. The simulation model will then make the column generation more efficient. It is possible to develop a column generation algorithm that only has to generate the routes once per simulation, instead of once per optimization. This makes the model more efficient if there are several rescheduling actions per simulation.

In section 10.2.2 three different SPPs are presented and discussed. There are advantages and drawbacks with all the SPP proposals. Similarities and differences between the models are presented in section 10.2.2.

We have chosen to use the third SPP proposal as an approach to solve our problem. The first SPP proposal has the simplest mathematical formulation, but this simple formulation makes the column generation much harder to create than in the chosen proposal. Transshipment and chartering of vessels have to be considered in the column generation in the first two SPP proposals, while in the chosen SPP proposal this is taken care of in the mathematical formulation. In the second SPP proposal there is no link between the cargos and the vessels except for in the objective function. This leads to a need for two column generators, one for the vessels and one for the cargos. This will require more computational time than if there is only one column generator.

The cargos are handled in a much better way in the third SPP proposal than in the two other models. As mentioned in section 10.2.2; in the first two SPP proposals each cargo is given a unique index and each cargo has an origin port, a

### 10.3 Applied Optimization Model

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destination port, a pick up time and a delivery time. In the third SPP proposal, the cargos are not given a unique index. Instead all cargos that have the same departure port and destination port have the same index. The cargos do not have a specified pick up and delivery time, but there is a number of cargos that has to be transported each month.

The chosen model, parameters and variables are for the readers convenience punctually summarized below (for the complete model see page 116):

- $x_v^r$  is equal to 1 if vessel  $v$  is assigned to route  $r$ , 0 otherwise
- $\delta_i^t$  denotes the amount of cargo  $i$  that is transported on a chartered vessel in time period  $t$
- $C_{vr}$  is the cost of assigning vessel  $v$  to route  $r$
- $C_i$  is the cost of transporting cargo  $i$  with a chartered vessel
- $b_{irv}^t$  is the number of times cargo  $i$  is transported in route  $r$  in time period  $t$  multiplied by the cargo capacity of the respective vessel  $v$
- $D_i^t$  is the amount of cargo  $i$  that has to be transported in time period  $t$

$$\min \sum_{v \in \mathcal{V}} \sum_{r \in \mathcal{R}} C_{vr} x_v^r + \sum_{i \in \mathcal{J}} \sum_{t \in \mathcal{T}} C_i \delta_i^t \quad (10.22)$$

subject to:

$$\sum_{r \in \mathcal{R}} x_v^r = 1 \quad \forall v \in \mathcal{V} \quad (10.23)$$

$$\sum_{v \in \mathcal{V}} \sum_{r \in \mathcal{R}} b_{irv}^t x_v^r + \delta_i^t = D_i^t \quad \forall t \in \mathcal{T}, i \in \mathcal{J} \quad (10.24)$$

$$x_v^r \in \{0, 1\} \quad \forall v \in \mathcal{V}, r \in \mathcal{R} \quad (10.25)$$

$$\delta_i^t \geq 0 \quad \forall i \in \mathcal{J}, t \in \mathcal{T} \quad (10.26)$$

- The objective function 10.22 aims to minimize the costs associated with the rescheduling process
- Constraint 10.23 ensures that all vessels are assigned to exactly one route

## 10. DEVELOPMENT OF THE OPTIMIZATION MODEL

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- Constraint 10.24 ensures that all cargos are transported
- Constraint 10.25 ensures that  $x_v^r$  is binary
- Constraint 10.26 ensures that  $\delta_i^t$  is non-negative

In the upcoming section (section 11) a column generation algorithm is developed and explained.

### 10.4 Recovery Actions

In section 8 different recovery actions are presented. The recovery actions are obtained from papers written by T Notteboom (2006) and Kjeldsen et al. (2012). Six different recovery actions are presented and discussed.

- Speed change
- Omit port
- Change order of port calls
- Space charter and transshipment over land
- Cut and run
- Change port productivity

Our model take use of four of these recovery actions. The cut and run strategy and the change of port productivity are not handled by our model. Our model reschedules the ships after a disruption in two steps. If the delay is smaller than a given amount of time, the model increases the speed of the affected vessel so that the delay is gained within the two next port calls. If the delay is greater than the same given amount of time, the optimization model will take use of three recovery actions; omitting a port call, transshipment and space chartering and changing the order of port calls. The model can then use a combination of the recovery actions to reschedule the fleet at a minimal cost.

The cut and run strategy is not a much used recovery strategy by big RoRo vessels. The strategy is mostly used in ports that are tide dependent and in

## 10.4 Recovery Actions

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ports that are closed during the night and in the weekends. Around the world, there are not many large ports that are tide dependent. Large RoRo vessels are seldom calling ports that are closed during night and weekends. Due to these two reasons the cut and run strategy is not taken into consideration by our model.

The recovery strategy that concerns "change port productivity" is not taken into consideration by our model. According to Kjeldsen et al. (2012) there are only a few ports worldwide that can increase the port productivity by a significant amount. In addition, only a small amount of time can be recovered by this strategy.

Kjeldsen et al. (2012) and Brouer et al. (2013) have produced disruption models for the liner shipping segment. The model in Kjeldsen et al. (2012) uses the same recovery actions as our model. Brouer et al. (2013) have chosen to exclude the transshipment/space charter recovery action. Our model and the model by Kjeldsen et al. (2012) allow that cargos are transported by a different vessel than originally intended. This is not allowed by the model by Brouer et al. (2013), which only considers the schedule of the vessel that is delayed. The model by Kjeldsen et al. (2012) and our model take the whole fleet into consideration when a vessel is delayed. The model by Brouer et al. (2013) does not take into account that the vessels are part of a fleet, which means it does not take advantage of the fleet structure when rescheduling. The model developed in this thesis and the model developed by Kjeldsen et al. (2012) are able to take advantage of the fleet when rescheduling a delayed vessel. These two models will then be able to represent the reality better than the model by Brouer et al. (2013).

## 10. DEVELOPMENT OF THE OPTIMIZATION MODEL

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# 11

## Column Generation

To get a set partition model to work, there is need for one or more column generation algorithms. The column generation is often the hard and complex part of solving a SPP.

In section 4.1.2 and section 4.1.3 in the Literature Review, some column generation algorithms are presented. The column generation algorithm will in our case be a route generator that generates the routes that the vessels can sail. There is a large variety in the different column generation approaches. Rosenberger, E. L. Johnson, and Nemhauser (2003) solved their problem with a column generator that searches for directed cycles with a minimum number of aircrafts. Two different methods are presented by Andersson and Värbrand (2000). The first approach they present is a branch and bound algorithm that iteratively solve the LP relaxation of their problem. The second approach presented by Andersson and Värbrand is a Lagrangian relaxation together with sub-gradient optimization. Huisman (2007) generates new duties that are similar to the original duties by complete enumeration and choose columns based on reduced cost. Rezanova and Ryan (2010) use a branch and price algorithm. More column generation algorithms are presented in e.g. the review articles by Wilhelm (2002) and Lubbecke and Desrosiers (2005). One of the reasons for the large diversity of column generation algorithms is that the column generator needs to be adjusted to the problem. Solving time and solution quality have to be considered when developing a column generation algorithm. There is a clear trade-off between the solution quality and the computing time

## 11. COLUMN GENERATION

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Compared to other problems, our problem is rather small and will probably be solved within a short amount of time regardless of which column generation algorithm that are used.

A complete enumeration algorithm is implemented in the model and tested. Complete enumeration is among others used by Huisman (2007) to solve a rather big disruption management problem. This is a simple column generation algorithm that generates all possible routes for the vessels. A downside is the generation of many bad and unnecessary routes. For our model there is one great advantage with the complete enumeration algorithm. The optimization part of the model runs every time the fleet is rescheduled. Instead of generating new columns for each time the optimization model is to be run, the columns have to be generated once per simulation. The model can then use the same columns for the remainder of the simulation and optimizations. The number of reschedulings per simulation depends on the amount of time that is simulated and on the number of vessels in the model. Test shows that with six months of operation and 10 vessels the optimization model is run between three and four times. If another column generation approach was used, it may have to calculate new columns for each rescheduling. Columns that work well for one situation, may not work in the same good way in another situation.

As mentioned in previous sections; to ensure an optimal solution, all possible columns have to be generated. This means that the mathematical formulation is solved to optimality with the complete enumeration approach. Tests show that with this column generation algorithm problems with 10 vessels and 7 clusters of ports are solved within 60 seconds, and the columns are generated within 4 seconds.

The column generation algorithm consists of several smaller algorithms. Each algorithm generates all possible routes between the given ports, but with different schedule lengths. The first algorithm generates routes with only one port in each schedule, the second algorithm generates routes with two ports and so on. In our algorithm we generate all possible routes with up to six ports in each route. The pseudo code below describes part of the algorithm.

In the figures below (figure 11.1 and 11.2) output sections from the column generation algorithm are shown. Figure 11.1 shows routes with three ports while figure 11.2 shows routes with six ports.

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---

**Algorithm 1** Column Generation with one port

---

**for all** Ports **do**

    Generate all possible routes which includes the given Port

**end for**

---

---

---

**Algorithm 2** Column Generation with two ports

---

**for all** Ports **do**

**for all** Ports **do**

        Generate all possible routes which includes the given Ports

**end for**

**end for**

---

---

---

**Algorithm 3** Column Generation with five ports

---

**for all** Ports **do**

**for all** Ports **do**

**for all** Ports **do**

**for all** Ports **do**

**for all** Ports **do**

                    Generate all possible routes which includes the given Ports

**end for**

**end for**

**end for**

**end for**

**end for**

---

## 11. COLUMN GENERATION

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0	0	0	1	6	2
0	0	0	1	6	3
0	0	0	1	6	4
0	0	0	1	6	5
0	0	0	1	6	7
0	0	0	1	7	1
0	0	0	1	7	2
0	0	0	1	7	3
0	0	0	1	7	4
0	0	0	1	7	5
0	0	0	1	7	6
0	0	0	2	1	2
0	0	0	2	1	3
0	0	0	2	1	4
0	0	0	2	1	5
0	0	0	2	1	6
0	0	0	2	1	7
0	0	0	2	3	1
0	0	0	2	3	2
0	0	0	2	3	4
0	0	0	2	3	5
0	0	0	2	3	6
0	0	0	2	3	7

Figure 11.1: Example from the column generation algorithm -

4	7	5	3	2	3
4	7	5	3	2	4
4	7	5	3	2	5
4	7	5	3	2	6
4	7	5	3	2	7
4	7	5	3	4	1
4	7	5	3	4	2
4	7	5	3	4	3
4	7	5	3	4	5
4	7	5	3	4	6
4	7	5	3	4	7
4	7	5	3	5	1

Figure 11.2: Example from the column generation algorithm -

In section 13 the column generation algorithm is calibrated. The computing time required to generate all the routes depends on how "far ahead in time the algorithm looks" and how many possible ports there are to visit. The number of possible routes increases exponentially both with the number of possible ports to visit and with the number of ports each route should contain. However, the solution quality gets better if there are more and bigger routes to choose from. Consider the figures below for the relation between the of number of ports and computation time.

If our problem is extended and the required computing time becomes too long, other column generators should be developed and tested. The new column generation algorithm must be much faster to solve than the complete enumeration, because the new algorithm may run many times during each simulation.

---

Our set partition model has many similarities with the model developed by Rosenberger, E. L. Johnson, and Nemhauser (2003). Consequently it is naturally to look into the column generation algorithm used in their model. A mix of several algorithms may also work well. To generate routes and schedules that do not differ to much from the original routes and schedules may also be a way to solve the problem. When solving our problem with the complete enumeration algorithm, the optimization model tends to choose routes that do not differ much from the original routes. Often, only one or two port calls from the original route are changed after a rescheduling action.

The complete enumeration algorithm may be a sufficient way to solve our model even if the problems get much bigger. There are examples of large and complex disruption management problems that are solved with a complete enumeration algorithm. The problem solved by Huisman (2007) is a rather big problem with more than 8 500 tasks and 770 duties where around 800 tasks have to be rescheduled due to disruptions. His problems are solved within 15 hours.

If a new column generator is implemented, the complete enumeration algorithm will give an indication on how well the chosen algorithm works, both in terms of solution quality and in terms of solving time.

## 11. COLUMN GENERATION

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# 12

## Simulation Model

### 12.1 Problem Definition

The main objective of this thesis is to develop a framework model that can investigate how a given fleet with given schedules will perform in day to day operations. See section 2 for more information.

A simulation model, that simulates the operation of a fleet and exposes the ships to disruptions, was developed (see electronic attachment). When a large delay occurs due to these disruptions the model will reschedule the fleet in attempt to regain the delay. As the simulation model in Thiers and Janssens (1998), our model is a traffic model. This means that navigating the a vessel is not treated in a technical way, but in terms of the time required for certain activities, e.g. sailing a certain distance (Thiers and Janssens, 1998). Our model is developed to work for liner shipping fleets, the same way SimAir (Rosenberger, E. L. Johnson, Schaefer, et al., 2002) work for the airline industry; the primary purpose is to evaluate schedules and recovery policies. However, there are some key diferences between our model and SimAir. SimAir does not consider the sources of a delay and does not simulate the delays individually, while our model is interested in the delay sources. The delays are simulated individually, which makes it possible to find out what incidents occur more often, and what incidents result in the highest costs.

## 12. SIMULATION MODEL

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### 12.2 Logical Structure of the Simulation Model

The simulation model's purpose is to simulate the operation of a fleet. The development of the model is based on read literature and our own judgement. The simulation model was designed in a way that one part takes care of the simulation of the ships' and cargos' movements, one parts simulates disruptions and impacts and a final part solves the rescheduling problem. These are explained later on in this section.

After the basic concepts of the model was determined, a flow chart was developed. Consider the flow chart illustrated in figure 12.1 on page 137.

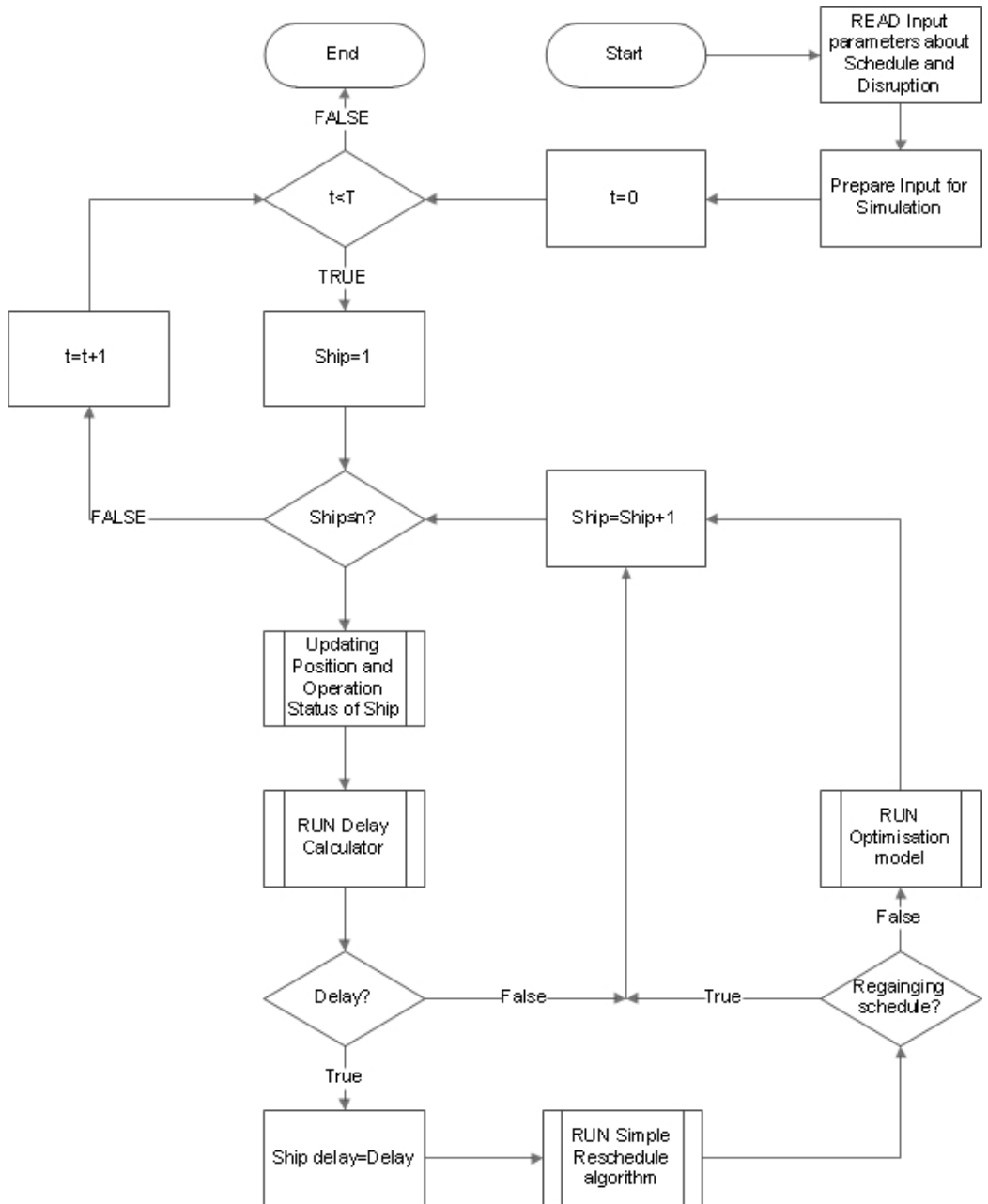
The flow chart shows the logic used in the simulation. The model simulates that the ships sail for a given amount of time  $T$ . As long as the accumulated time in the simulation is less than  $T$ , the model will keep running. The simulation model has information about the current positions of each ship, what the ships' previous and next harbour is, what the current speed is and how much cargo they carry. This information is updated every time step  $\text{delta } t$ . The next step in the model increases the time  $t$  with a given time interval,  $\text{delta } t$ . The model uses then calculations and random variables to find out if some disruption has occurred to one or more of the ships during the current time interval. These calculations follow the Monte Carlo principle, which is explained in section 9.2. The next step finds out what kind of incident occurred and calculate the amount of delay. Based on the ships' particulars and schedules, a rescheduling is done to reduce or eliminate the delay. The rescheduling process is discussed in section 8 and in section 10.4. After the rescheduling is done, the simulation continues to run by increasing time  $t$  and updating the ships' positions. All ships will now have new assigned routes. When these routes are finished, the ships will start over in their original schedules, see section 15.1 for more.

### 12.3 Classification of the Model

As mentioned in section 4.2, Angeloudis and Bell (2011) assert that the model has to be classified. A number of classifications may be applied, each classification focuses on different aspects.



### 12.3 Classification of the Model



**Figure 12.1:** Flow chart of the simulation

## 12. SIMULATION MODEL

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*Static or dynamic.* Our model simulates the operation of a fleet for a longer period of a time, where parameters and variables change continuously. Hence, the model is dynamic.

*Timing.* Our simulation is time dependent. The model is modeled in discrete time slots. The delay will be calculated in each time slot. This is in contrast to Rosenberger, E. L. Johnson, Schaefer, et al. (2002) in the SimAir model, that update their model each time a disruption occurs. Many simulation models make use of the Markov chain process as a stochastic discrete time process. Our model have some similarities with this methodology. One of these similarities is that our model is memoryless, except that some incidents can not occur when other incidents have happened. The probability of an incident only depends on the vessel's present state and whether a certain incident has happened.

*Deterministic or stochastic.* The disruptions occur randomly, therefore the model is stochastic. A version of the Monte Carlo simulation is applied to calculate the delay, for more about this see section 9.

### 12.4 Unit Overview

The following three units are used in the simulation:

- Ships (dynamic)
- Ports (static)
- Cargos (dynamic)

A unit is considered static when its particulars are consistent throughout the simulation, and considered dynamic when its particulars change. Ships and cargos change their positions during the simulation run and are therefore considered to be dynamic. Ports are static objects in a set coordinate system and are therefore static units.

All ships do by default have the same optional discrete speeds, but the cargo capacity differs from vessel to vessel. Some ports in the world are not accessible for all ships due to e.g. depth or length limitations. To account for this some vessels are not able to enter all ports in the model, making the fleet less homogeneous (see section 15.1.2 for more).

---

## 12.5 Simulation Model Variables

All ports are plotted in a coordinate system. The distances between the ports are calculated automatically in the script based on the coordinates. The coordinates of the seven ports are shown in appendix D.

There is only one type of cargo included in the simulation model. Each cargo has a specific origin and a specific destination port, and they are physically transported between the ports by the ships. This means that if a rescheduling happens and one of the ships changes its immediate port of destination, the cargo on board will arrive in the wrong port, and a space charter has to be arranged. This is a cost which is included in the optimization model.

## 12.5 Simulation Model Variables

The model has several different kinds of variables. They may be divided into four groups:

1. Input variables
2. State variables
3. Monitoring variables
4. Output variables

### 12.5.1 Input Variables

The input variables are adjustable, and the values of some of the input variables have a great impact of the performance and the properties of the simulation. This is discussed in section 13. Several of the variables are used in the optimization process as well. The most important input variables are presented below.

- $t$  is the starting time.
- $\delta t$  is the time step.
- $T$  is the total simulated time.
- *Planning period* is the time when the ships have to be back on the original schedule.

## 12. SIMULATION MODEL

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- *Delay parameters* are the parameters determining the delay.
- *Cargo* is an index showing port of origin and destination for all cargos.
- *SC cost* is the cost of a space charter (see section 15.1 for more).

In addition, there are several other input parameters. All of the input parameters may be found in appendices A, B and D.

### 12.5.2 State Variables

State variables are used to define the current state of the dynamic units in the simulation. The most important state variables are the ones defining the ships' state. These are presented below.

- *Operation status* defines whether a ship's status is (1) At Sea, (2) Arrival in port, (3) Departure from port and (4) Alongside.
- *Reschedule status* defines if the ship (1) need to reschedule, (2) is sailing with lower speed, (3) is sailing with higher speed and (4) is sailing with max speed.
- *Port schedule* indicates the last and next port call.
- *Current speed*
- *Remaining time in harbor*
- *Delay status* are the parameters indicating the current amount of delay.

### 12.5.3 Monitoring Variables

After a simulation is ran, the user may want to analyze the simulation run. Monitoring variables are variables that only log the statistics of incidents, ship movements, rescheduling actions taken etc. There is a lot of statistics available after each simulation run, some of them are presented below:

- *Frequency of each type of delay*
- *Total delay*

- *Distance sailed*
- *Cargo delivered*

### 12.5.4 Output Variables

Whenever a rescheduling takes place, the optimization software needs input from the simulation model to be able to solve the optimization model. The input is calculated by the simulation model and sent to the optimization software each time a rescheduling takes place. These output variables are:

- *Positions of the ships*
- *Cargo to be delivered the two following months*
- *The routes generated in the column generator*
- *What routes each ship is allowed to sail*
- *Data on what cargos are delivered in the generated routes*

## 12.6 Scripts

The main script *Main.m* and the most important subscripts, i.e. *Simulation.m*, *DelayCalculator.m* and *Reschedule.m*, are briefly explained in this section. For a more detailed explanation, see appendix C.

### 12.6.1 Main.m

As mentioned in section 12.2, the simulation model is divided into three parts where each part solves their own task. The three parts are handled by three different scripts; *Simulation.m*, *DelayCalculator.m* and *Reschedule.m*. *Main.m* is the main script in the simulation model, which allows the three aforementioned scripts to run in the correct sequence. The script *Main.m* manages the time steps and calls the others scripts to do the calculations. The algorithm is presented below.

## 12. SIMULATION MODEL

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### Algorithm 4 Main.m

---

```
READ ScheduleInput.m
READ DelayInput.m
RUN Preperation.m
while  $t < T$  do
  for all Ships do
    RUN Simulation.m
    RUN DelayCalculator.m
    if Delay occurred then
      RUN Reschedule.m
    end if
  end for
   $t = t + 1$ 
end while
Print Output
```

---

### 12.6.2 Simulation.m

*Simulation.m* is the script that handles the movement of ships and cargos. This script calculates the position of the ships, whether the ships are in port or in transit, the physical movement of the cargo etc. The script uses ship speed, the time step  $\delta t$ , the distances between the ports and the ship schedules as its most important variables.

### 12.6.3 DelayCalculator.m

For each time step  $\delta t$ , the simulation model controls if a disruption have occurred. These events are ship specific and do not affect the other ships in the simulation, making the ships independent of each other ( $P(A)=P(A|B)$ ). The script *DelayCalculator.m* calculates the delay in the operation. The different kinds of disruptions are discussed in section 7. The pseudo code for the script may be found below.

---

**Algorithm 5** DelayCalculator.m

---

*Ship* and *time* is known

**for all** *Incidents* **do**

**if** Current Operation Status of Ship = Operation Status of Incident **then**

**if** Incident is not a Forbidden Incident **then**

            Calculate consequence

**if** *Consequence* > *LowerLimit* **then**

*Consequence* impacts *Ship*

**end if**

**end if**

**end if**

**end for**

---

The calculations of the consequences are based on given distributions and randomly generated numbers, as discussed in section 9. Whether an incident is forbidden or not is discussed in section 7.1

#### 12.6.4 Reschedule.m

The script *Reschedule.m* solves the rescheduling problem in two steps, (1) try a simple algorithm and if this do not solve the problem, (2) run the developed optimization model to solve the problem.

The simple algorithm's only tool is changing the speed of the disrupted ship. As defined in the model, there are only three discrete speed options available, (1) slow steaming, (2) normal speed and (3) high speed. If the change of speed does not make the ship regain its delay within the given planning period, the optimization model has to reschedule the fleet. The rescheduling process reschedules all the ships so that all the freights can be done at a minimal cost. It is a 2-step process using route generation and optimization.

The column generation algorithm calculates all possible routes and its total distances. This is only done once in each simulation run, as the routes are independent of ship positions. Then all the ships' positions as well as the distances from all ships to the first port in all generated routes are calculated.

## 12. SIMULATION MODEL

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The route generation ends by calculating what port each ship should sail to after the new generated route has been sailed. The end ports should be the ports where the ships are as close to their original schedules as possible, as it is a goal to get all the ships back on their original schedule.



# 13

## Calibration of Input Parameters

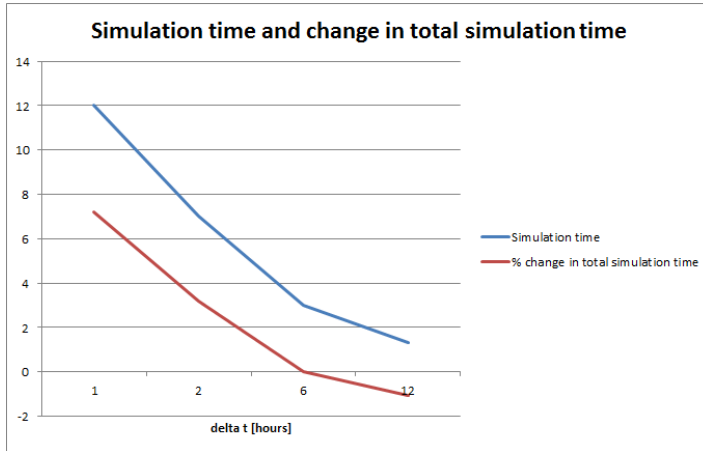
In section 12.5.1 some key input variables and parameters in the model were presented. These are the starting point of the simulation, the time step, the total simulation time, the planning period and the delay parameters. The space charter cost is also an important input value. In this section these input parameters are to be calibrated. The impact of changing the parameter values is investigated. Some of the parameter changes will increase or decrease the computing time required to solve the model, while other parameter changes will have direct impact on the result.

The time step,  $\delta t$ , decides how often the simulation model is updated. Smaller time steps results in more calculations needed to be done each time the simulation is run. Fewer disruptions will occur for each time step with smaller time steps. Instead of an accumulation of disruptions each time the simulation is updated, the disruptions are more evenly spread out in time. This leads to a more accurate and realistic model, but it also leads to a longer computing time. Larger time steps causes a faster, but more inaccurate model. The time step size is not used in the rescheduling process, making it a less important variable in the simulation. It can therefore be set to a quite large number without affecting the result. In our final simulation code we set the time step to six hours, as this

### 13. CALIBRATION OF INPUT PARAMETERS

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leads to a quite accurate, but also fast simulation. The effect of the time step on the computing time is presented in figure 13.1 below.

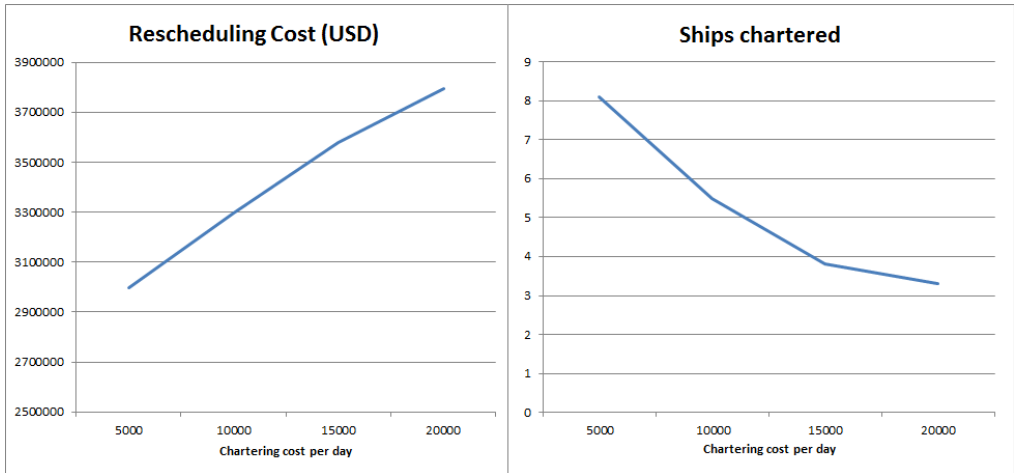


**Figure 13.1: Simulation time and percentage change in total computing time -**

The total simulation time, i.e. the total amount of days to be simulated, is denoted  $T$ . There may be some effects that a simulation that run for a short time does not capture, e.g. in the beginning of each simulation all ships are in a port. The simulation should therefore run for so long that it is not affected by any start up effects. For this reason we want at least two rescheduling actions to take place each time the simulation is run. The total time  $T$  is therefore set to 180 days. The computation time for the simulation part increases linearly with  $T$ . The rescheduling process is not affected by this parameter.

Space chartering a cargo is more expensive than transporting the same cargo with a vessel in the fleet. The amount of cargo transported with a chartered vessel will change with space charter cost. If the price of space chartering increases, the amount of cargo transported with chartered vessels decrease. An increase in charter price also increases the rescheduling cost. We set the space chartering cost to twice the cost of carrying the cargo with our own fleet. The effects of the space charter cost are presented in figure 13.2.

Another parameter that is calibrated and tested is the size of the routes to be generated in the column generation. The column generation takes longer time



**Figure 13.2: The effects on the solution when space chartering cost is changed -**

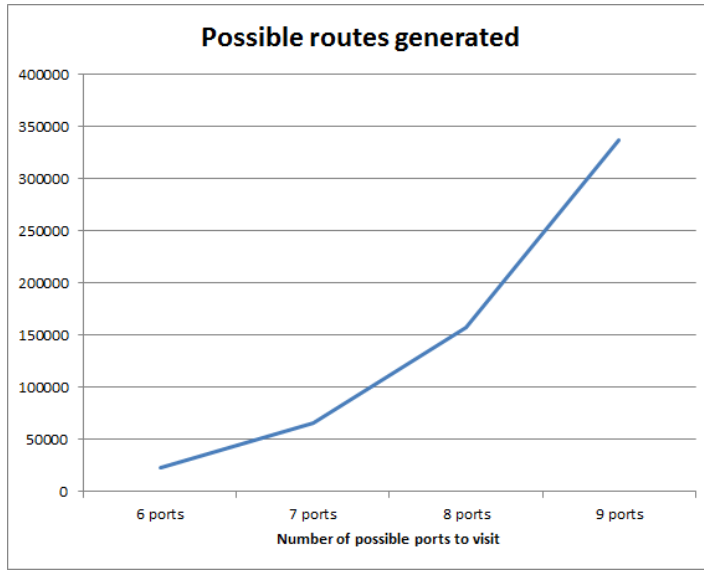
the more ports there are to be generated. The more ports there are in the routes that are to be generated, the more possible routes there is (see section 11). The number of possible routes increases with a factor of  $n - 1$  for each port call that is added to the generated routes. The result of the rescheduling process gets better if there are more routes to choose between. There is a tradeoff between time used by the column generation algorithm and the rescheduling quality. In figure 13.3 below the effect of number of ports allowed in the reheduling algorithm is shown.

The planning period is the time a given vessel has at its disposal to get back on schedule. It is more costly to have a short planning period than a long planning period. With a long planning period there is a greater freedom in how to get the vessels back on schedule after a disruption. An increase in the planning period will require a longer computing time for the model, this because the optimization model will have more schedules to choose from. As mentioned in the previous paragraph, for every additional port included in the route generation, the number of additional routes increases by a factor of  $n - 1$ . An increase in the planning period will have the same effect.

The delay input parameters were calibrated. Regarding Fagerheim (2013),

### 13. CALIBRATION OF INPUT PARAMETERS

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**Figure 13.3: Possible routes generated -**

the total delay for one ship during one year is approximately 15-20 days excluded distance deviation. This was the basis during the calibration. The final delay input parameters may be found in appendix A. As discussed in section 9, a lower limit is applied for delays. This was calibrated to be 15 hours and 36 for respectively delayed and off-hire.

# 14

## Results

In this section the test instances are described and the results from the computational study are presented. MATLAB in a 64-bit Windows 7 environment was used as the programming language for the simulation. The simulation is not very comprehensive; therefore an advanced programming language with increased control was not needed. MATLAB is at the same time a programming language all of our group members have a basic knowledge and understanding of. The column generation algorithm is also implemented in MATLAB. Xpress IVE was used to solve the optimization problems. All computational experiments were performed on a Lenovo ThinkPad W520, with an Intel Core i7-2820QM 2,3 GHz quad-core processor and 8 GB RAM. All reported times are rounded to full seconds of CPU time.

To test the model, six test instances have been generated. The test instances are characterized by the number of ships, the number of ports and the number of different cargos to be transported as shown in table 14.1. For each test instance six months of operation was simulated.

The different computing times varies for each individual run due to the stochastic parameters in the model. Some of the runs experience many delays and some runs experience few delays. Therefore each test instance was run 15 times, and the values presented in this section are based on the average values of each test instance. Table 14.2 shows the average number of delays the different test instances experienced each during each run.

## 14. RESULTS

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Test instance	Ships	Ports	Cargos
1	6	6	6
2	6	7	8
3	8	6	10
4	8	7	12
5	10	7	10
6	10	7	12

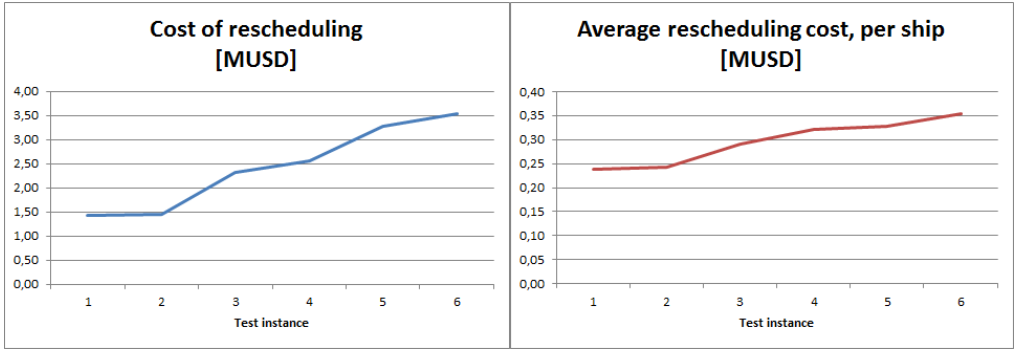
**Table 14.1:** Test instances generated for testing the performance of the model

The number of incidents that need to be handled by the optimization model increases when the problems get bigger and more vessels are involved. When the model handles more vessels it is natural that more delays occur. It is the same probability for each vessel to experience a delay, which means that when the number of vessels increases the total number of delays has to increase as well. The number of delays is not dependent on the number of ports and cargos. The variations that occur when the number of ports and cargos is changed, as shown in table 14.2, are due to the stochastic nature of the incidents.

Test instance	Average number of rescheduling incidents
1	2,3
2	2,0
3	3,0
4	2,7
5	3,8
6	3,2

**Table 14.2:** Average number of rescheduling incidents

The cost of rescheduling in the different test instances are shown in figure 14.1.



**Figure 14.1: Cost of rescheduling, MUSD -**

The performance of the model for the generated test instances is summarized in table 14.3.

Test instance	Average rescheduling cost	Average rescheduling cost per ship [MUSD]	Average computing time optimization [sec]	Average computing time for simulation and optimization [sec]
1	1,43	0,24	12	30
2	1,46	0,24	30	84
3	2,33	0,29	18	33
4	2,56	0,32	45	108
5	3,28	0,33	53	234
6	3,55	0,35	60	192

**Table 14.3:** A summary of the results obtained from running the model on the test instances

As expected, the model's computing time increases as the size of the test instances increases. The computing time increases heavily when the number of ports increases. The different computing times vary for each individual run due to the stochastic parameters in the model.

From table 14.3 it can be observed that the total cost of a rescheduling is

## 14. RESULTS

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more expensive when the problem to solve gets bigger. When more ships are included in the simulation model, more disruptions will occur. For the problem instances with the same number of vessels the total cost is slightly higher for the test instances with the highest number of ports and cargos. More cargos have to be transported and the vessels also have to transport cargo to more ports, which makes the rescheduling more complex and the rescheduling cost larger.

The average rescheduling cost per vessel increases when the test instances become larger. It might be natural to think that the average rescheduling cost per vessel should have decreased due to the theory about economy of scale. With a larger fleet there are more possible rescheduling actions to choose from, hence there should be a larger freedom in the assignment of cargos. The reason for the increasing rescheduling cost per vessel is that more cargos have to be transported in the larger problems. More cargo to transport causes a tighter schedule. When a tight schedule is disrupted the effects become more costly because more costly solutions may have to be applied, e.g. the chartering of vessels.

In table 14.4 below some computing times for the column generation algorithm is presented.

Number of ports	6	7	8	9
computing time [sec]	2	4	10	19

**Table 14.4:** Computing time for the column generation Algorithm

The table shows that the computing time increases when the number of ports increases. When the problems get bigger, the computing time required by the column generation algorithm becomes a larger part of the total optimization time and the running time for the whole model.

When a disruption causes a delay that needs to be handled by the optimization model, the vessels on the fleet are assigned to new routes. In table 14.5 the original routes before a rescheduling for the different vessels are presented. In table 14.6 the new routes after a rescheduling due to a delay is presented.

All the vessels have been assigned to new routes. The new routes do not differ too much from the original routes; for most of the vessels only one or two port calls are changed. A tendency in the new routes is that most ships have port 2 or 3 as their first port call. The reason for this is that port 2 and port 3



---

Port number	1	2	3	4	5	6
Vessel 1	2	3	1	2	4	3
Vessel 2	4	3	1	2	7	3
Vessel 3	3	1	2	4	3	1
Vessel 4	4	3	1	6	7	3
Vessel 5	2	3	1	2	4	3
Vessel 6	3	1	2	3	1	3
Vessel 7	6	3	7	3	4	6
Vessel 8	7	1	2	3	7	3
Vessel 9	3	1	2	3	1	2
Vessel 10	4	3	1	2	4	3

**Table 14.5:** Original routes

Port number	1	2	3	4	5	6
Vessel 1	3	1	2	4	3	4
Vessel 2	3	1	2	7	3	1
Vessel 3	3	1	2	1	2	3
Vessel 4	2	4	3	1	2	3
Vessel 5	2	6	5	4	3	1
Vessel 6	2	4	3	1	3	1
Vessel 7	2	6	7	3	7	3
Vessel 8	2	1	2	3	7	3
Vessel 9	2	6	2	3	1	2
Vessel 10	2	3	1	2	3	1

**Table 14.6:** New routes after a delay

## 14. RESULTS

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are in this simulation model the most busy ports where the most cargos are to be transported to and from.

The model provides some output values after each simulation run. As shown in the tables above the costs, computing times, number of reschedulings and the routes are provided. In addition the model provides an event log that shows what incidents occurred during the previous simulation run. The event log provides information on how many times each incident occurred and on the total and average delay due to each incident. In figure 14.2 an excerpt from the event log is shown. The excerpt shows the impact on the model from machinery problems and extreme weather. The event log can be used to investigate what incidents caused the most delays. Often when a rescheduling takes place the delay incurred to the ship in question is a result from two or more delays. E.g. first a delay due to machinery problems occurs, then the ship starts sailing with reduced speed. The accumulated delay grows so large that the model has to reschedule the fleet to be able to deliver all cargos on time.

```
Machinery down, Delayed
Number of incidents: 13
Total delay: 233.2
Average delay when incurred: 18

Machinery problems, Reduced speed
Number of incidents: 24
Total time of reduced speed: 419.6
Average time of reduced speed when incurred: 17

Break-down of vital parts of the ship, Delayed
Number of incidents: 3
Total delay: 48.5
Average delay when incurred: 16

Extreme weather, Reduced speed
Number of incidents: 6
Total time of reduced speed: 100.3
Average time of reduced speed when incurred: 17

Extreme weather, Delayed
Number of incidents: 2
Total delay: 35.7
Average delay when incurred: 18
```

Figure 14.2: Excerpt from the event log -

### 14.1 Compared With Other Models

It is hard to compare different models. The same assumptions are not applied to the different models and the problems that are solved are not the same. To our knowledge there is no one that has developed a day to day simulation and optimization model for the liner shipping segment. However, there are made some disruption management models that handle disruptions and rescheduling actions. It is then natural to compare the optimization part in our model with other disruption management models in the liner shipping segment, i.e. the models in Kjeldsen et al. (2012) and Brouer et al. (2013).

The model by Brouer et al. (2013) only takes the affected vessel into consideration when rescheduling after a delay, which makes their model much faster than our model and the model by Kjeldsen et al. (2012). In the last two models it is the interaction between the vessels that is computational expensive. Therefore it is hard to achieve an actual and fair comparison between our optimization model and the model in Brouer et al. (2013).

Our model and the model by Kjeldsen et al. (2012) use the same recovery actions when they try to get the ships back on schedule, which makes a comparison possible. Both in our thesis and in the study by Kjeldsen et al. different test instances were generated to test the performance of the models. Test instance 2 in our thesis and test instance 6 in the study by Kjeldsen et al. include six ships and seven ports. The number of cargos is eight in our test instance, while it is 102 in the test instance by Kjeldsen et al. However, in our model a cargo has a different meaning than in the study by Kjeldsen et al. (see section 10.2.2). Kjeldsen et al. (2012) solve their test instance with a planning period of 10 days, while in our model the planning period is 60 days. The time steps in our model are set to six hours, while in the model by Kjeldsen et al. (2012) the time steps are set to four hours. As explained in section 13, the time steps do not affect our optimization model's solving time. It is unknown if this affects the model by Kjeldsen et al. (2012).

Our model solves the optimization part of the test instance on average within 30 seconds. Kjeldsen et al. (2012) solve the test instance with six ships and seven ports within 205 seconds, but the best objective is found within 6 seconds. The computing time of 30 seconds is a rather good result by our optimization model compared to Kjeldsen et al. (2012). The computer used in this thesis has approximately the same processor speed (2,3 GHz vs 2,53 GHz) as the computer

## 14. RESULTS

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used by Kjeldsen et al. (2012). But due to more processor cores (4 cores versus 2 cores) and more available RAM (1,8 GB versus 8 GB) in addition of being a newer generation of processor, the total computing power of the computer used in this thesis is quite superior. Without a direct comparison of computing power it is impossible to know the exact impact in computing time this constitutes. Comparison between the number of calculations needed in the optimization part should therefore be considered, but this information is not provided by Kjeldsen et al. (2012).

The solution quality is not compared, because there were given different values on the costs associated with the operation of the fleet of vessels.

# 15

## Discussion

In this section we will discuss the development of the model, the assumptions made, strengths and weaknesses found as well as the usefulness of the model. To our knowledge, none has used a disruption management model to investigate the qualities of a corresponding deployment model in the maritime transport segment. Nor is there anyone that has solved a disruption management problem in the liner shipping segment with a simulation optimization model. Only two studies in the field of disruption management in liner shipping are produced, both are recently published (2012 and 2013). These two studies have been important inspiration when developing our model. The two disruption management models by Kjeldsen et al. (2012) and Brouer et al. (2013) do not cover all subject that are covered in this thesis. Hence other papers have also been important inspiration, especially papers about airline and railway disruption management have been used.

### 15.1 Assumptions made

Some assumptions and simplifications have been made when developing our model, both in the optimization part and in the simulation part. In this section the assumptions and simplifications and their impact on the result will be discussed.

## 15. DISCUSSION

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### 15.1.1 Optimization Model

In our model a vessel with a minor delay will increase the speed so that the vessel is back on schedule within the two next ports. If it is not possible to regain the delay so that the ship is less than 24 hours late to the second port, the optimization model will take use of the three recovery actions; omitting a port call, transshipment and space chartering and changing the order of port calls to get back on schedule. The 24 hour requirement is developed so that a ship has to be very late to port before a costly rescheduling action takes place. For vessels that are able to regain the delay within the two next port calls it may be better to use one or more of the other recovery actions than speed increase to regain the delay. Small delays may therefore be regained in a more efficient way than by the method use.

In the column generation algorithm all possible routes for the vessels are generated. The cost for assigning a ship to each route is then calculated. This makes the long routes more expensive than the short routes. To overcome that only short routes are chosen in the rescheduling phase, a "penalty fee" is added to all routes, depending on the length of the routes. The penalty fee is calculated based on average sailing distances and port stays in the planning period of two months. This leads to some inaccuracy in the total cost due to variances in the total distance sailed and number of ports visited in the planning period, but it should be sufficient. Observations show that the routes chosen for the ships are largely similar to the original routes, implicating that the penalty fee does not affect the optimal solution too much. Without the penalty fee the model would choose only the shortest routes with only one or two port calls, excluding many possible routes that might be better. Therefore the model is more accurate with the penalty fee than without.

In the simulation model the vessels' sailing speed has a discrete distribution. There are only three steps in the speed for the vessels, one "slow" speed, one "normal" speed and one "high" speed. The reason for choosing a discrete speed distribution instead of a continuous distribution is to better represent a real world situation. A ship will not change it's sailing speed from e.g. 19 knots to 19.4 knots. The ship would most likely sail at a "high speed" to regain it's delay before decreasing it's speed back to normal transit speed. When the optimization model is rescheduling it calculates new routes for all the vessels. These routes are based on the same "normal" transit speed for all vessels on all routes.

### 15.1.1.1 Objective Function

There are also made some assumptions regarding the objective function (15.1). Two terms are included in the objective function. The first term sums up the costs associated with assigning routes to the vessels, and the second term sums up the costs associated with space chartering.

$$\min \sum_{v \in \mathcal{V}} \sum_{r \in \mathcal{R}} C_{vr} x_v^r + \sum_{i \in \mathcal{J}} \sum_{t \in \mathcal{T}} C_i \delta_i^t \quad (15.1)$$

In the model the cost associated with assigning routes to the vessels depends on the distance sailed, number of port calls and the penalty fee because a short route was selected. A cost is also added if the ship carries cargo and the first port in the new route is not the destination port of the cargo. This is a simplification, when there are other costs associated with the sailing and assigning routes to the vessels. The cost of sailing is also dependent of cargo condition, it is more expensive to sail a full loaded vessel than an empty one. The weather condition also has impact on the sailing cost, it is more expensive to sail in bad weather with high waves than in good weather with flat water. In reality, the cost variation between the selected routes would most likely be greater. The cost function also does not take into account that some cargos and ships are heavier than others, treating all cargo and all ships equally in terms of transportation cost.

The cost associated with space chartering,  $C_i$  is only dependent on distance and size of the cargo transported. In real life this cost is dependent on more than these two factors. Often it is more expensive per cargo unit to transport a small amount of cargo than a large amount of cargo. This makes it more expensive to transport large amounts of cargo on a chartered vessel, and cheaper to transport small amounts of cargo on a chartered vessel.

In the model it is possible to space charter all cargos, independent of the required amount of cargo to be transported. This may not be the reality in the real world.

In the real world there are also other costs associated with the rescheduling after a delay. When rescheduling in real life there will be some extra work for the shipping company that has to reorder and cancel port calls. This extra work will have a cost that is not accounted for. This leads to that many and large

## 15. DISCUSSION

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changes in the schedule will be more expensive in real life than in the model, and that few and small changes will be more expensive in the model compared to real life. The variation in cost of administrating the rescheduling process is considered small enough to be neglected.

### 15.1.1.2 Restrictions

Due to the assignment constraint (15.2) all vessels need to be assigned to new routes. Our model always has to take all the ships into consideration when rescheduling, and can therefore not exclude any ships from the rescheduling process. This is not considered as a problem since all possible routes are generated, which means that if an optimal solution is where some ships stay on their original schedule, this will be a part of the optimal solution.

$$\sum_{r \in \mathcal{R}} x_v^r = 1 \quad \forall v \in \mathcal{V} \quad (15.2)$$

After all vessels are assigned to new routes, the delays that all ships already have experienced are deleted. Delays that are currently occurring, like ships sailing at reduced speed or with an increased resistance factor will still remain. A downside of this is that these factors are not considered in the optimization model.

Constraint 15.3 ensures that all cargos are transported and that the freight demand is met. A given amount of cargo has to be transported.

$$\sum_{v \in \mathcal{R}} \sum_{r \in \mathcal{R}} b_{i,r}^t x_v^r + \delta_i^t = D_i^t \quad \forall t \in \mathcal{T}, i \in \mathcal{J} \quad (15.3)$$

The constraint only specifies the demand on a monthly basis, a result of this is that it is possible to transport all the cargos in the same day. However, as the model does not want ships to sail with ballast water, the cargo is evenly spread out over the routes that are chosen. In reality there may be some operational restrictions that our model does not consider, e.g. that the cargos must be picked up three times a month with intervals of 10 days. Such operational constraints are not considered in our model, resulting in a higher flexibility to



## 15.1 Assumptions made

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generate routes than in real life, and will make the result better than without this simplification. The simplification may also lead to the generation of routes that are not operationally feasible. On the other hand, such constraints can easily be implemented in the column generation algorithm if they were to be considered.

### 15.1.2 Simulation

As mentioned in the Literature Review; one of the drawbacks with a simulation is that the mathematical model may not take into account all the aspects of the reality. Many of the simplifications made in the simulation model have resulted in a model that needs less calculations and thus is faster at a cost of realism.

The simulation model is made memory less, however this will not be true in all cases. As an example, it is more likely that a storm with strong headwind arises if there has been a strong headwind the day before. And engine trouble is more likely to occur if there have been some mechanical breakdowns earlier on. This simplification makes the simulation less accurate. Data on delays and incidents' probability distributions can be included so that the total number of delays and disruptions that occur during the simulation is the same as in the real world. This way the distributions and impacts are based on real life delays where the connections between the delays are disregarded.

All the vessels in the simulation model operate independent of each other. As a result of this, two different vessels that are in the same area can experience two different weather systems. One of the vessels may be delayed due to bad weather conditions, as the other vessel does not experience any bad weather. This assumption will not influence the vessels individually, but the interaction between the vessels may be disturbed. Rescheduling actions will be influenced by the fact that all vessels operate independently in the simulation model. A ship available for assistance in the simulation model might not be available in real world.

Heterogeneous fleets are a common characteristic for the maritime transport segment, this applies in particular for RoRo fleets. In our model the only features that differ the ships apart are the cargo capacity and that some of the vessels are not able to enter some of the ports. Except for this all vessels are treated in the same way in the simulation model. Age and area of operation are not accounted for. In the real world delays will occur more often for old ships than

## 15. DISCUSSION

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for new ships. They will also occur more often for ships that operate in areas with harsh environments. In our simulation, all ships will be treated equally, which leads to less variation in operation as none of the ships will experience significant more disruptions due to the age of the ship or the area of operation.

RoRo vessels are mainly used to transport three types of cargo; cars, high and heavy, and break bulk. In our simulation model there is no differentiation between these cargos; instead of three types of cargos there is only one type of cargo. This means that all vessels are able to transport all types of cargos, and there is no limit in how much of any type of cargo a vessel can transport except for the overall cargo capacity. This simplification makes both the optimization and simulation simpler than if all three cargos had been implemented. Many more calculations would have been necessary if this simplification had been left out. This is also a simplification that leads to less variation in operation in the model than in the real world. The route assigning is much easier when only considering one type of cargo; all vessels can then be treated in the same way. With three types of cargo, the cargo compatibility requirements for all the vessels have to be considered while assigning the routes. The cargo simplification makes it easier to compare the results from our model with the models by Kjeldsen et al. (2012) and Brouer et al. (2013). These models are made for the container shipping segment and only have one type of cargo. With three types of cargos in our model and one type of cargo in their models the comparison would have been more complicated.

In the simulation, all costs are homogeneous for all the vessels and all the ports. In reality the costs are vessel, port and cargo specific. This makes the fleet more homogeneous in the simulation model than in the real life. In the model the fuel cost varies with the velocity difference squared ( $\Delta$ Fuel consumption =  $f(\Delta V^2)$ ). This is an assumption that is not true for all speed changes, but as an overall function it is quite accurate.

Dry-docking is usually done every fifth year. In the simulation model, dry-docking and bunkering is neglected. Incidents and delays related with these states are accounted for.

The sailing distances between the ports are static. The same sailing route will be sailed each time a vessel sails from port A to port B, and the same sailing route will be sailed from port B to port A, just in the opposite direction. The ports in the model are placed randomly in a coordinate system. They are modeled

## 15.1 Assumptions made

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as islands and there are no other islands in the coordinate system. There are therefore no obstacles the vessels have to take into consideration when sailing between ports. In the real world the vessels are not able to sail the straight line between two ports and the ships have to navigate through narrow straits and around islands. Hence the distance sailed will normally be longer than the straight lines between the ports. This can be accounted for by manually plotting the distances between the ports instead of letting the preparation script in the simulation model calculate the distances. In addition, no canals are included in the model, which may be a source of disruption. Static distances also lead to that there is no deviation in sailing distance between the sailings. The deviations can be a result of different weather conditions, ocean currents etc. Therefore sailing from port A to port B may take a longer time than sailing from port B to port A.

The time spent in port is the same for all vessels and static. There is no differentiation in terms of loading and unloading volume. In the real world the length of the port stay is dependent on how much cargo that is to be handled during the stay. It can also be dependent on which port the vessels are loading cargo. This leads to less variation in operation for the vessels. The sum of the time spent in port for all vessels will be correct, but for the small ships the time spent in port will be longer in the simulation than in real life, and for the big ships the time spent in port will be shorter in the simulation than in real life.

When the vessels are loading in the ports, they always load until they are fully loaded. In the real world, the cargo on board may have different destination ports. In our model, all cargo on board have the same destination port. This leads to a more restrictive route assigning. If a cargo is to be transported between port A and port B, one of the vessels in the fleet has to pick a route that is sailing directly between these two ports without a visit in another port in between.

### 15.1.3 Incidents and Delays

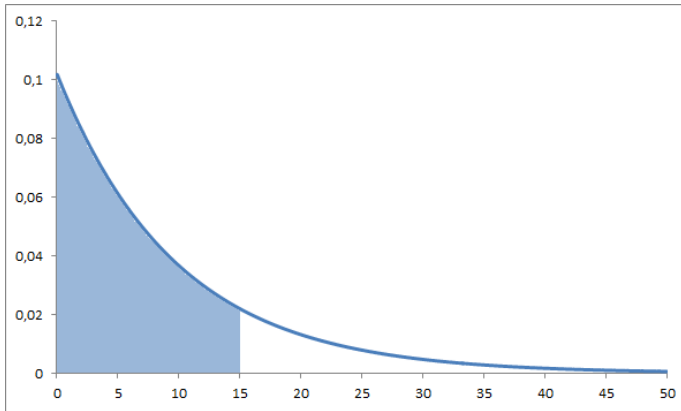
During operation of a fleet, several incidents may occur. The intention of the model is to validate deployment models for daily operations. Hence, the most normal incidents are included, and the extreme incidents, e.g. tsunami, are excluded.

To determine the incident's frequency and impact, two stochastic distributions were applied; exponential and Weibull-distribution. Other literature

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Exponential distribution were represented the duration of sailing with reduced speed, delayed and off-hire. An exponential distribution may give a great amount of minor delays and a minor amounts of major delays. The minor delays may be handled easy by increasing the sailing speed of the vessel. Therefore, a lower limit for valid delays were established. A consequence of this, is that the majority of the delays will have a impact close to the lower limit. In figure below, one may see the probability distribution for delay when machinery problem occurs. The colored area under the graph represents the valid impact.



**Figure 15.1: The probability distribution for an exponential function for machinery problems with consequence delayed with  $\mu = 9.77$  -**

When a ship has to sail with reduced speed, the master and his crew are determining the speed based on the environment's condition, in other words, the term reduced speed do not represent one constant speed. In the developed model in this thesis, the model calculates the duration of the reduced speed, and not the speed. In this way, the impact on the schedule regarding reduced speed varies. For the incident reduced speed, the ship's reduced speed was assumed to be 14 knots.

As discussed in section 13, the delay input parameters are calibrated based on correspondance with Fagerheim (2013). Fagerheim (2013) informed that WWL did not have any incident specific delay statistics currently available. Therefore, the input parameters for the different incidents are just assumptions. Anyway,

collecting data regarding delays and disruptions would increase the accuracy of the simulation model.

## 15.2 Use of the Model

The goal of this thesis is to build a framework to evaluate the deployment model in the MARFIX project. The model has more areas of use than to be a verification model for deployment models. A shipping company may apply the model to evaluate rescheduling policies, or to decide what recovery actions to take use of in case of a disruption. The effects of vessel breakdowns and port closures may also be investigated by the model. In this section the different applications of the model will be discussed. Advantages and disadvantages with the model developed are also discussed.

There can be some issues regarding use of theoretical models. Sometimes a theoretical model shows results that are inconsistent with what the company's experience suggests. The reason may lie in the assumptions made to simplify the model. A theoretical model should therefore be used as a guidance together with other models and own experience.

### 15.2.1 Evaluation of a Deployment Model

In this thesis a simulation and optimization model is developed. This model is made to analyze and verify a given deployment model considering the day to day operation of the fleet. The model is developed in such a way that it is easy to change and understand the input parameters. It is also made as general as possible so that the model is able to handle many kinds of fleet and port configurations. The probabilities and the distributions have to be customized to the given fleet and area of operation.

If a shipping company want to verify their deployment model, they have to add vessel data, port data, cargo data and route data into the model. Then they have to run the model a sufficient number of times, this due to the random numbers in the simulation. It is then possible to evaluate the behavior of the deployment model. It will also be possible to make some small changes in the deployment model, and investigate the result of these small changes. This way the deployment model that best fulfills their criterias can be found.

## 15. DISCUSSION

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The model that is developed has weaknesses and strengths. The optimization part of the model is modeled as a set partition model. This leads to a two-step optimization model; first the routes have to be generated, then the mathematical formulation can be solved. Both the set partition model and column generation algorithm take advantage of the structure that occur in transportation problems. The mathematical formulation is simple, small and easy to solve. Complete enumeration is chosen as the column generation algorithm. The same routes will then be used each time the fleet is rescheduled. The complete enumeration generates many unnecessary and poor routes. If large problems that include many different ports are to be solved, some problems might arise. The calculations related to the optimization part will then demand a large amount of computations. Our computer lacked sufficient RAM when the problem consisted of 10 ships, 9 ports and 12 cargos. The number of vessels in the model does not have the same impact on the computing time as the number of ports (see section 11). The computing time increases exponentially when more ports are included in the column generation. This makes the model better built to handle problems with a small number of ports than a problem with a large number of ports.

The simulation part and the optimization part are developed to match each other. The simulation model calls on the optimization model when there is need for rescheduling actions. The optimization model then uses the output from the simulation as input parameters.

However, there are some uncertainties associated with such a simulation. In the development of the model there are made many assumptions and simplifications. These are presented and discussed in section 15.1 above. The assumptions and simplifications will affect the results.

### 15.2.2 Rescheduling after a Disruption

During the analyzation and verification of a deployment model, our model optimizes the reheduling process. The model takes the input parameters, including the vessel positions, the freight forward obligations and the original schedules into consideration. This is the same that the model in Brouer et al. (2013) does. This model is developed to evaluate a given disruption scenario and to select an appropriate recovery action. Brouer's model was applied to four real life cases from Maersk Line and results were achieved in less than 5 seconds with solutions comparable or superior to those chosen by the company's operations

managers. Based on the results, cost savings of up to 58% may be achieved by the suggested solutions compared to realized recoveries of the real life cases.

There are also many similarities between the reheduling by our model and the model by Kjeldsen et al. (2012). The model by Kjeldsen et al. (2012) constructs a set of vessel schedules and cargo routings that allows resumption of scheduled service after a delay.

Both of the before mentioned models are developed to reschedule a liner fleet after a delay. The optimization part of our model works in the same way as these models, and should be able to solve such problems. In section 14.1 the results from the model by Kjeldsen et al. (2012) and our optimization model is compared to each other. This comparison shows that with the same number of vessels and ports our model find new schedules much faster than the model by Kjeldsen et al. The model by Kjeldsen et al. is able to find the best objective value faster than our model, but has to run much longer to ensure that there is no better objective to be found.

Some changes may have to be done in our optimization model if it is to solve only rescheduling problems; the optimization model is now customized to work together with the simulation model. As mentioned earlier the column generation algorithm is due to the complete enumeration, tailored to solve more rescheduling problems with the same columns. If the optimization model is to be used to solve one rescheduling per time the column generation algorithm is used, the algorithm may be changed. A column generator that generates routes that do not differ to much from the original could be a good starting point. On the other hand, the complete enumeration algorithm may be sufficient, especially for fleets that are not visiting a large number of different ports. The number of possible routes increases rapidly when the number of ports is increasing (see section 11).

Christiansen, Fagerholt, Nygreen, et al. (2007) mention that several companies prefer to rely on intuition and experience when doing strategic, tactical and operational planning, instead of operational research. To our knowledge, there have only been made two studies that concern disruption management in the liner shipping segment. Historically, the usual way to get a vessel or fleet back on schedule after a delay has been to increase the speed on the disrupted vessel. The models by Kjeldsen et al. (2012) and Brouer et al. (2013) have shown that there can be significant cost savings by using operational research

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when rescheduling after a delay. The optimization model by Brouer et al. (2013) solves real life cases. Computational results show similar or improved solutions to historical data. The model tend to omit port calls and change the order of port calls instead of increase the vessel speed.

Table 14.5 and table 14.6 in section 14 show that also our optimization model tends to omit port calls and change the order of port calls. Our model also takes all the vessels into consideration when rescheduling. Most of the vessels get new routes after a rescheduling.

The results from these models show that optimization research has a future in the day to day operation in liner shipping. Optimization models are able to solve operational problems in a new way, they are also able to handle much more information than the operators handle today.

### 15.2.3 Other Applications

A shipping company can also use the model to check their rescheduling strategies and the effect the decisions have. They can simulate the different rescheduling strategies they are using, and find what strategy that are most favourable. The shipping company can then find if its daily rescheduling routines should be changed.

The simulation and optimization model can be used by a shipping company to investigate the effects on their fleet from bigger accidents. The effects of port closures and vessel breakdowns can be investigated. As an example, in March 2011 many ports where closed down due to the nuclear disaster at the Fukushima Daiichi power plant in Japan. How to react on such an incident can be hard to decide. The model developed in this thesis could be an useful tool. By making it impossible for all vessels to visit the closed ports, running the simulation model with this as an input could give valuable guidance.

Another situation that can occur is that a ship is unavailable for a longer time period. This can happend due to wreckage or breakdown on some vital equipment as propeller, shaft or rudder. The vessel will then not be available to perform its freight forward obligations. The effect of this can be investigated by our model. The model can then be an useful tool to solve the problems thats occur in a better way.

A shipping company may also use the model to investigate the effect of new versus old equipment. With older equipment more and larger delays may occur.



## 15.2 Use of the Model

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The shipping company can update the probability parameters and examine the effects of lower and higher probabilities for accidents. The shipping company can then use the model as a support tool in investment decisions.

## 15. DISCUSSION

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# 16

## Conclusion and Further Work

In this master thesis, we have developed and discussed a simulation optimization framework model to verify and investigate deployment models in the liner shipping segment. The framework model is able to test different deployment models in a day to day operation. A fleet may look good on the strategic and tactical levels, but it may fall short when it is exposed to disruptions and delays on the operational level.

The framework model is tested on six different test instances. Each test run simulated half a year of operations. Due to the stochastic simulation, multiple runs for each test instance was performed and average values were found. The solving time varied with the size of the problems; the smallest test instance was solved within 30 seconds, while the largest test instance was solved within 234 seconds. When the problems get larger, the column generation algorithm requires a larger ratio of the total solving time. The optimization model takes all the vessels' routes into consideration when rescheduling, which means all the vessels are assigned to new routes. However, normally the new routes do not differ much from the original routes. The test runs show that the model is well suited to simulate day to day operations in the liner shipping segment. The optimization part is also able to find good ways to recover from large delays.

The framework model consists of two parts, one simulation part and one optimization part. The simulation model simulates the day to day operation of a liner fleet. The simulation model is modeled as a dynamic, time dependent

## 16. CONCLUSION AND FURTHER WORK

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and stochastic model. It is made as general as possible, making it easy to implement different fleet compositions into the model. SimAir, which is described in Rosenberger, E. L. Johnson, Schaefer, et al. (2002), has been an important inspiration when developing the simulation model.

The liner shipping disruption management models by Kjeldsen et al. (2012) and Brouer et al. (2013) have been important sources of inspiration for the optimization model. Also disruption management models from the airline industry and railway segment are used as inspiration. The optimization model consists of a mathematical formulation and a column generation algorithm. The mathematical formulation is modeled as a set partition model, which makes it possible to utilize the structure that can occur in transport problems. By using the set partition approach the mathematical model itself got small and simple, and a column generation algorithm was included. We developed and implemented a complete enumeration algorithm, which is a simple and often time consuming algorithm that generates all possible routes for the vessels. The reason this algorithm was chosen is that during a simulation there might be a need of more than one rescheduling. The optimization model can then use the same routes each time it is run and thus reduce the total computing time. The optimization model considers omitting port calls, changing the order of port calls and space chartering cargo as possible recovery actions.

A number of possible extensions of the framework model warrants further research. The model developed in this master thesis is built as a framework that can test and verify deployment models. As this thesis is a part of the MARFIX project it is natural to implement and test the MARFLIX deployment model. The fleet and its schedule must be implemented together with appropriate probability distributions and impacts. The model is then able to test different versions of the deployment model and find the best alternative.

If the MARFLIX deployment model or other deployment models are to be tested in the framework model, the simplifications and assumptions discussed in section 15.1 should be re-evaluated. A natural extension of the model would be to allow the model to handle different types of cargos. RoRo vessels usually handle three types of cargo; cars, high and heavy and break bulk. The MARFLIX deployment model contains vessels that have different capacities for the three types of cargos. The different kinds of cargo should therefore be implemented in the model to test the MARFLIX fleet correctly.

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Another possible extension of the model is to allow each ship to simultaneously carry cargos with different destination ports. Real world liner vessels usually transport cargos with more than one destination port at the same time. This extension will create more freedom in the route assigning, and the model will be more realistic.

It would also be interesting to make the model more heterogeneous by differentiating on vessel age, area of operation and time of the year. E.g. older vessels normally experience more and longer delays than newer vessels, and more bad weather will occur in the winter than in the summer.

As mentioned in section 11, if large problems is to be solved with the framework model a new column generator algorithm has to be considered. The amount of possible routes generated becomes too large for the optimization software to handle; therefore a heuristic method should be developed for larger problems.

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# Appendix A

## Incidents

Incident	Consequence on schedule	Alpha	Beta
Wind	Delayed	0.45	3
Current	Delayed	0.45	3

**Table A.1:** Incidents at sea with gamma distribution

Incident	Consequence on schedule	$\mu$
Congestion	Delayed	11.1702
Late arrival of pilot	Delayed	13.9619
Collision in harbor	Delayed	8.3771
Collision in harbor	Off-hire	16
Late arrival of tugs	Delayed	8.3771
Too low tide	Delayed	11.1701
Too heavy weather	Delayed	18.1512

**Table A.2:** Incidents for arrival to port with exponential distribution

## A. INCIDENTS

---

Incident	Consequence on schedule	$\mu$
Machinery down	Delayed	9.7741
Machinery problems	Reduced speed	11.1702
Break-down of vital parts of the ship	Delayed	8.3771
Fire onboard	Delayed	1.397
Fire onboard	Off-Hire	14.4
Man Over Board	Delayed	2.5142
Pollution spill	Delayed	0.8383
Mutiny	Delayed	0.2795
Sickness onboard	Delayed	1.397
Fog	Reduced speed	9.7741
Waves	Reduced speed	12.1
Iceberg danger	Reduced speed	1.397
Extreme weather	Reduced speed	8.3771
Extreme weather	Delayed	6.9807
Grounding	Delayed	1.9543
Grounding	Off-Hire	14.5
Collision with whales	Delayed	0.8383
Collision with whales	Off-Hire	15.5
Collision with other vessels	Delayed	1.9543
Collision with other vessels	Off-Hire	14
Collision with other things	Delayed	2.234
Collision with other things	Off-Hire	14.4
Piracy	Delayed	6.9807
Piracy	Off-Hire	16
Ships nearby in distress	Delayed	8.3771

**Table A.3:** Incidents at sea with exponential distribution

---

Incident	Consequence on schedule	$\mu$
Stevedores work too slow	Delayed	17.6
Labor strike	Delayed	4.4
Blockout	Delayed	3.3
Cargo arrives too late to port	Delayed	4.4
Deficiencies on Port State Control	Delayed	8.8
Deficiencies on Classification Society Control	Delayed	6.6
Deficiencies on Custom Control	Delayed	7.7
Break-down of vital parts of the ship	Delayed	8.8
Pollution spill	Delayed	4.4
Moorings break	Delayed	3.3
Mutiny	Delayed	1.1

**Table A.4:** Incidents alongside with exponential ditribution

Incident	Consequence on schedule	$\mu$
Late arrival of pilot	Delayed	13.9619
Collision in harbor	Delayed	8.3771
Collision in harbor	Off-hire	14
Late arrival of tugs	Delayed	8.3771
Break-down of vital parts of the ship	Delayed	13.9619
Too low tide	Delayed	11.1702
Too heavy weather	Delayed	18.1512

**Table A.5:** Incidents departure from port with exponential ditribution

## A. INCIDENTS

---



# Appendix B

## Several Incidents in a Row

		<b>This cannot occur</b>						
<b>If this occur</b>	<b>Incident</b>	Congestion	Late arrival of pilot	Collision in harbor	Collision in harbor	Late arrival of tugs	Too low tide	Too heavy weather
		Congestion	1	1			1	1
	Late arrival of pilot	1	1			1	1	
	Collision in harbor			1				
	Collision in harbor				1			
	Late arrival of tugs	1	1			1	1	
	Too low tide	1	1				1	
	Too heavy weather							1

**Table B.1:** Several incidents in a row: arrival to port

## B. SEVERAL INCIDENTS IN A ROW

---

		<b>This cannot occur</b>						
<b>If this occur</b>	<b>Incident</b>	Late arrival of pilot	Collision in harbor	Collision in harbor	Late arrival of tugs	Break-down of vital parts of the ship	Too low tide	Too heavy weather
		Late arrival of pilot	1	1	1	1	1	1
	Collision in harbor		1					
	Collision in harbor			1				
	Late arrival of tugs	1	1	1	1	1	1	1
	Break-down of vital parts of the ship	1	1	1	1	1		
	Too low tide	1	1	1	1	1	1	1
	Too heavy weather	1	1	1	1		1	1

**Table B.2:** Several incidents in a row: departure from port

---

	<b>Incident</b>	<b>This cannot occur</b>		
<b>If this occur</b>	Stevedores work too slow	1		
	Labor strike	1	1	1
	Blockout	1	1	1
	Cargo arrives too late to port			1
	Deficiencies on Port State Control			1
	Deficiencies on Classification Society Control			1
	Deficiencies on Custom Control			1
	Break-down of vital parts of the ship			1
	Pollution spill			1
	Moorings break			1
	Mutiny			1

**Table B.3:** Several incidents in a row: alongside

## B. SEVERAL INCIDENTS IN A ROW

		<b>This cannot occur</b>																												
		Machinery down	Machinery problems	Break-down of vital parts of the ship	Fire onboard	Fire onboard	Man Over Board	Pollution spill	Mutiny	Sickness onboard	Fog	Waves	Wind	Iceberg danger	Countercurrent	Extreme weather	Extreme weather	Grounding	Grounding	Collision with whales	Collision with whales	Collision with other vessels	Collision with other vessels	Collision with other things	Collision with other things	Piracy	Piracy	Ships nearby in distress	Denied access to scheduled port	
<b>If this occur</b>	<b>Incident</b>																													
	Machinery down	1																												
	Machinery problems		1																											
	Break-down of vital parts of the ship			1																										
	Fire onboard				1																									
	Fire onboard	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
	Man Over Board						1																							
	Pollution spill							1																						
	Mutiny								1																					
	Sickness onboard									1																				
	Fog										1																			
	Waves											1																		
	Wind												1																	
	Iceberg danger													1																
	Current														1															
	Extreme weather											1	1	1	1	1	1													
	Extreme weather											1	1	1	1	1	1													
	Grounding																	1												
	Grounding	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
	Collision with whales																				1									
	Collision with whales	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
	Collision with other vessels																					1								
	Collision with other vessels	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
	Collision with other things																							1						
	Collision with other things	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
	Piracy																									1				
	Piracy																										1			
	Ships nearby in distress																												1	
	Denied access to scheduled port																													1

**Table B.4:** Several incidents in a row: at sea

# Appendix C

## The Simulation Model Explained

This appendix explains each script included in the simulation model individually. The input variables will be explained where an explanation is necessary. The scripts are found in the electronic attachment.

### C.1 Main.m

To run the simulation model, the user must open and run the script named Main.m. This is the main script that, as explained in section 12.6.1, will run each sub-script in the correct order.

#### C.1.1 Input Scripts and Preparation

Main.m will begin by running the input script ScheduleInput.m, which contains details the other scripts will need to run their tasks, e.g. port coordinates and cargo departure and destination ports etc. See the tables in appendix D for information on the input values used here.

The next script to be run is Preparation.m. In this script input values from ScheduleInput.m are used to calculate several different values and indices

## C. THE SIMULATION MODEL EXPLAINED

---

used later on in the simulation model, e.g. the number of ships, route lengths, distances between ports etc.

The scripts `Print.m` and `Print2.m` are output scripts that log important simulation calculations related to the ships' movements, delays, destinations and sailing speed. This way the user is able to investigate how the delay occurred and accumulated, what speed the ships sailed at etc. The log is updated for every time step  $\Delta t$ .

The last script to be run before the simulation starts is `DelayInput.m`. This script contains important parameters for each disruption, which are used in the calculation of the delay incurred and the probability of disruptions. See appendices A and B for the full list of input variables.

### C.1.2 The Simulation Scripts

After the previously mentioned scripts have been run, the simulation is run. `Main.m` will now follow a three-step script run, which is followed for every time step  $\Delta t$  and for every ship in the simulation. The three-step script run is explained in section 12.6.1 and contains of three scripts: `Simulation.m`, `DelayCalculator.m` and `Reschedule.m`.

The script `Simulation.m` calculates the ship movements based on given schedules, ship speed, delays, time in port etc. It is one of the most comprehensive scripts in the simulation model. Each time step the script has to update the ships' positions, what cargo they carry, whether they are in a port and if so, what port to sail to next. When doing the calculations the script has to take several variables and scenarios into consideration; whether the ship is sailing with reduced speed, with increased speed or if it is sailing on a new schedule and if so, consider if the ship in question is finished sailing in the new schedule and has to start over again in the original schedule. All possible scenarios have individual calculations and variables, and all of these have are included in `Simulation.m`.

When the position of a ship is updated, the script `DelayCalculator.m` will calculate if a disruption has occurred. The script will calculate a random number for each incident and use Monte Carlo Simulation, as explained in section 9.2, to find out if a disruption has happened and if the ship is delayed. The input variables from `DelayInput.m` are used here.

### C.1.3 Rescheduling after a Delay

If a ship experiences a delay, the script `Reschedule.m` will run. This script will, as mentioned in section 12.6.4, try to regain the ship's delay in two steps; first increase ship speed and then reschedule. If a rescheduling is needed the script `Rerouting.m` will run. This script runs a series of subscripts to calculate the different input parameters used in the optimization model.

The first script, `NextPorts.m`, will calculate the next 12 ports the ships are to visit and, based on these ports, calculate what cargo is to be transported in the next two months of operation.

The next script, `ShipPositions.m`, will calculate the ships' positions in the coordinate system and based on that, calculate the distance to all ports in the coordinate system.

If the column generator has not been run before in this simulation run, the next scripts will be `ColumnGen.m` and `MonthlyCargo.m`. `ColumnGen.m` will calculate all possible routes with up to six port calls and calculate the distance of each of these routes. `MonthlyCargo.m` will calculate what cargo is transported in each of the generated routes.

`EndPorts.m` is the next script to run. This script's main objective is to find out what port each ship should sail to after any given generated route. The end port is chosen to be the port in the original route where the ship is as close to the original schedule as possible after it has sailed the new route. The script will also calculate the cost of sailing each route with each ship based on ship positions, end port and route distance.

`ObjectiveFunction.m` will prepare the costs for each route and each ship so that they may be sent to the optimization software in the correct format. It will also calculate the cost of chartering cargos and the cost of not sailing to the port where the current cargo was intended.

`Restrictions.m` will prepare the parameter values for each constraint so that they can be sent to the optimization software in the correct format. It will also modify the parameters to be ship specific, to account for the cargo capacity and port accessibility of each ship.

`MoreCargo.m` will calculate the cargos that are transported in the remaining planning period after each the ship is back on the original schedule. This varies depending on ship capacity and what route the ship in question chooses to sail.

## C. THE SIMULATION MODEL EXPLAINED

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The script is now ready to call on the optimization software. The output to the optimization software is the different parameter values calculated previously as well as information about the developed optimization model. The information consists of the type of constraints and the lower bounds for the variables.

After the optimization software is run the script will process the solution and turn the solution into new schedules for each ship. This is done in the script `NewSchedules.m`.

When `Rerouting.m` is finished, `Rescheduling.m` will continue to run. It will reset the ships' delays and prepare some indices used in `Simulation.m` so that the new schedules are followed in the simulation script.



# Appendix D

## Input Variables

<b>Cargo number</b>	<b>Origin port</b>	<b>Destination Port</b>
Cargo 1	1	2
Cargo 2	1	3
Cargo 3	1	7
Cargo 4	2	3
Cargo 5	2	4
Cargo 6	2	7
Cargo 7	3	1
Cargo 8	3	7
Cargo 9	3	4
Cargo 10	5	3
Cargo 11	6	4
Cargo 12	7	3

**Table D.1:** Cargo information

## D. INPUT VARIABLES

---

Port number	X	Y
Port 1	2500	2500
Port 2	100	200
Port 3	3000	-200
Port 4	1500	-2000
Port 5	-200	-2500
Port 6	-2000	-100
Port 7	-2000	1500

**Table D.2:** Port coordinates

Vessel number	Capacity
Vessel 1	1
Vessel 2	1,2
Vessel 3	1
Vessel 4	1,3
Vessel 5	0,8
Vessel 6	1,5
Vessel 7	1,1
Vessel 8	0,4
Vessel 9	0,8
Vessel 10	1

**Table D.3:** Vessel capacity

---

<b>Vessel Number</b>	<b>Status</b>	<b>Cargo on board</b>	<b>Cargo on board 2</b>	<b>% of leg sailed</b>	<b>Operation status</b>
Vessel 1	0	0	0	0	0
Vessel 2	0	0	0	0	0
Vessel 3	0	0	0	0	0
Vessel 4	0	0	0	0	0
Vessel 5	0	0	0	0	0
Vessel 6	0	0	0	0	0
Vessel 7	0	0	0	0	0
Vessel 8	0	0	0	0	0
Vessel 9	0	0	0	0	0
Vessel 10	0	0	0	0	0

**Table D.4:** Current

<b>Vessel Number</b>	<b>Can not enter port</b>	<b>Can not enter port</b>
Vessel 1	0	0
Vessel 2	5	0
Vessel 3	5	6
Vessel 4	5	0
Vessel 5	7	0
Vessel 6	0	0
Vessel 7	5	0
Vessel 8	4	6
Vessel 9	5	0
Vessel 10	6	0

**Table D.5:** Forbidden ports

## D. INPUT VARIABLES

---

Vessel number	1	2	3	4	5	6	7	8	9	10	11
Vessel 1	1	2	3	7	2	4	3	7	2	5	3
Vessel 2	2	4	3	1	2	3	4	1	2	3	1
Vessel 3	2	3	1	2	4	3	1	2	3	1	0
Vessel 4	2	4	3	1	6	4	3	1	2	3	1
Vessel 5	3	1	2	3	1	2	4	3	1	2	4
Vessel 6	1	3	7	2	3	1	3	1	7	4	2
Vessel 7	3	1	3	4	5	1	3	5	3	4	5
Vessel 8	1	2	3	7	3	1	2	3	7	3	2
Vessel 9	2	6	7	3	1	2	3	1	2	6	7
Vessel 10	2	4	3	1	2	4	3	1	2	7	3

**Table D.6:** Vessel routes

---

<b>Input variables and parameters, SceduleInput</b>	<b>Value</b>	<b>Explanation</b>
t	0	Starting time
deltat	6	Time step
T	24*180	Ending time
Trec	24*60	Planning period
PortStay	30	Time used in port
Speed	[19 23 17]	Transit, high and low speed
RedSpeed	14	Reduced speed
CostPortDelay	50000	Cost of being late in port
Pot	2	The exponential power, used in fuel consumption calculations
Cfuel	600	Cost of fuel, USD/mt
EngineS	20000	Engine size
FuelCon	176	Specific fuel consumption
ApproachingPortDistance	2	Used in defining operation status
DeproachingPortDistance	2	Used in defining operation status
distancecost	10	Cost of sailing 1 nautic mile, based on about 5000 USD/day when sailing at normal speed
portcost	1000	Cost of visiting 1 port
spotchart	15000	Spot chartering cost, USD/day
DurationChangedResistance	36	Duration of the impact "changed resistance"
penalty	50000	Cost of not delivering a specific cargo
VeryLargeNumber	99999999	Used in the objective functions for ports where some ships can not sail
LateinPort	24	How late a ship may be before a rescheduling takes place

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**Table D.7:** Values and explanation of input parameters

## D. INPUT VARIABLES

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