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Chapter 4

The Vessel Schedule Recovery Problem (VSRP) - a MIP model for handling disruptions in liner shipping

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[1]

Abstract Containerized transport by liner shipping companies is a multi billion dollar industry carrying a major part of the world trade between suppliers and customers. The liner shipping industry has come under stress in the last few years due to the economic crisis, increasing fuel costs, and capacity outgrowing demand. The push to reduce CO_2 emissions and costs have increasingly committed liner shipping to *slow-steaming policies*. This increased focus on fuel consumption, has illuminated the huge impacts of operational disruptions in liner shipping on both costs and delayed cargo. Disruptions can occur due to adverse weather conditions, port contingencies, and many other issues. A common scenario for recovering a schedule is to either increase the speed at the cost of a significant increase in the fuel consumption *or* delaying cargo. Advanced recovery options might exist by swapping two port calls or even omitting one. We present the Vessel Schedule Recovery Problem (VSRP) to evaluate a given disruption scenario and to select a recovery action balancing the trade off between increased bunker consumption and the impact on cargo in the remaining network and the customer service level. It is proven that the VSRP is $\mathcal{NP}$-hard. The model is applied to four real life cases from Maersk Line and results are achieved in less than 5 seconds with solutions comparable or superior to those chosen by operations managers in real life. Cost savings of up to 58% may be achieved by the suggested solutions compared to realized recoveries of the real life cases.

Keywords: disruption management, liner shipping, mathematical programming, recovery

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4.1 Introduction

Disruptions occur often in a global liner shipping network. According to Notteboom (2006) approximately 70-80% of vessel round trips experience delays in at least one port. The common causes are bad weather, strikes in ports, congestions in passageways and ports, and mechanical failures. More exceptional causes include piracy and crew strikes on the vessels.

Example: The vessel Maersk Sarnia is deployed on a scheduled service providing transport of container cargo between South-East Asia and the west coast of Central America, see Figure 4.1. During the pickup of cargo in South-East Asia the weather conditions cause Maersk Sarnia to suffer a 30 hour delay when leaving Kwangyang in South Korea. The delay can cause the vessel to miss an important scheduled port call in the transhipment port of Balboa in Panama. As a result large parts of the cargo will miss their onward connections and most cargo will not be delivered on time.

In order to mitigate the negative effects of the delay on Maersk Sarnia the operations center at Maersk Line has several options:

- Omit the upcoming port calls at Yokohama, Lazaro Cardenas, or Balboa.
- Speed up significantly to try to reach Balboa on time.
- Swap the port calls of Lazaro Cardenas and Balboa.
- Accept the delay and catch up the schedule returning to South-East Asia from Balboa.

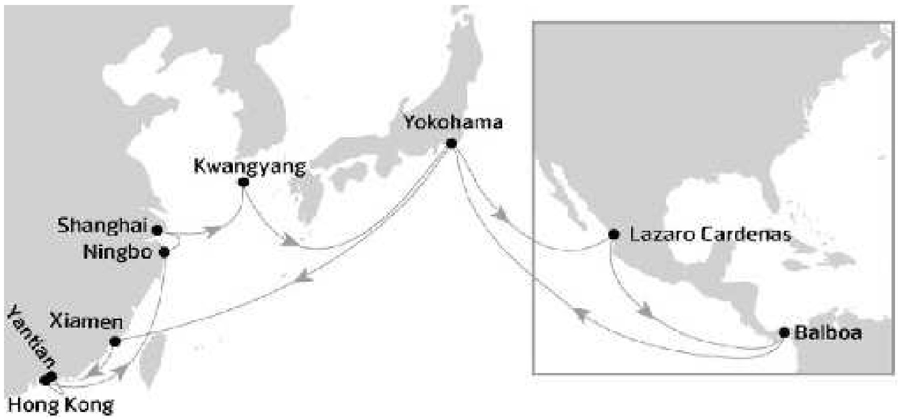


Figure 4.1: A trans-pacific round trip is depicted. Cargo is collected in transshipment ports in Asia and sailed to transshipment ports in Central America. The round trip takes 56 days implying that 8 vessels is required to maintain a weekly service. Feeder vessels are used to connect all ports in a geographical area.

Currently when a disruption occur, the operator at the shipping companies manually decides what action to take. For a single delayed vessel a simple approach could be to speed up. However, the cost of bunker fuel is a cubic function of speed (Alderton, 2004) and vessels' speeds are limited between a lower and upper limit. So even though an expensive speed increase strategy is chosen, a vessel can arrive late for connections, propagation delays to other parts of the network.

In recent years liner companies have had an increased focus on minimizing the bunker consumption in order to provide environmentally friendly transport and to minimize the operational costs (Maersk, 2010). On the other hand, on time delivery is very important for a global liner shipping company as delayed cargo carries a high cost by customers and key clients. Nevertheless, the negative effects of miss-connections or delaying a key clients merchandise can be hard to measure against a concrete cost of for example bunker. Furthermore, the ripple effect of the recovery on to the remaining network is very complex to overview for a human. In the considered example Maersk Sarnia recovered the situation by a general speed increase with a high bunker cost, but

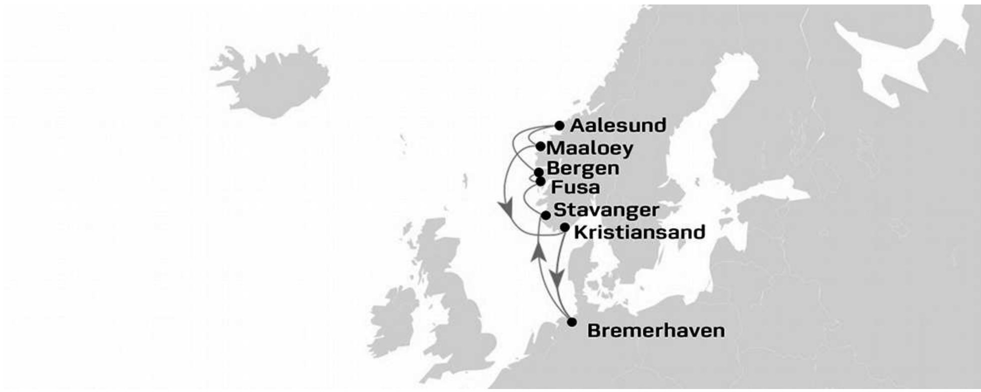


Figure 4.2: A feeder service collect containers in the hub in Bremerhaven and transport them to their destinations in Norway.

nevertheless the speed increase did not ensure timely delivery of containers to the hub port of Balboa, and final recovery was done returning to Asia. As a result all the cargo was delayed and some cargo missed the onward connection at the hub. The mathematical model presented in this paper suggested omitting the last port call in Asia reaching the transhipment port without increasing the vessel speed and on time. The cost saving, including a delay penalty, of the suggested solution is more than 20 %.

A standardized way of handling disruptions based on mathematical grounded decision support may significantly lower the cost of handling disruptions as seen in the airline industry (Rakshit et al., 1996; Yu et al., 2003) and simplify implementation of strategic decisions among stakeholders. According to UNCTAD (2010) *slow-steaming* has resulted in a significant increase in delays and they expect carriers to resume higher speeds in order to increase reliability and productivity. According to Notteboom (2006) reliability is generally achieved by introducing sufficient buffer time into a service. We believe that a mathematical decision support tool as the one presented in this paper may result in sustaining a *slow-steaming* policy, while increasing reliability of service without the need to introduce additional buffer time. In this paper, we introduce a mathematical model for handling the most common disruptions in liner shipping called the Vessel Schedule Recovery Problem, VSRP.

We make four contributions: First, we propose a novel formulation for the VSRP inspired by similar models within the airline industry. To the best of our knowledge the present article is the first to apply optimization to handle disruption management within the domain of liner shipping networks. Secondly, We prove the VSRP to be NP-complete. Third, we report computational results for four cases representing common disruptions, selected by experienced personnel at Maersk Line Operations Center. The recovery options identified by the mathematical model are comparable or superior to the decisions implemented in real life with cost savings of as much as 58%. The model is solved by a MIP solver within seconds for the selected cases. Fourth, a set of generic test instances is used to provide insights into the network sizes that may be handled in seconds by the current model and solution methods.

The remainder of the paper is organized as follows. Section 4.2 introduces disruption management in the liner shipping business. Section 4.3 describes related literature. In Section 4.4 we introduce the *Vessel Schedule Recovery Problem (VSRP)*, the graph topology, and a mathematical model for the VSRP along with proofs of the $\mathcal{NP}$- completeness of the problem. In Section 4.5 we introduce the four real life cases and the generic test instances and report computational results. Following this section we conclude that a decision support tool based on mathematical optimization of a disruption scenario could greatly aid an operations manager in evaluating the different recovery options.

4.2 The Liner Shipping Business

Liner shipping of containers is the backbone of world trade. Even though containerization simplifies the operations and reduces the cost per transported unit, the earned return is less than 10% on assets (Stopford, 2009). Customers demand fast and reliable delivery, while the shipping companies constantly search to cut costs. These issues have motivated major investments in improving the daily operations at large shipping companies (Notteboom, 2006). The liner shipping company referred to as a *carrier* has a public schedule of services. A service consists of a cyclic route with a scheduled time for each port call en route. Containers travel through the network as passengers in a public transit network, often combining several services. The port calls of a service, must usually happen at a predefined time and place in the port, often called the *berth slot*. This is defined by the physical place that the vessels moors, the berth, and a time window where the vessel is serviced. Most carriers provide weekly frequency of port calls. In recent years major companies are using slow-steaming to lower the variable cost and the CO2 emission (Løfstedt et al., 2011; Rosenthal, 2010; Maersk, 2010). To stay competitive, research has been focused on designing the network to operate as efficiently as possible. For shipping companies, a division of the ports into *hubs and spokes* is common(Christiansen et al., 2007). The network is not a traditional *hub and spoke network design* with direct links between two hubs or a spoke and a hub. As an alternative large vessels operate *main lines* between a set of hub ports and smaller vessels operate *feeder lines* connecting a set of spokes to a hub. An example of a *main line* service between hub ports is given in Figure 4.1 and an example of a *feeder* service servicing a hub and several spokes is given in Figure 4.2.

The motivation for this hub-and-spoke network design is to benefit from the economies of scale on container vessels (Stopford, 2009). The majority of containers are transhipped at least once during transport adding to the operational complexity and the impact of a disruption. Liner shipping companies operate with a head haul and a back haul direction. In the head haul direction vessels are almost full as opposed to the back haul direction. The head haul generally generates the majority of the revenue retrieved by operating the full service. As described above disruptions are accounted for and handled in the network by adding buffer time. Customer demand for fast delivery results in increased speeds and nearly no buffer time on the head haul, whereas the back haul is slower and has more buffer time. Due to the complexity of recovering from a disruption additional buffer time is included on the back haul with the option of a slight speed increase to catch up with the schedule on the back haul.

The most important variable costs in a liner shipping network is the bunker cost, the cost of using passageways such as the Suez and Panama canals, and the cost of calling ports to load and unload cargo. The fixed cost of operating a network in terms of asset costs on vessels, containers, and equipment are significant. Whenever a vessel fails to operate in accordance with the original schedule it is hurting the shipping company's business (and the business of their customers) (Notteboom, 2006). The utilization of vessels will often be affected negatively as containers miss-connect, resulting in a higher cost per transported unit. Furthermore, it might be necessary to arrange alternative transport for the miss-connected units also adding to the cost. Finally, the customers demand a reliable service and expect on time delivery. A major concern is therefore how to handle disruptions when they occur.

For larger liner shipping companies the information about disruptions are gathered in the company's Operational Control Center (OCC), from where decisions are also taken with respect to how the disruptions should be handled. Decisions here are taken in real-time and any system to support this process should support real-time decision making. The reason for this is two-fold. 1) Weather is changing quickly in some parts of the world, which may cause a port to close for a period of time. In such a case it is important to make a reasonable quick decision regarding whether the port should be skipped, which typically will lead to a change of course and the possibility of slowing down and saving on bunker fuel. 2) The other and more important reason is that controllers working in the OCC are in some periods faced with the need for taking many decision and evaluating various alternatives. This is where the requirement for a quick response becomes imperative. For this reason controllers at Maersk have stated 10 seconds as a reasonable response time for a disruption management system.

4.2.1 From airline disruption to liner shipping disruption

Operations research has for many years been applied extensively in the airline industry (Barnhart, 2009). Initially OR was mainly used in the planning phase, but during the last two decades OR has also found its way into the disruption management tools, which are used on the day of operation where the planned schedule is being executed.

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 airline and liner shipping businesses have evident similarities, but also some core differences (Christiansen et al., 2004). Larger airlines and larger liner shipping companies both operate a hub and spoke network, where either passengers or containers need to flow from an origin, through one or more hubs to a destination. Here, they need to arrive with the least possible amount of delay. In this way vessels resemble aircraft and containers resemble passengers. While crew recovery is a significant part of disruption management for an airline, this is not the case for a liner shipping company, as crew always follow the vessel and do not have work rules, which significantly limit the utilization of the vessel. Traditional aircraft recovery as described by Thengvall et al. (2001) or Dienst et al. (2012) makes use of 3 recovery techniques: *Delays*, *Swaps* and *Cancellations*. In addition to these techniques Marla et al. (2011) show that a large improvement in the number of passenger miss-connections can be obtained if *speed-changes* are included as a fourth recovery technique. In the following we discuss how each of these techniques can be applied to disruption management in a liner shipping network:

- *Delays.* For an airline the most straight forward way of handling a disruption is to delay flights and let the delays propagate to the subsequent flights of an aircraft. After a number of delay propagations the initial delay will have disappeared due to the fact that the gap between flights is usually a bit longer than the required turn time and most aircrafts are idle over night. For an airline this recovery technique is unfortunately also the one which, when applied alone, often ends up causing a lot of miss-connections (Dienst et al., 2012). In liner shipping it is also possible to delay the departure of a vessel, but port calls do not have additional slack built into them and container vessels are constantly in service, which means that delay propagation will not be able to resolve a disruption on its own. It will need to be combined with some of the techniques presented below in order to have the desired effect of recovering from a disruption.

- *Swaps.* This is a very efficient recovery technique for an airline, as it can be used to eliminate a lot of delay propagation to subsequent flights. Swaps are possible as an aircraft becomes empty after each flight. As a result one aircraft may be substituted for another. Unfortunately, this technique is not applicable to a liner shipping company, as a container vessel servicing a certain service is never empty and it is both extremely costly and time consuming to empty it completely. While vessels cannot be swapped in the VSRP it is for a liner shipping company possible to swap the order in which ports are being visited, whenever these ports are located geographically close to each other.

- *Cancellations.* This technique is usually not preferred in the aircraft recovery problem, but it is an efficient way of recovering, whenever the airline experience large delays or reduced runway capacity. For a liner shipping company this technique is unfortunately not directly applicable as it would interrupt the service operation of the vessel. In the VSRP it is however possible to cancel or omit a port call. In this case containers, which are destined for the omitted port, are then off-loaded at a subsequent nearby port and containers for on-loading in the omitted port are being held for the next vessel on that service, or another service covering the same ports, which often results in a delay of up to a week.

- *Speed changes.* Including speed changes from a network perspective as an integrated part of disruption management turns out to be a very effective way of balancing passenger delays versus fuel burn for an airline (Marla et al., 2011). This is in spite of the fact that a flight usually can only be sped up with 8-10% compared to its planned speed. For a vessel, which is originally scheduled to sail at a slow steaming speed of e.g. 16-18 knots, it is possible to speed up with 40% to e.g. 22-24 knots. This additional speed flexibility may be promising for the application of this technique in a liner shipping network.

As it is seen there are some clear similarities in the techniques, which can be applied in recovering a disruption in an airline network, and the techniques, which can be applied in recovering a disruption in a liner shipping network. The aircraft swapping technique available to an airline provides increased interaction between aircrafts in an airline network as opposed to vessels in a liner shipping network. An additional complication in a liner shipping network is that vessels operate around the clock and cannot naturally recover by using some of the overnight slack, which is often available in an airline network. For this reason recovering from a liner shipping disruption may take days and even weeks as opposed to a typical maximum of 48 hours for airlines. If a container fails to connect to a succeeding vessel the impact will often be more severe in liner shipping. International airports have a number of daily departures for a given destination presenting the option to re-accommodate passengers with a slight delay on a subsequent flight. For liner shipping a missed connection will normally result in a major delay.

We must estimate the effect on the cargo on-board with regards to missed onward connections and delays in order to assess a given recovery plan. Ideally the container groups would be reflowed on the residual capacity of the entire liner shipping network simultaneously with a recovery plan for the delayed vessels. This would significantly increase the graph of our instance as the containers on-board will include services, not considered in the disruption scenario. Additionally, reflowing the cargo is a large scale multicommodity flow problem. Mathematical models incorporating a large multicommodity flow problem such as capacitated network design (Frangioni and Gendron, 2009) and liner shipping network design (Álvarez, 2009) are severely restrained by the size of the problem and excessive solution times for general MIP solvers. We expect similar issues if incorporating the reflow of miss-connected containers into the VSRP and most certainly the application will no longer be able to provide real time suggestions when considering reflowing containers on the residual capacity of the network in a joint optimization. This is furthermore supported by findings in the airline literature where Bratu and Barnhart (2006) concludes that a combined model for solving a combined aircraft recovery and passenger re-accommodation model is too complex to solve to make it useful for real time optimization. Similarly the review Clausen et al. (2009) shows that full passenger re-accommodation is always handled in a subsequent optimization phase. An approach, which has been useful in the airline industry (Marla et al., 2011) is not to solve the full passenger re-accommodation problem together with aircraft recovery, but rather let the aircraft recovery be guided towards passenger friendly solutions by penalizing misconnecting passengers. A similar approach could be deployed for disrupted containers.

4.3 Literature review

Notteboom (2006) analyze the negative effects of disruptions in liner shipping and the actions taken by liner shipping companies to mitigate them. The recent paper by Notteboom and Vernimmen (2009) demonstrates how the increased bunker price has a significant impact on the liner shipping business. The cost of fuel is a dominant cost driver when transporting containers, nevertheless shipping companies are willing to burn extra fuel to arrive according to the schedule. Disruption management is a major concern for liner shippers given this trade-off. Notteboom and Vernimmen (2009) argue that the increased price on bunker has resulted in lowering the speed of vessels to save fuel, which in turn gives the vessels more buffer time and the operators more possibilities to recover from a disruption.

Even though the research within maritime transportation has gained increased focus during the last decades, we have encountered no journal papers devoted to disruption management in (liner) shipping. This can be caused by various things; firstly as mentioned the usage of mathematical modeling in maritime transportation is still in its infancy and secondly the market of liner shipping is extremely competitive. The development of decision support software will often be carried out for a major player in the market and therefore not necessarily published. After the submission of this article another model on disruption management in liner shipping was published in the thesis of Kjeldsen (2012). A heuristic is presented for solving a relaxed version of the model and computational results are provided for a set of generated disruption scenarios. The work by Yang et al. (2010) and Li et al. (2009) addresses disruption management for berth allocation in container terminals. Their papers are focused on how to recover the berthing schedules when vessels are delayed from the terminal point of view. Yang et al. (2010) presents an MIP Model and a heuristic solution approach. The problem handled is very different from the VSRP dealing with disruptions from the carriers point of view. The work of Du et al. (2011) allocates berths considering fuel consumption and has a good review on other berth allocation literature. Well-established OR departments at many airlines have addressed the severe economical impact of flight delays and how to mitigate the effects of delays through disruption management based on OR. In 2008 the Joint Economic Committee under the U.S. Congress published a report estimating the infused cost to the American society to more than $40 billion (JEC, 2008). The order of magnitude of the cost of disruptions has later been confirmed in a more theoretically profound study by Ball et al. (2010) even though their final estimate is $\approx 20\%$ lower. Both Rakshit et al. (1996) and Yu et al. (2003) document significant savings by implementing real-time decision support systems to handle the disruptions at major US airlines where the later estimates the annual saving to amount to $40 million for Continental Airlines.

Disruption management research for airlines generally deals with recovering the 3 resource areas aircraft, crew and passengers. The full problem of optimizing all of these areas simultaneously is, however, so complex that no work has been published so far, which cover all 3 areas in one single integrated model. Most of the published models address one single resource. A few of the models focus on one resource area, while including specific aspects of other areas. For a good general introduction to disruption management in the airline industry the reader is referred to Yu and Qi (2004) and Barnhart (2009). The paper of Kohl et al. (2007) describes a large scale EU-funded project, called Descartes, which addresses various aspects of disruption management for all 3 resource areas. The reader is also referred to an extensive survey of operations research used for disruption management in the airline industry by Clausen et al. (2009). In order to adapt disruption management techniques applied to the airline industry to the liner shipping industry the aircraft recovery problem resembles vessel recovery and the recovery of passenger itineraries resembles container recovery. Since liner shipping companies do not have to deal with crew recovery, this literature review will only focus on aircraft and passenger recovery.

The first model on the *Aircraft Schedule Recovery Problem*, presented in the literature, is a network flow model by Teodorović and Guberinić (1984), who contributed by solving small problems with 3 aircraft and 8 flights. This work was extended by Teodorović and Stojković who extended the model in later papers. The solvable problem sizes still remained small with 14 aircraft and 80 flights. Jarrah et al. (1993) presented the first work, which were applicable in practice based on instances from United Airlines. They published 2 models, which in combination were capable of producing solutions handling all 3 traditional recovery techniques delays, swaps and cancellations. The drawback of handling this in 2 separate models was that delays and cancellations could not be traded off against each other. This drawback was resolved in the work by Yan and Yang (1996) who were capable of trading off delays, swaps and cancellations in one single model based on a time-line network. Thengvall et al. (2001) extended this model to also include so-called protection arcs, which serve the purpose of keeping the proposed solutions somewhat similar to the original schedule. This is important for real-life application of the suggested solutions as an unlimited number of changes cannot be applied to the schedule last minute. The work by Dienst et al. (2012) extends this model to also cover aircraft specific maintenances and preferences in an aircraft specific recovery model.

The *Passenger Recovery Problem* is an area of disruption management, which has been addressed to a rather limited extent by published research. Our observation from airlines show that most of these use a sequential re-accommodation process, which is carried out after an aircraft recovery schedule has been decided upon. Vaaben and Alves (2009) do a comparison of sequential passenger re-accommodation with re-accommodation based on an MIP-model. The main contribution in the area of passenger recovery is done by Bratu and Barnhart (2006), who present two models. Both are basically aircraft recovery models with some crew recovery guidance. One of them also includes passenger recovery, but is not solvable in real time. The other one is solvable but does not include complete passenger recovery. Instead it penalizes passenger miss-connections.

The work by Marla et al. (2011) extends on the work by Dienst et al. (2012) and Bratu and Barnhart (2006) by doing aircraft specific recovery with penalized passenger miss-connections, while at the same time also introducing the additional recovery technique of *speed changes*, which enables the model to balance the trade-off between passenger delay cost and fuel burn cost in a network perspective. The purpose of the present paper is to investigate if the application of similar disruption recovery techniques in a liner shipping context will be beneficial.

4.4 The Vessel Schedule Recovery Problem - (VSRP)

A given disruption scenario consists of a set of vessels V, a set of ports P, and a time horizon consisting of discrete time-slots $t \in T$. The time slots are discretized on port basis as terminal crews handling the cargo operate in shifts, which are paid for in full, even if arriving in the middle of a shift. Hence we only allow vessels arriving at the beginning of shifts. Reducing the graph to time-slots based on these shifts, also has the advantage of reducing the graph size, although this is a minor simplification of the problem. 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 recovery horizon, T, is an input to the model given by the user, based on the disruption in question. Inter continental services will often recover by speeding during ocean crossing, making the arrival at first port after an ocean crossing a good horizon, severe disruptions might require two ocean crossings. Feeders recovering at arrival to their hub port call would save many missed transhipments giving an obvious horizon. In combination with a limited geographical dimension this ensures that the disruption does not spread to the entire network.

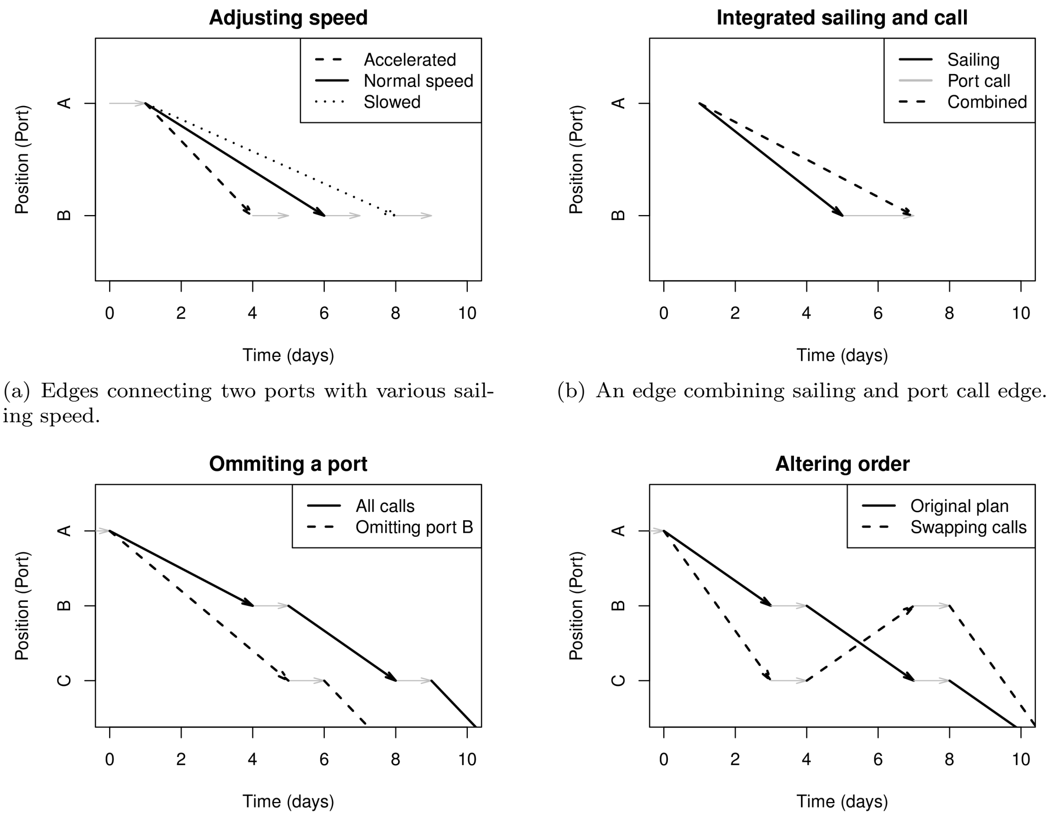
The disruption scenario includes a set of container groups C with planned transportation scenarios on the schedules of V. A feasible solution to an instance of the VSRP is to find a sailing for each $v \in V$ starting at the current position of v and ending on the planned schedule no later than the time of the recovery horizon. The solution must respect the minimum and maximum speed of the vessel and the constraints defined regarding ports allowed for omission or port call swaps. The optimal solution is the feasible solution of minimum cost, when considering the cost of sailing in terms of bunker and port fees along with a strategic penalty on container groups not delivered “on-time” or misconnecting altogether.

4.4.1 Graph topology

A disruption scenario is conceptualized as a directed graph in a time-space network similar to the one used by Thengvall et al. (2000, 2001, 2003), Marla et al. (2011) and Dienst et al. (2012). The horizontal axis corresponds to a point in time within the given planning horizon, and the vertical axis corresponds to a geographical position; a port in the context of VSRP. A simple example of a time-space network is presented in Figure 4.3(a). Here, two geographical positions are given and a vessel can connect from the initial position A to the next position B with three different speeds.

A directed graph $G = (N, E)$ with node set $N = \{p^t \in N | p \in P, t \in T\}$ where p^t denotes port p at time t representing the time-space network. n^- and n^+ denotes the in- and out-going edges of node $n \in N$ respectively. $N_v \subseteq N$ is the set of all nodes for vessel $v \in V$. The set consists of a source node n_s^v corresponding to the current position of the vessel and a sink node n_t^v corresponding to the scheduled position at the end of the recovery horizon. Additional nodes are created for the set of port calls $h \in H_v$ within a time window of $\{a_v^h, b_v^h\}$ defining the earliest and latest arrival time respectively given the vessels minimum and maximum speed, the current position and the remaining set of port calls.

Define the edge set $E = E_s \cup E_g$ where E_s represents a sailing of a vessel $v \in V$ such that $E_s = \{(p^t, q^{t'})|p^t, q^{t'} \in N, p \neq q, t \leq t'\}$ and $E_g = \{(p^t, p^{t'})|p^t, p^{t'} \in N, t < t'\}$. The duration of a port call is fixed for each vessel $v \in V$ according to the scheduled port call duration from the original schedule. Because the port call duration is fixed port call edges E_g are included in the sailing edges E_s, thereby removing the set E_g as seen in Figure 4.3(b). Including the edge set E_g in E_s reduces the number of columns in the mathematical model. For illustrative purposes the port call edges are still visualized in Figures 4.3(c) and 4.3(d), while the remainder of the figures in this paper only visualize the combined edges.



(a) Edges connecting two ports with various sailing speed.

(b) An edge combining sailing and port call edge.

(c) Edge corresponding to omitting a port call and decreasing speed.

(d) Edges corresponding to changing the order of port calls.

Figure 4.3: Possible moves in the time-space network model. Port call edges are gray.

The edge sets $E_v \subseteq E_s$ are the edges that define feasible sailings among the nodes of N_v for a given vessel $v \in V$. $c_e^v \in \mathbb{R}_+$ is the cost of using edge $e \in E_v$ for vessel type $v \in V$ consisting of the bunker cost at a given speed and port fee for port $p = \mathit{target}(e)$. t_e^v is the time it takes to traverse edge $e \in E_s$ given speed, distance and port call time. The edge set $E_s = \bigcup_{v \in V} E_v$ is defined according to the planned schedule and the possible recovery actions defined below:

- **Adjusting vessel speed** (Figure 4.3(a))
  In the span of the minimum and maximum speed of vessel $v \in V$ several edges may connect ports A and B. Define the set of edges $L_h \subset E_v$ covering port call $h \in H_v$ as $L_h = \{(A^t, B^{t'})|A, B \in H_v, A < B, t \leq b_v^A, a_v^B \leq t' \leq b_v^B, t < t', \forall t' = a_v^B + K \cdot \delta_B\}$ where K is a positive integer denoting the shift and δ_B is the duration of a shift at terminal B.

- **Omitting a port call** (Figure 4.3(c))

Vessels might omit port calls to recover a delay or simply to save the port cost. Omitting port calls will result in miss-connected containers. Allowing to omit port B on a sailing from port A via port B to port C corresponds to having an edge (A^{t_A}, C^{t_C}) where $t_C - t_A$ corresponds to the sailing time. Edges L_h with differing sail speeds must be created as described in above bullet.

- **Swap order of calls** (Figure 4.3(d))
In some cases, a delayed vessel needs to call a number of ports close to each other. It might be possible to swap port calls within a designated geographical area. In the time-space network a swap is included by adding, first an omitting edge, followed by an edge back to the original port call. Again this must be executed for differing vessels speeds, as described in first bullet.

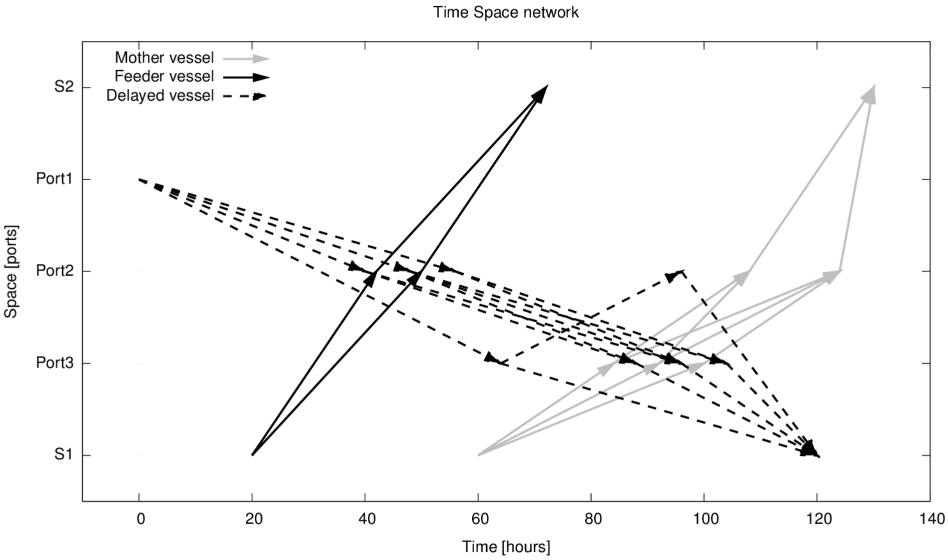


Figure 4.4: Example of a time-space network for a test problem with three vessels, sinks and sources, three ports, speed adjusting edges, and port swap for the *delayed* vessel. In the network only the edges taking part in a feasible path are shown.

Figure 4.4 gives an example of a full time-space network for a small test instance. Three vessels are affected by the delay of the *delayed* vessel.

The set of vessels is

$$V = \{delayed, feeder, mother\} = \{d, f, m\}$$

and for each vessel a set of port calls is given. These are

$$H_d = \{P_1, P_2, P_3, S_1\}$$
$$H_f = \{S_1, P_2, S_2\}$$
$$H_m = \{S_1, P_3, P_2, S_2\}$$

where P_i is Port i and S_i corresponds to onward sailing according to schedule. For each of the port calls $h \in H_v$ a set of possible sailings L_h covering the call is given. As an example vessel d has the set of four possible sailings/legs covering the call in Port 2:

$$L_{(d,P_2)} = \{ \quad (P_1, 0) \to (P_2, 38) \quad , \quad (P_1,\ 0) \to (P_2, 48) \quad , \\ (P_1, 0) \to (P_2, 58) \quad , \quad (P_3, 62) \to (P_2, 98) \quad \} \qquad .$$

The cost of each of these edges is the sum of the bunker cost from sailing with the necessary speed between the ports and the cost of calling Port 2. The cost of using leg $(P_1, 0) \rightarrow (P_2, 38)$ is higher than the cost of using leg $(P_1, 0) \rightarrow (P_2, 58)$ as the sailing time is smaller $(38 < 58)$ resulting in a higher sailing speed and consequently an increased bunker fuel burn.

The problem has characteristics that are not directly reflected in the graph. These are the flow of containers, extended port stays due to omissions, limits on the capacity of a port, and port closure in a period of time. The extended port stay due to an omission can readily be handled in the graph construction by adjusting the duration of the set of sailing edges in E_s, that represent the omission. This has not been done to simplify modeling, as the effect will small. The port capacity issue can be modeled by constraining the number of vessels arriving (or used legs) at each port in each given time interval. Port closures are included by removing all edges corresponding to arriving at a port while it is closed.

4.4.2 Transportation scenarios - the impact of a recovery on the affected cargo

In order to evaluate which container groups will suffer from missed onward connections and delays we define a transportation scenario for each container group in terms of their origin, destination and planned transhipment points. $B_c \in H_v$ is defined as the origin port for a container group $c \in C$ and the port call where vessel v picks up the container group. Similarly, we define $T_c \in H_w$ as the destination port for container group $c \in C$ and the port call where vessel w delivers the container group. Intermediate planned transshipment points for each container group $c \in C$ are defined by the ordered set $I_c = (I_c^1, \ldots, I_c^m)$. Here $I_c^i = (h_v^i, h_w^i) \in (H_v, H_w)$ is a pair of calls for different vessels $(v, w \in V | v \neq w)$ constituting a transshipment. Each container group c has m^c transshipments. M_c^e is the set of all non-connecting edges of $e \in L_h$ that result in miss-connection of container group $c \in C$. $c_c^d \in \mathbb{R}_+$ is the cost of a delay to container group $c \in C$ exceeding a day of the planned arrival and $c_c^m \in \mathbb{R}_+$ is the cost of one or several misconnections to container group $c \in C$, which is added to the delay penalty in the model.

The cost of delaying the arrival of a container at its destination is to a large extent related to the loss of goodwill from the affected customers. This may vary by the type of container and the importance of the customer to the liner shipping company. In general refrigerated containers are more costly to delay than non-refrigerated, but more detailed classification by container type and customer value may be applied. The cost classifications used in the case-studies in this paper have been supplied by Maersk Line and are based on their internal approximations of these costs.

4.4.3 Mathematical model

The mathematical model is inspired by the work within aircraft recovery with speed-changes by Marla et al. (2011). Like others before Marla et al. (e.g. Dienst et al. (2012)) we 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.

Define binary variables (x_e) for each edge $e \in E_s$ set to 1 iff the edge is sailed in the solution. Define binary variables (z_h) for each port call $h \in H_v \quad \forall v \in V$ set to 1 iff call h is omitted. For each container group c we define binary variables $o_c \in \{0, 1\}$ indicating whether the container group is delayed or not and y_c to account for container groups misconnecting. $O_e^c \in \{0, 1\}$ is a constant set to 1 iff container group $c \in C$ is delayed when arriving by edge $e \in L_{T_c}$. $M_c \in \mathbb{Z}_+$ is an upper bound on the number of transshipments for container group $c \in C$.

$$S_v^n = \begin{cases} -1 & , n = n_s^v \\ 1 & , n = n_t^v \\ 0 & \text{Otherwise} \end{cases}$$

is applied to the flow conservation constraints.

`Minimize:`

$$\sum_{v\in V}\sum_{h\in H_v}\sum_{e\in L_h} c_e^v\, x_e \quad + \quad \sum_{c\in C}\left[c_c^m\, y_c + c_c^d o_c\right] \tag{4.1}$$

`Subject To:`

$$\sum_{e\in L_h} x_e + z_h = 1 \qquad \forall v\in V, h\in H_v \tag{4.2}$$

$$\sum_{e\in n^-} x_e - \sum_{e\in n^+} x_e = S_v^n \qquad \forall v\in V, n\in N_v \tag{4.3}$$

$$y_c \le o_c \qquad \forall c\in C \tag{4.4}$$

$$\sum_{e\in L_{T_c}} O_e^c\, x_e \le o_c \qquad \forall c\in C \tag{4.5}$$

$$z_h \le y_c \qquad \forall c\in C, \forall h\in B_c\cup I_c\cup T_c \tag{4.6}$$

$$x_e + \sum_{\lambda\in M_c^e} x_\lambda \le 1 + y_c \qquad \forall c\in C, e\in\{L_h | h\in B_c\cup I_c\cup T_c\} \tag{4.7}$$

$$x_e \in \{0,1\} \qquad \forall e\in E_s \tag{4.8}$$

$$z_h \in \mathbb{R}_+ \qquad \forall v\in V, h\in H_v \tag{4.9}$$

$$y_c, o_c \in \mathbb{R}_+ \qquad \forall c\in C \tag{4.10}$$

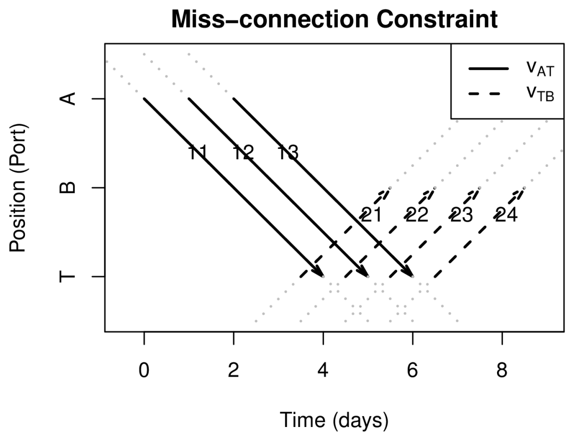
The objective function (4.1) minimizes the cost of operating vessels at the given speeds, the port calls performed along with the penalties incurred from delaying or misconnecting cargo. The weighted sum scalarization (Ehrgott, 2005), the ϵ-constraint method (Ehrgott, 2005), and variable fixing has been implemented for the VSRP with promising results in the thesis by Dirksen (2011).

Constraints (4.2) are *Set-Partitioning* constraints ensuring that each scheduled port call for each vessel is either called by some sailing or omitted. (4.3) are *Flow-Conservation* constraints. Combined with the binary domain of variables x_e and z_h they define feasible vessel flows through the time-space network. 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 (4.4).

Each container group has a planned arrival time upon which it can be decided whether or not a given sailing to the destination will cause the containers to be delayed. Constraints (4.5) ensure that o_c takes the value 1 iff container group c is delayed when arriving via the sailing represented by edge $e \in E_s$. The right hand side does not have to be multiplied despite the number of summed variables may be larger than one due to the cover constraint (4.2) as this constraint ensures that only one incoming edge $x_e, e\in L_{T_c}$ can have flow. Constraints (4.6) ensure that if a port call is omitted, which had a planned (un)load of container group $c\in C$, the container group is misconnected. Constraints (4.7) are coherence constraints ensuring the detection of container groups' miss-connections due to late arrivals in transshipment ports. For each of the possible inbound sailings of a container transshipment a constraint is generated. On the left-hand side the decision variable corresponding to a given sailing, x_e, is added to the sum of all decision variables corresponding to having onward sailing resulting in miss-connections, $\lambda \in M_c^e$.

The constraint is illustrated in Figure 4.5. When implementing the constraint the variables corresponding to inbound sailings are summed.

The variable x_e is required to be binary, whereas the remaining variables are only required to be non-negative. Binary x_e combined with constraints (4.2) implies z_h to be binary. Given the binary domains of x_e and z_h combined with constraints (4.6), (4.7) and a minimization implies y_c to be binary. Finally, Minimization, binary domains of x_e and y_c combined with constraints (4.4) and (4.5) imply that o_c is binary.



A container group transship from vessel v_{AT} to vessel v_{TB} at port T. It has three inbound (x_{11}, x_{12}, x_{13}) and four outbound $(x_{21}, x_{22}, x_{23}, x_{24})$ opportunities. The miss-connection constraint gives the following three equations:

$$\begin{aligned} x_{11} \quad\quad\quad\quad\quad\quad + x_{21} &\leq y + 1 \\ x_{12} \quad\quad\quad + x_{21} + x_{22} &\leq y + 1 \\ x_{13} + x_{21} + x_{22} + x_{23} &\leq y + 1 \end{aligned}$$

Figure 4.5: Example of the miss-connection constraint (4.7).

4.4.4 Model extensions

The model can be extended to incorporate additional features of a given problem instance such as the berth occupation constraint.

$$\sum_{v \in V} \sum_{h \in H_v} \sum_{e \in L_h} U_e^{pt} x_e \leq 1 \qquad \forall p \in P, t \in T \tag{4.11}$$

$U_e^{pt} \in \{0, 1\}$ is a constant set to 1 iff edge $e \in L_h$ occupy a berth in port $p \in P$ in time slot $t \in T$. The constraint ensures that only a single vessel can enter and use a berth at a given time. This constraint will not handle berth allocation in general, which specified methods exist for, as mentioned in literature review. But when several vessels have to compete for a single berth available at a terminal, this constraint can be used to model the liner shipping company's choice of prioritization, irrespective of the terminal's options.

4.4.5 Complexity

The VSRP is NP-hard if omissions of ports is allowed, or if port swaps are allowed. Even if only one of the recovery actions is allowed, the problem is NP-hard as shown in the following: If ommissions of ports are allowed in VSRP, the NP-hardness can be proved by reduction from the *0-1 Knapsack Problem (KP)*. Given an instance of the KP with a knapsack of capacity c, and n items having profit p_i and weight w_i, we transform it to an instance of the VSRP by using a single vessel and n ports which can be omitted. The cost of omitting a port is set to $-p_i$ and the duration of a port call is set to w_i. Sail times between ports are set to zero, and the recovery horizon is set to c, ensuring that a maximum profit subset of the items is chosen satisfying the capacity of the knapsack.

If port swaps are allowed in VSRP, the NP-hardness is shown by reduction from the *Traveling Salesman Problem* (TSP). Given an instance of TSP with n nodes and edge costs c_{ij}, we construct an instance of the VSRP by introducing n ports which can be visited in arbitrary order. Port calls and travel times are set to zero, while the sail cost between ports is c_{ij}. The cost of omitting a port is set to infinity ensuring that all ports are visited following the shortest Hamiltonian cycle.

The above reductions prove that the VSRP with allowed omissions is weakly $\mathcal{NP}$-hard and the VSRP with multiple omissions to be strongly $\mathcal{NP}$-hard. Extended proofs for the $\mathcal{NP}$-completeness of the VSRP may be found in Dirksen (2011).

4.5 Computational results

The program has been run on a MacBook Pro with 2.26 GHz processor and 2 GB of memory running Mac OSX using IBM ILOG CPLEX 12.2.0.0 as MIP solver. To test the performance and applicability of the developed model, it has been run on four real instances and a number of auto generated instances.

4.5.1 Real-life Cases from Maersk Line

The cases used to evaluate the VSRP are based on historical events at Maersk Line (ML). They are selected to represent the most common disruption scenarios and recovery options. Each case includes information about vessel schedules, port distances, container movements, recovery options, vessel speeds, and costs. ML handles these types of disruptions on a daily basis. The purpose of the cases is to test the suggested model, but also to clarify typical disruptions and how they are currently handled. An overview of the cases is given followed by a detailed presentation. The cases are

1. **A Delayed Vessel**
   The vessel Maersk Sarnia is delayed out of Asia due to bad weather. The vessel is, filled with cargo, about to cross the Pacific Ocean and unload in Mexico and Panama.

2. **A Port Closure**
   The port Le Havre in France is closed due to a strike. The vessel Maersk Eindhoven arriving with cargo from Asia can either wait for the port to open (giving an expected 48 hour delay) or omit the call in Le Havre.

3. **A Berth Prioritization**
   The port in Jawaharlal Nehru (India) does not have the capacity for a ME3-service vessel and a MECL1-service vessel to port at the same time. As the MECL1-service vessel is delayed and the vessels will arrive at the port simultaneously, it is necessary to decide which vessel to handle first.

4. **Expected Congestion**
   The feeder vessel Maersk Ravenna is planned to call three Colombian ports. Due to port maintenance at the last port to call, a delaying congestion is expected if arriving as planned. ML has to decide if the plan should be changed to avoid the congestion.

4.5.2 Case results

The computational results for the cases are promising. Good recovery strategies have been generated within 5 seconds, which proves the model applicable as a real-time decision support tool for liner shipping companies. The optimization based recovery strategies are generated with a strategic penalty for delaying and misconnecting containers. The two penalties are given the same value, i.e. $c_c^m = c_c^d$. For each of the cases discretization of the time horizon is $\delta = 3$ hours. Table 4.1 shows different size measures for the four cases. The results from the optimized runs (**OPT**) have been compared to the real life solution (**RS**). **RS** is the realized sailings for the affected vessels and the realized impact on containers. All presented costs are relative to the real cost to preserve the relativeness of bunker, port fees and container impact of a solution. However, the costs have no relation to real life costs.

An overview is given in Table 4.2. The results clearly show potential in the mathematical model. The experts at ML have indicated that in two out of the four cases they would prefer **OPT**, in one **OPT** is the same as **RS**, and in the last **RS** is preferred. However, in the case where **RS** is preferred, the recovery strategy is based on re-flowing cargo, which is not considered by the VSRP. The tendency is clearly that the model generates competitive solutions and would be a substantial support to the operator resulting in better recovery solutions using significantly less time. However, based on just four cases it is not reasonable to conclude that the optimized solutions are generally superior. The computational times are less than 5 seconds with CPLEX consuming roughly half the execution time, while graph generation consumes the rest. Please note that Case 1 (A Delayed Vessel) has a much longer planning horizon than the remaining cases, which accounts for the increase in running times. Even for Case 1 the solution time is indeed acceptable for a operational application.

4.5.3 Case 1 (A Delayed Vessel)

Within the planning horizon of Case 1 Maersk Sarnia delivers containers to a single ML vessel in Lazaro Cardenas and seven ML vessels in Balboa. Each vessel may be delayed to the originally planned arrival time. The vessel Maersk Sarnia is allowed to omit Yokohama and either Lazaro Cardenas or Balboa. The **OPT** is structurally different to **RS**. Both are plotted in Figure 4.6. ML has chosen to call all ports with a speed increase (**RS**). However, the speed-up is not sufficient to reach the head haul ports in time. The optimized solutions (**OPT**) is to omit the call in Yokohama resulting in 400 misconnected containers while the remaining ports are called in time. The combined costs and penalties of **RS** are 24% higher than the costs and penalties of **OPT**. The experts at ML confirm that omitting Yokohama was a superior solution and note, that they were unable to convince a single important stakeholder of the superiority of this solution. It is very clear that the generalized mathematical assessment provided by a decision support tool would have been a strong argument in the discussion.

4.5.4 Case 2 (A Port Closure)

In Case 2 (A Port Closure) either Le Havre is called 48 hours delayed, or Rotterdam is called at the planned time. In Le Havre 649 containers need to be loaded and 1911 need to be unloaded. The time-space network of the case is presented in Figure 4.7.

Again **OPT** is different in structure compared to **RS** (Figure 4.8). However, as noted earlier **RS** is based on re-flowing containers not considered by the VSRP. Surprisingly, the data for the suggested solutions show that **OPT** is a better alternative with respect to cost. In real life the delay turned out to be 72 hours and a solution was obtained by allowing to merge two port calls. This option was not available to the model and hence the results are not comparable.

4.5.5 Case 3 (A Berth Prioritization)

In the third case, the additional berth occupation constraint (4.11) is added to ensure that the vessels call the port in India one at a time. The berth prioritization case is interesting as four of the connecting ML vessels may be delayed significantly and still reach their next port to call. **OPT** and **RS** result in the same solution presented in Figure 4.9. The runs confirm the decision of **RS** and verify the applicability of a decision support system in an operational setting, providing fast solutions. In this case the decision would have been reached in a matter of seconds as opposed to hours.

Case	**V**	**PC**	**CG**	**C**	**RH**	N	E	x_e	z_h	y_c / o_c	**Constraints**
1	8	26	23	5145	961	301	7073	7073	10	23	1706
2	6	22	19	12358	969	118	290	290	10	19	122
3	10	33	24	5671	548	171	411	411	13	24	221
4	1	5	6	838	166	103	416	416	3	6	300

Table 4.1: An overview of the relative sizes of the cases in terms of the number of vessels **(V)**, the number of port calls in the scenario **(PC)**, the number of container groups included **(CG)**, the total number of containers **(C)**, the recovery horizon in hours **(RH)**, the size of the graph (N, E), and the number of variables (x_e, z_h, y_c, o_c).

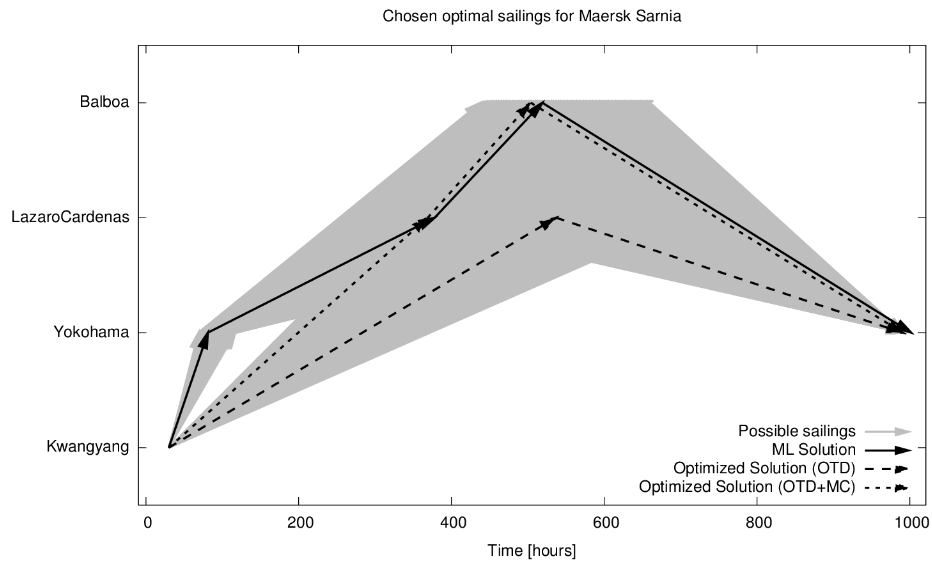


Figure 4.6: Case 1: Suggested recovery solutions for Case 1 (A Delayed Vessel).

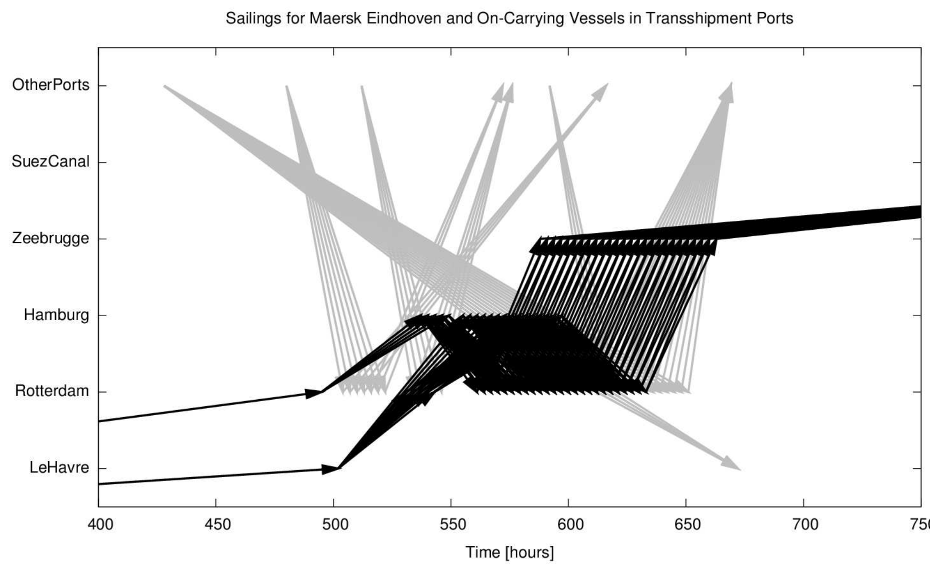


Figure 4.7: Time-space network for Case 2.

		Sailing Cost		Delays		Misconnections		Solve	
		RS	OPT	RS	OPT	RS	OPT	Time	Best
Case	1	1,000,000	914,063	(2449)	(0)	(26)	(400)	4.529	OPT
	2	1,000,000	977,392	(3111)	(3111)	(58)	(58)	0.718	RS
	3	1,000,000	1,000,000	(687)	(687)	(0)	(0)	0.681	Equal
	4	1,000,000	1,033,334	(222)	(0)	(0)	(0)	0.518	OPT

Table 4.2: Overview of results for the cases. The costs are relative, the container impact in units, and the time to solve in seconds. The best-column shows which solution the ML experts would prefer today.

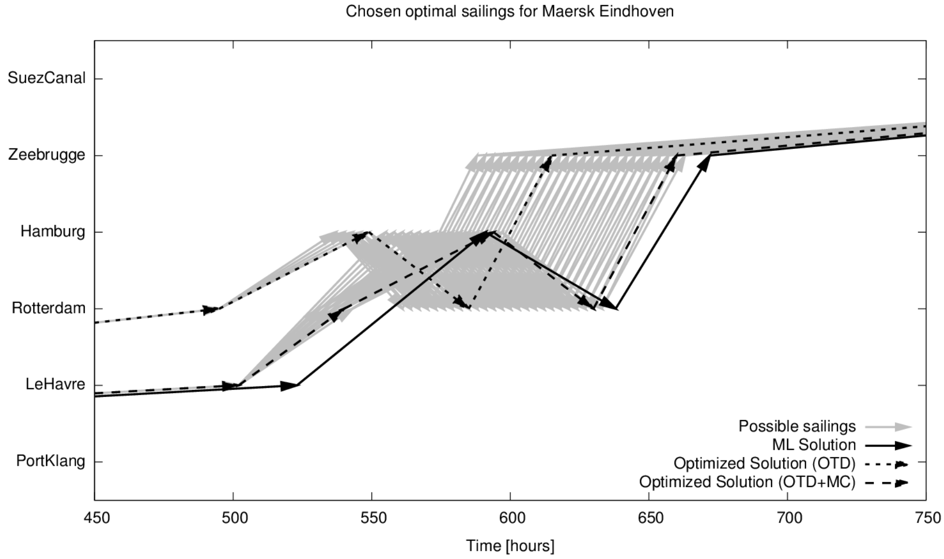


Figure 4.8: Suggested recovery solutions for Case 2.

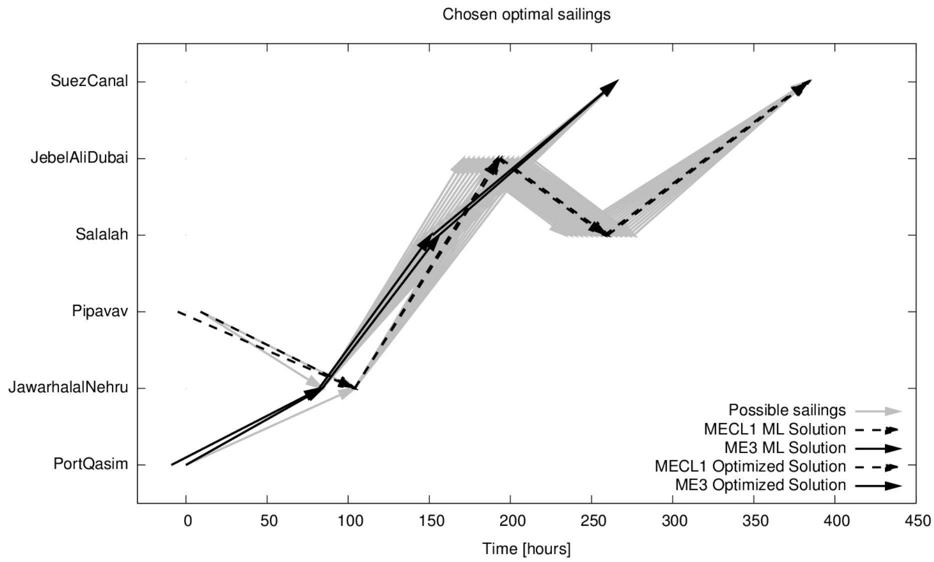


Figure 4.9: Time-space network and solution for Case 3. The ME3-vessel (full line) or the MECL1-vessel (dashed line) calls Jawaharlal Nehru in India first.

4.5.6 Case 4 (Expected Congestion)

The last case where a feeder vessel is expecting port congestions in the last port differs completely from the former cases. The feeder only carries direct import and export cargo to and from Colombia, meaning that no additional vessels need to be taken into account and that a single run is generated as misconnections are not possible. The expected port delay (of 24 hours if Santa Marta is called after $t = 100$) combined with the possibility of calling the three ports in Colombia in any order defines the problem. The time-space network of possible sailings along with the solutions is given in Figure 4.10. **RS** was to alter the order of the port calls to ensure that Santa Marta was visited long before the expected congestion. This resulted in a delay to the cargo in Cartagena. Contrary to **RS**, **OPT** suggests continuing as planned, but speeding up to arrive at Santa Marta before the expected congestion. This solution displays slightly increased bunker cost but ensures that all containers are delivered on time. According to the experts at ML, the optimized solutions should have been implemented. The costs and penalties reveal a saving amounting to a stunning 58%.

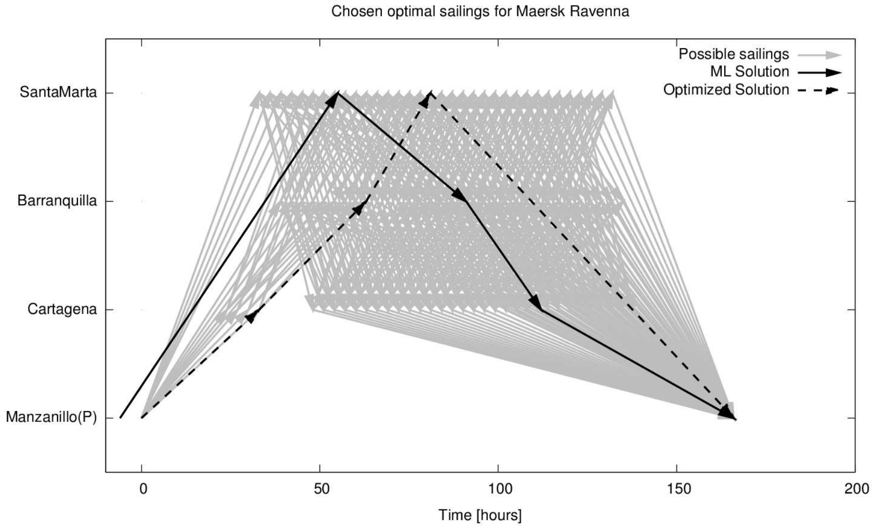


Figure 4.10: Suggested recovery solutions for Case 4 (Expected Congestion) in the time-space network.

4.5.7 Auto generated test instances

The four cases utilize different parts of the solution space satisfactorily, but lack in size and are thus relatively fast to solve. To test the scalability of the model, a set of random instances have been generated, refer to Figure 4.11 for an example. η^2 ports are placed in a squared grid, where distances and sailing times are proportional to Euclidean distances. Vessels are generated with a random schedule of $\kappa < \eta^2$ ports to call. Container itineraries are generated such that each intermediate call for each vessel and arriving container group is added with some probability. For these instances the computational time grow with increasing number of calls per vessel and number of vessels in instance as seen in Figure 4.12. It can be seen that the computational time handles an increased number of vessels well, but is impacted harder by an increased number of port calls. It seems viable that the model will solve in minutes for instances with up to 10 vessels and port calls making it viable for use in a wide range of real world problems. For more details on how the instances are generated and details on computational time please refer to the thesis by Dirksen Dirksen (2011).

4.6 Conclusion and future work

To the best of our knowledge this paper is the first literature on decision support for disruption management in a liner shipping network. We have presented a novel mathematical model for the Vessel Schedule Recovery Problem (VSRP). The model addresses frequently occurring disruption scenarios in the liner shipping industry. The model is based on disruption management work from airline industry and adapted to liner shipping. We show the VSRP to be NP-complete. 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. Computational results for four real-life cases show similar or improved solutions to historic data. The solutions have been verified by experienced planners. A set of generic test instances have been provided and computational results indicate that the model

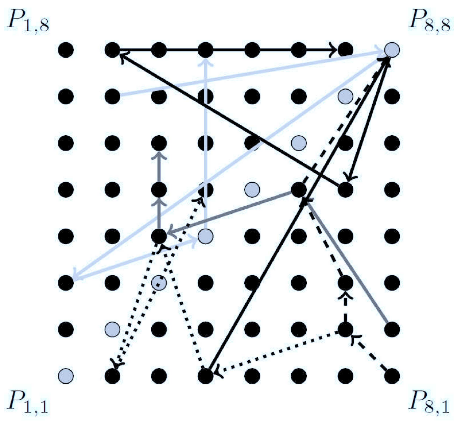
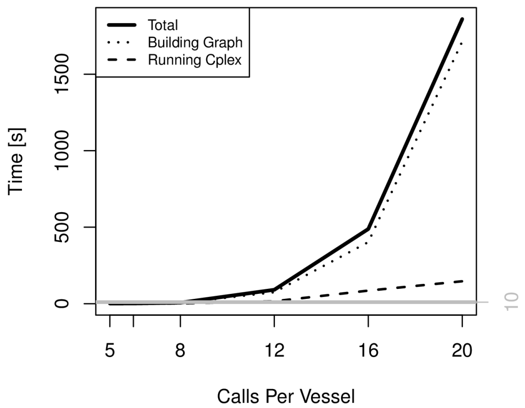
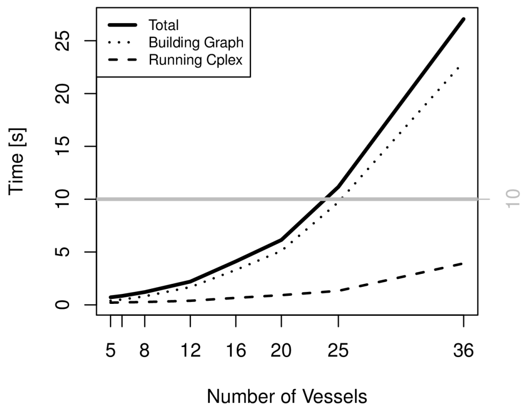


Figure 4.11: Graphical explanation of the standard way random instances of the VSRP are generated.



(a) Computational times increasing the number of port calls per vessel, with 5 vessels



(b) Computational times increasing the number of vessels, with 5 port calls

Figure 4.12: Computational times for generic generated problems with varying number of ports and vessels respectively. The times are average values based on 5 repeated runs.

is capable of handling larger disruption scenarios than the real-life cases in seconds. However, with an increasing number of vessels, the computational time show exponential growth and can no longer reach an optimal solution within ten seconds, for larger instances. An analysis of the four real life cases, show that a disruption allowing to omit a port call or swap port calls may ensure timely delivery of cargo without having to increase speed and hence, a decision support tool based on the VSRP may aid in decreasing the number of delays in a liner shipping network, while maintaining a *slow steaming* policy. This initial work on disruption management in liner shipping show potential for interesting extensions. Other recovery modes than the three considered (speed adjustment, port call omission and port call swap) could be investigated, e.g. reducing the time spent at port by unloading but not loading, merging port calls or adding protection arcs. Another extension would be to reroute the non-satisfied cargo on the remaining, or even third party network. The connection with berth scheduling problems with disruption of fixed scheduled services as considered here could also be explored further.

Acknowledgements

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