BART VAN RIESSEN

Optimal Transportation Plans and Portfolios for Synchromodal Container Networks

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Optimal Transportation Plans and Portfolios for Synchromodal Container Networks

Optimale transportplanning en portfolio's voor synchromodale containernetwerken

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Dedicated to my grandparents, who have each in their very own way contributed to who I am now.

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Bart van Riessen,
Rotterdam, January 2018

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Clarification of contribution

The research for this dissertation was carried out at Erasmus University Rotterdam (EUR) and Delft University of Technology (TU Delft) in cooperation with business partner Hutchison Ports ECT Rotterdam (ECT), and its subsidiary European Gateway Services (EGS). The groundwork was laid during my internship at ECT for my master thesis research in 2012-2013, under supervision of my current promotors, prof Rommert Dekker (EUR) and prof Rudy Negenborn (TU Delft); and prof Gabriel Lodewijks (TU Delft). From 2013 onwards, I have worked in an industry position at ECT, in combination with a separate, independent position at Erasmus University Rotterdam for academic research in continued cooperation with my promotors. My industry position provided three crucial aspects for this dissertation: first-hand insight in the problems and developments at EGS, access to data for case studies and input on related topics from colleagues and from interns for whom I was company supervisor. Although none of my colleagues or interns provided direct input for this thesis, they provided crucial information and inspiration for the research.
The chapters of this dissertation are based on separate article publications and can be read independently. Therefore, each chapter has a separate introduction, literature overview and notational framework. The chapters are provided in chronological order of the underlying research. Consequently, each chapter contains some repetition on the topics of the EGS case and the concept of synchromodal container transportation networks. Here, for each chapter a clarification is provided regarding the contributing authors and the relation with ECT and/or EGS.

- Chapter 1: This introductory chapter is based on the research proposal, written by myself, under supervision of my promotors. For this dissertation it was extended with a recent literature overview.

- Chapter 2: This work is based on Part I of my master thesis. For this dissertation, the research was substantially extended mostly by myself, especially the case study in Section 2.5, under supervision of my promotors. The data used in the case study is directly obtained from EGS, but perturbed by myself before using in the research to protect the confidentiality.

- Chapter 3: The work in this chapter is based on Part II of my master thesis. For this dissertation, the case study in the original study was extended mostly by myself, under supervision of my promotors. The data used in the case study is directly obtained from EGS, but perturbed by myself before using in the research to protect the confidentiality.

- Chapter 4: The majority of the research and writing for this chapter was done independently by myself, under supervision of my promotors. The studied operational planning decisions and decision support for the intermodal problem were identified by me and discussed with experts from EGS. Michel van de Velden contributed with a detailed review of the initial manuscript.

- Chapter 5: The majority of the research and writing for this chapter was done independently by myself, under supervision of my promotors. This research starts from the premise of a differentiated transportation portfolio offered by EGS. That premise is the direct result of the work by interns at ECT; Michiel Verkaik, Yiyang Lin and Jorge Lecona as well as one of my colleagues at ECT; Elias Becker. Kevin Wardana and Ishara Schutte verified the results independently in their bachelor theses.

- Chapter 6: This chapter was the result of cooperation with Judith Mulder, who contributed numerous times in brainstorming about the methodology, and its proofs. She provided the Proof 6.1. The remainder of the research, implementation and writing was done independently by myself, under supervision of my promotors.

- Chapter 7: The concluding chapter was written by myself to cover academic conclusions and practical implications, under supervision of my promotors.

None of the research was commissioned by ECT or EGS. ECT and EGS are acknowledged for providing me with the opportunity to conduct research into the EGS network during an internship and for participating in the research for this dissertation with me and my co-authors holding independent positions at Erasmus School of Economics and Delft University of Technology.

1 Introduction

In this introductory chapter the background, the problem statement and the outline of the research is described. We provide an overview of relevant research around topics of synchromodal container transportation. Synchromodality refers to creating the most efficient and sustainable transportation plan for all orders in an entire network of different modes and routes, by using the available flexibility. We identify three topics that are relevant for practical implementation of synchromodality. For each topic we describe practical relevance and introduce our research on these topics in the next chapters. Also, our case of European Gateway Services is introduced, a major network orchestrator of container transportation in the Rotterdam hinterland. This chapter is structured as follows. In Section 1.1, the problem statement is provided with three subtopics. In Section 1.2 the case is introduced that we use for illustrating our research results. In Section 1.3, an overview of literature is provided for synchromodal transportation in general (Section 1.3.1) and for each of the three considered topics (Section 1.3.2-1.3.4). Section 1.4 gives our research approach for the three topics. Section 1.5 provides an outline of the remainder of the dissertation.[1]

1.1 Background and problem statement

In recent years intermodal networks have received renewed attention for two reasons: focus on shifting containers from truck transportation towards barge or rail transportation and an increased competition on hinterland transportation between players in maritime transportation, especially in North West Europe. In the 900km Hamburg – Le Havre range, multiple major container ports are located. Port authorities have put focus on modal shift towards more environmental friendly transportation modes. E.g. the ports of Rotterdam, Antwerp and Hamburg have

[1] This chapter is an adapted version of Van Riessen, B., Negenborn, R. R. and Dekker, R. (2015, September). Synchromodal Container Transportation: An Overview of Current Topics and Research Opportunities. In *Proceedings of the 6th International Conference on Computational Logistics (ICCL'15)*, Delft, The Netherlands, (pp. 386-397). The original publication is available via http://dx.doi.org/10.1007/978-3-319-24264-4_27.

stated modal split requirements for the hinterland transportation of containers (Van den Berg and De Langen, 2014). In *Port Vision 2030* the Port of Rotterdam Authority (2011) aims for a modal shift in the hinterland transportation of containers. In 2015, 53% of the containers were transported by truck between the terminals in the Port of Rotterdam and inland destinations in North-West Europe (Topsector Logistiek, 2016). In 2035 this must be reduced to 35%. To achieve this modal shift, containers must be transported on *intermodal corridors*, using barge or rail services between deep-sea terminals and inland terminals. Although intermodal corridors are operating already for decades, many practical problems remain: demand for container transportation is volatile, seasonal and imbalanced, resulting in low utilisations of rail and barge services. Also, because of the complexity of operations, and dependency on terminal infrastructure, a barge or train is sensitive to disruptions, resulting in late delivery. Several researchers have stressed the complexity of achieving the required modal shift, i.e. in Veenstra *et al.* (2012) the need for an integrated network approach is emphasised, and Van der Horst and De Langen (2010) mention the mind shift that is required for achieving more integrated inland transportation. Efficient planning methods for transportation are essential to achieve this, while meeting customer requirements for synchronising the container supply chain and a further reduction of delivery time, costs and emissions. These trends motivate the use of inland container transportation networks, with multiple possible transport corridors and modes. In such an *intermodal network*, containers can be transported by one or more consecutive rail and barge services, using *intermediate transfers* of the containers at network terminals. This type of operation potentially allows more balanced planning for higher utilisations and can offer alternative services in case of disruptions. However, it requires new methods to guarantee efficient operation, in terms of cost, reliability and emissions. These intermodal container transportation networks are generally formed by the cooperation of multiple barge service operators, rail service operators and terminals. Roso et al. (2009) defined the concept of a *dry port*: 'a hinterland terminal in close connection to the sea port, where customers can leave or pick up their standardised units as if directly at a sea port.' Based on this concept, Veenstra *et al*. (2012) introduced the concept of an *extended gate*: a dry port for which the deep-sea terminal can choose to control the flow of containers to and from that inland terminal. The combination of intermodal planning and such a new business model is in recent years referred to as synchromodal transportation (Lucassen *et al.*, 2012, SteadieSeifi *et al.*, 2014, Behdani *et al.*, 2014, Tavasszy *et al.*, 2015). These studies mention the flexible deployment of modes, the possibility of last minute changes to the transportation plan (*switching*) and a central network orchestrator that offers integrated transport.

In such a synchromodal network, customers of the network operator do not book transports on specified services, but place orders with specific delivery time requirements. The network operator accepts orders without regarding the service schedule, considering some threshold (e.g. a minimum delivery time of 24h).

Subsequently, the orders are planned on the transportation network, minimising costs and satisfying delivery time requirements as much as possible. In practice multiple problems need to be addressed in order to operate such a synchromodal network. With this dissertation, we aim to propose solutions for three aspects to enable synchromodal networks in practice.

1.1.1 Problem Statement

The main challenge for a container transportation network operator is the continuous construction of an efficient transportation plan. That is, the allocation of containers to available inland services (train, barge or truck). Creating the transportation plan for the network of inland services is referred to as *planning* in this dissertation, i.e. allocation of all orders to available services in the network. Creating more planning flexibility should help to raise the utilisation rate of inland barge and rail capacity and thus decreasing costs and emissions. Also, the planning flexibility can be used to deal with uncertainties and disturbances, and thus increasing the on-time performance and reliability of the transportation.

In this study, we define a corridor as a direct connection between a deep-sea terminal and an inland terminal area. In practice, the inland transportation in North-West Europe is generally considered per corridor and not for the network as a whole. Based on our experience with practice, this is the case for mainly three reasons: Firstly, no suitable methods for creating an integrated network plan exist yet. Secondly, adapting the plan in real-time responding to delays and other changes occurs manually, by planning operators that focus on specific corridors and inland connections. Thirdly, because of the customer's restrictions for its transportation orders, the network orchestrator misses the flexibility to switch between modes and routes and thus cannot achieve the benefits of synchromodal planning. In Section 1.3, we will show the research gaps in literature on these topics.

The research for this dissertation has been motivated by the development of synchromodal container networks. Our goal is to address the literature gaps and develop methods for optimal portfolios and optimal transportation plans that **enable synchromodal planning in inland container networks**. For achieving this objective, three topics of research are considered in more detail:

1. Integrated network planning: Methods for creating an integrated transportation plan for intermodal transportation networks that are operated by a network orchestrator.
2. Methods for real-time network planning: Methods for creating the transportation plan in real-time and updating it continuously as new information arrives.
3. Balancing customer value and planning flexibility: Methods for optimising a differentiated portfolio to allow flexible transportation planning.

With this chapter, we do not aim to provide a complete overview of all developments on synchromodal transportation, but merely an overview of the ongoing research for the Rotterdam case from practice. This chapter highlights recent developments and introduces the three topics of research that this dissertation contributes to. All three topics are focused on implementing the concept of synchromodal container transportation: optimisation of integral network planning, methods for real-time decision making for planning and the creation of a product portfolio that allows for more flexibility in the network planning problem.

1.2 Case study

In this dissertation we will investigate to what extent a synchromodal business model contributes to efficiently planning intermodal networks, since without flexibility, little network optimisation is possible. We consider these developments with respect to the case of European Gateway Services (EGS), a subsidiary of the container terminal operator Hutchison Ports ECT Rotterdam (ECT). EGS started with the introduction of regular train services on the corridor between Rotterdam and the inland terminal TCT Venlo. Fig. 1.1 shows the EGS network in 2012, with three deep-sea terminals in Rotterdam and seven hinterland terminals. In 2017, the concept has been extended to 21 hinterland terminals, and a yearly throughput of over 800.000 TEU (European Gateway Services, 2017). The network operator runs over a hundred weekly barge and rail services between the deep-sea ports of Rotterdam and Antwerp and the inland destinations. In four of the inland terminals, ECT has a stake, while the other terminals are third parties. Some of the inland services are fully operated by EGS (with long-term lease of capacity), while other services are carried out in cooperation with other operators, for the purpose of risk and capacity sharing. ECT started with the development of the EGS hinterland network in 2007. Its aim is to strengthen ECT's position in the European hinterland. Adding network connections is a time-consuming process, since market capture depends largely on frequency, and proven reliability, which both is difficult to achieve on new corridors. As a network operator, EGS takes incoming orders for transportation between a deep-sea location and an inland location (or vice versa). When a container arrives at an inland terminal, the customer can arrange for a pick-up by truck. In some cases, the transportation order is to deliver at an inland location (e.g. a warehouse); in such cases EGS also takes care of the last-mile transportation between an inland terminal and the inland location. The last mile transportation can be carried out by terminal trucking equipment, or by subcontracted third parties.

At the start of our research, in 2012, EGS had no integral planning approach available, yet. Instead, each corridor was planned and operated separately, mostly by accepting orders on a first-come-first-serve basis. Therefore, from an operational point of view, in such a setting the corridors do not support each other, and customers are not provided with alternatives in the case of disruptions. EGS is

continuously developing on two fronts: on the one hand integrating the planning process for the entire network and on the other hand offering a lead-time based transport portfolio that allows switching of containers. This process has shown to be dependent on several factors, such as information exchange with partners, IT developments and a mind shift of all people involved (sales executives, planners and customer contacts).
The company's goal is to provide network-wide synchromodal transportation, meaning to optimise all network transportation in an integrally operated network, making use of all transportation options in the most flexible way. A more general description of synchromodal transportation follows in the Section 1.3.1.

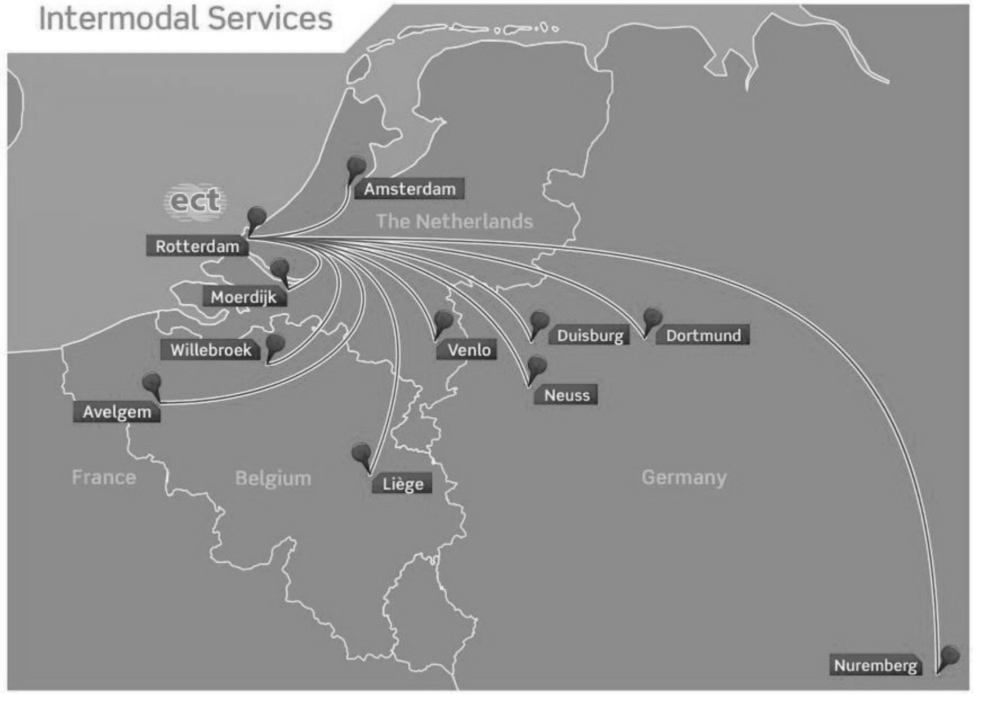

Fig. 1.1 Overview of connections in the EGS network in 2012 (EGS, 2012)

1.3 Literature overview

In this section, first an overview of literature on the topic of synchromodal transportation is provided. Subsequently, relevant literature on three topics is presented: methods for integrated network plans, methods for real-time planning and methods for creating planning flexibility. We highlight the literature gaps that we will address.

1.3.1 Synchromodal transportation

In recent years a large amount of literature has been published on the topic of synchromodal transportation. Most studies focus on creating efficient transportation plans, as is the purpose in the long line of research of intermodal planning problems, noted in the overviews of Caris *et al.* (2013), SteadieSeifi *et al.* (2014), Reis (2015) and Dong *et al.* (2017). The recent studies into synchromodal transportation generally aim to include more practical elements into the more general models of intermodal transportation as in Crainic and Kim (2007). These new elements in the models usually depend on the perspective of the researcher and together create an ambiguous definition of the concept of synchromodality. Pfoser *et al.* (2016) created a framework to identify critical factors in synchromodality. Based on a literature review of several studies relating to the concept, they identified 7 factors related to synchromodality: cooperation, transport planning, intelligent transport systems (ITS), infrastructure, legal framework, mental shift and service offering. This dissertation's focus is mostly related to service offering (including pricing) and transportation planning. For this, a network operator can employ a business model with lead-time based transportation services, rather than just selling transportation slots. As such, the network operator gains flexibility to optimise utilisations, and operate the network more efficiently. In this section we provide an overview of recent research contributions on these topics. Several studies focused on efficient network planning in a synchromodal setting, i.e. by considering the combination of committed and uncommitted capacity (Ypsilantis, 2016, pp. 47-82; Van Riessen *et al.* 2015-a), real-time planning (Nabais *et al.*, 2013; Van Riessen *et al.* 2015-b, 2016; Van Heeswijk *et al.*, 2016), generating options (Kapetanis *et al.*, 2016; Mes and Iacob, 2016) or including vessel routing (Fazi *et al.*, 2015). Other studies have considered the pricing and properties of transportation services, usually in combination with logistics planning. For instance, Li *et al.* (2015) designed a pricing scheme based on average costs, rather than actual costs per itinerary and thus allowing a reduction of the standard price due to network efficiencies. Dullaert and Zamparini (2013) study the impact of lead time variability in freight transport. Crevier *et al.* (2012) compared a pricing strategy for specific itineraries, with a strategy of pricing per transportation request. Bilegan *et al.* (2013) introduced a revenue management strategy of accepting or rejecting bookings on a railway corridor. Similarly, Wang *et al.* (2016) consider accept-reject decisions for a barge transportation network, including some customers with long term commitments. Table 1.1 provides an overview of planning-related studies and categorises them regarding the perspective of the optimisation problem, the dimensions of flexibility and the considered decisions. Regarding the optimisation perspective, most studies consider the cost minimisation problem of the transportation provider provided a certain available capacity. This is different from the logistics service provider's perspective, which usually has no invested capacity and therefore can optimise container transports one at a time. Most studies mention to some extent three dimensions of flexibility: mode, route and timing. In Table 1.1, we restricted the categorisation to those dimensions that specifically influenced the modelling choices. Finally, we distinguished between 5 types of decisions: the scheduling of transportations, accepting or rejecting bookings, the deployment of (barge or rail) services, the pricing of transportation services or the conditions of the transportation service. From these decision types, the first typically is aimed at the operational level, whereas the other three are typically tactical decisions. Although it has not been published yet, the work presented in Chapter 6 of this dissertation is added to the table for comparison. The contents of the remaining chapters will be outlined in Section 1.5.

From Table 1.1 it can be observed that most studies consider either the perspective of the transportation provider, or the logistics service provider. Also, most studies considered a problem that combined routing and timing – in most cases, the mode is considered implicitly in the definition of the service schedule. Only some considered mode-specific constraints, such as the potential for rerouting with barges (Fazi *et al.*, 2015) or the possibility of transhipments. Finally, almost all studies considered an operational planning problem, for optimal allocation of cargo to an available schedule. In some cases, this was combined with a service schedule design problem. We address three gaps in the literature. Firstly, existing models for integrated network planning lack elements required for synchromodal planning (Section 1.3.2). Secondly, few models are suitable for applying to practice in real-time (Section 1.3.3). Finally, offering synchromodal services in intermodal networks introduces a new problem to optimally balance customer value and planning flexibility (Section 1.3.4).

Table 1.1 Overview of synchromodal studies and main differentiators

	Perspective			*Flexibility*			*Decision*			
							Operational		*Tactical*	
	Transportation provider	Logistics service provider	Shipper	Mode*	Route	Time	Transportation scheduling	Accept/reject orders	Service deployment	Product definitions: (c)onditions/(p)ricing
Bilegan *et al.* (2013)	•	◦	◦	•	◦	•	•	•	◦	◦
Fazi *et al.* (2015)	•	◦	◦	•	•	•	•	◦	•	◦
Kapetanis *et al.* (2016)	◦	•	•	◦	•	•	•	◦	◦	◦
Li *et al.* (2015)	•	◦	◦	◦	•	•	◦	◦	◦	• (p)
Li *et al.* (2016)	•	◦	◦	•	•	•	•	◦	◦	◦
Mes and Iacob (2016)	◦	•	◦	◦	•	•	•	◦	◦	◦
Nabais *et al.* (2013)	◦		◦	◦	•	•	•	◦	◦	◦
Rivera *et al.* (2016)	◦	•	◦	•	•	•	•	◦	◦	◦
Van Heeswijk, *et al.* (2016)	◦	•	◦	◦	•	•	•	◦	◦	◦
Van Riessen *et al.* (2015-a) & Ch. 2	•	◦	◦	•	•	•	•	◦	•	◦
Van Riessen *et al.* (2015-b) & Ch. 3	•	◦	◦	◦	•	•	•	◦	◦	◦
Van Riessen *et al.* (2016) & Ch. 4	•	◦	◦	◦	•	•	•	◦	◦	◦
Van Riessen *et al.* (2017) & Ch. 5	•	◦	◦	◦	◦	•	◦	◦	◦	• (c)
Wang *et al.* (2016)	•	◦	◦	◦	•	•	•	•	•	◦
Ypsilantis (2016, pp. 47-82)	•	◦	◦	•	•	◦	◦	◦	•	• (p)
Chapter 6	•	◦	◦	◦	•	•	◦	◦	◦	• (c)

* Most studies do consider mode to some extent, often as property of a route. In the table, we have marked a study as considering 'mode', only if the study specifically considered mode-related aspects.

1.3.2 Integrated Network Planning

The global throughput in container transportation continues to grow and constitutes a growing portion of the global transportation (Drewry Shipping Consultants, 2007). Meanwhile, supply chains get increasingly interconnected and shippers demand higher levels of service, such as short delivery times and reliability (Crainic and Laporte, 1997; Crainic, 2000; Veenstra *et al.*, 2012). The logistic expression for integrated transportation is intermodality. The International Transport Forum defined intermodal transportation as: *Multimodal transport of goods, in one and the same intermodal transport unit by successive modes of transport without handling of the goods themselves when changing modes* (UNECE, 2009). The planning of intermodal transportation requires a network-wide approach (Crainic 2000; Jansen *et al.* 2004; Crainic and Kim 2007). Consolidation of flows between hubs in intermodal networks is cost efficient as it benefits of the economies of scale

(Ishfaq and Sox, 2012). Transportation used to be optimised based purely on costs. However, Crainic and Laporte (1997) signal that carriers and transporters cannot only optimise the transportation on cost efficiency anymore. Apart from low tariffs, customers demand for a higher quality of service. According to Crainic and Laporte, quality of service consists of three parts: on-time delivery (time window), delivery speed (service time) and consistency of these aspects. Veenstra *et al.* (2012) mention reliability as an important quality of service. Ishfaq and Sox (2010) mention six performance targets for intermodal logistic networks: cost, service frequency, service time, delivery reliability, flexibility and safety. They propose methods to optimise the costs of intermodal logistic networks, while meeting service time requirements. The other performance targets are neglected in their work.

Some of the existing tactical service network formulations use strict constraints on delivery time (Ziliaskopoulos and Wardell, 2000) or no due time restrictions (e.g. Crainic, 2000). Strict constraints do not accurately model the flexibility that transportation planners have in consultation with customers. If no time restrictions are considered at all, the existing time pressure in the container transportation is neglected. Several formulations model the economies of scale that occur when cargo is consolidated on an arc (e.g. Ishfaq and Sox, 2012). These abstract formulations of economies of scale cannot directly represent the current situation. The current practice in intermodal container networks is that multiple service and terminal operators cooperate and in this perspective, economies of scale are exploited by selecting services operated by the network operator (self-operated services) or use subcontracted transport. The difference in cost structure between these two cannot be modelled in the existing formulations for the economies of scale. We aim to address these two aspects in the problem of integrated network planning: accurately modelling time pressure, while allowing overdue delivery and modelling a combination of self-operated and subcontracted services. The first issue was also studied by Arikan *et al.* (2014) for the Danube region between Southern Germany and Hungary. They applied a stochastic service network design model with penalties for overdue deliveries.

1.3.3 Real-Time Network Planning

For efficient synchromodal transport plans it is essential to allow real-time switching, i.e. real-time planning updates. This was recognised by many studies that refer to synchromodal transportation (Lucassen *et al.*, 2012, SteadieSeifi *et al.*, 2014, Behdani *et al.*, 2014, Tavasszy *et al.*, 2015), but not many real-time planning methods that provide a network-wide plan exist yet. The previous section mentioned various planning models that are aimed for solving the network transportation problem offline (Crainic and Laporte, 1997; Crainic, 2000; Crainic and Kim, 2007; Ishfaq and Sox, 2010, 2012, Van Riessen *et al.* 2015-b). Ziliaskopoulos and Wardell (2000) and Janssen *et al.* (2004) proposed an online method, but focused on the planning of single corridors. Nabais *et al.* (2015) and Li (2016) proposed more advanced methods for solving the online problem. Their methods uses model predictive control to achieve a required modal split, but the approach requires real-time automated data processing and is less insightful to human planning operators. Li *et al.* (2013) used a sequential linear programming method. We aim to facilitate synchromodal planning by proposing a real-time network planning solution that is insightful for human planning operators.

1.3.4 Balancing Customer Value and Planning Flexibility

As Van der Horst and De Langen (2008) stated, the container inland transportation chain lacks information integration and stakeholders do not fully trust each other, making integrated solutions difficult. Nonetheless, creating more planning flexibility is vital to enable synchromodal planning. Therefore, the network operator has an incentive to introduce a range of transportation services with varying levels of flexibility. Such new product ranges have been studied recently by Lin (2014) and Wanders (2014). These propositions consider different tariff classes for varying levels of service and the level of decision flexibility that the network operator receives from the customer. In other areas of transportation, incentives of stakeholders are studied with stated preference surveys, e.g. for the valuation of time for travellers (Wee et al., 2013): "travellers are confronted with hypothetical choice situations between a fast, expensive alternative and a cheap one". To our knowledge, no stated preference studies exist that looked specifically into customer incentives for container transportation, although some studies are in progress (Khakdaman, 2017).

In aviation, the development of revenue management (RM) enabled these industries to increase utilisations (Carmona-Benítez, 2012), e.g. by "selling the right seats to the right customer at the right time" (Zeni, 2001) and by creating customer incentives for using flexible services (Petrick, 2012). The concept of different service propositions in transportation is very similar to the concept of different fare classes for the same flight in aviation. Barnhart *et al. (*2003) give an overview of operations research in airline revenue management. The primary objective of airline revenue management models is to determine the optimal fare mix: how much seats of each booking class should be available, provided the demand forecasts and the limited total number of seats? Some studies on revenue management in freight transportation focused on an online policy: whether to accept or reject an incoming order. Pak and Dekker (2004) proposed a method for judging sequentially arriving cargo bookings based on expected revenues. If the direct revenue of a booking exceeds the decrease in expected future revenue, the order is accepted. Bilegan *et al.* (2013) apply a similar approach on rail freight application and Wang *et al.* (2016) consider accept-reject decisions for barge transportation. In their approach the decision of accepting or rejecting an arriving transport order is based on the difference in expected revenue with and without that order. We propose a solution at a more tactical level, by translating fare mix models from airline revenue management towards the setting of intermodal hinterland transportation of containers. The setting of container transportation introduces a new issue to the fare mix problem, as the operator has the opportunity to select from various transport modes, routes and time for some of the containers.

1.4 Research questions and approach

As introduced in Section 1.1.1, the main goal of this dissertation is to address the literature gaps and develop methods for optimal portfolios and optimal transportation plans that enable synchromodal planning in inland container networks. In this section our main and supporting research questions are provided as well as our research approach.

1.4.1 Main research question

In order to enable synchromodal planning in inland container networks in practice, our main research question is as follows:

How can synchromodal networks operate optimally?

Our research question aims for practical solutions, since it focuses on network operation. At the same time, it aims for finding optimal methods for different aspects of network operation. We consider this main research within the scope of synchromodality. As introduced in Section 1.3.1, synchromodality has an ambiguous definition, based on various publications (Table 1.1). In this dissertation, we consider synchromodality as the combination of a service-based business model and network-wide intermodal operation. We consider the perspective of the network operator. Our aim is to maximise the profits of the service-based business model and minimise costs of the network-wide intermodal operation, within acceptable service levels. Based on the literature overview of Section 1.3, our research must address three subtopics in order to answer the main research question: methods for integrated network plans, methods for real-time planning and methods for creating planning flexibility. All these three aspects contribute to the development of synchromodal transportation to such a level that it can be implemented in practice. Sections 1.4.2-1.4.4 introduce the sub research questions regarding these topics and provide an overview of our approach. Finally, all topics combined must lead to a synchromodal network than can be operated and monitored optimally in real-time.

1.4.2 Integrated Network Planning

The first aspect of our study considers the development of planning in integrated networks. Container transportation is currently organised with A-B connections. However, a network operator carries out services to several closely located inland terminals in the hinterland. A service network between all network locations provides more alternative routes using intermediate transfers. This allows consolidation of flows and an increase of overall capacity. Existing service network design methods are not applied in practice for several reasons: models with more flexible time restrictions are required and self-operated and subcontracted services must be combined. The following research questions are studied:

1. How must a service network design model accommodate for flexibility in overdue delivery as well as subcontracted and self-operated services?

In this research an exact method is developed to determine the optimal number of services on all corridors in the network. The service network design must incorporate combinations of self-operated and subcontracted transport and allow for overdue delivery (at a penalty cost) to model current container transportation networks.

Besides, the online planning of the network transportation is important, dealing with continuous disturbances in the network. In case of disturbances, the manual planners have to switch disturbed containers to other routes. This is time-consuming and the network potential for alternatives is often not fully used in practice. Last-minute switching is difficult, resulting in delays. For this, an assessment of the impact of disturbances must be developed. With this assessment, the network operator can find the most important network aspects to improve for increasing reliability and robustness of the transportation and decrease the cost impact of disturbances. The following research questions are considered:

2. How can optimal transportation plans be created for synchromodal networks?
3. How can the effect of disturbances in synchromodal networks be quantified?

With our proposed method, we aim to compare the quality of online updates of an automated optimal method and a method that mimics the manual updates for various disturbances. This provides insight in the gravity of disturbances and the benefit of automating online planning updates. With this part of the research the new *Linear Container Allocation model with Time-restrictions* (LCAT) is developed, which will be the bases of the research questions for real-time network planning in the next section.

1.4.3 Towards Real-Time Network Planning

The second research topic aims for enabling real-time network planning, to allow synchromodal transportation in practice. As mentioned in Section 1.3, several studies have proposed optimisation methods for determining the optimal allocation of containers to all available inland transportation services, considering capacity, costs, lead times and emissions. The proposed methods are suitable for solving the *offline* planning problem, in which an optimal network plan is created for a batch of transportation orders collectively. From practice we found three issues with the implementation of a centralised offline approach in intermodal networks:

- The nature of the inland transport logistics requires a real-time approach, and does not allow for integral planning models that are applied in intervals.
- Proposed centralised optimisation methods depend strongly on automation, both for terminals, as for other parts of the supply chain. Such an automation level is often not easy to implement. On top of that, information from direct communication between manual operators is often essential (Douma, 2008).
- Finally, the supply chain of container logistics lacks information integration (van der Horst and de Langen, 2008). In the case of intermodal networks, manual planning operators often do not have real-time capacity information about the inland services.

We aim to find a solution for the following research question:

4. How can the results of the LCAT model be translated into a white box decision support method for human planning operators?

To answer these questions, a general method for obtaining a real-time decision support system (DSS) is required that addresses all three aforementioned issues. The model must be based on an intrinsic analysis of the offline LCAT model, translating the offline model's optimal solutions to a decision tree for online decision support. A decision tree is a white box method that is comprehensible for manual planners and allows manual changes if necessary. It will therefore more easily be accepted for use in daily practice. The human planner responsible for a central network planning must be able to check available capacity on a proposed service manually. Hence, real-time up-to-date information is not critical for the method's performance. Note that this method aims to support planning decisions for incoming transportation orders, however, the effect of real-time decision support in case of disturbances or disruptions is not included in the study**.** In case of a disruption during the operational phase, a different type of real-time decisions must be made in order to solve the disruption and fulfil all transportation requests.

1.4.4 Balancing Customer Value and Planning Flexibility

The research topics on integral and real-time network planning as described in previous sections provide insights into efficient network planning, from an offline and a real-time perspective, respectively. Also, we highlighted the potential gain in network performance with more planning flexibility. However, in the prevalent set-up of the transportation product, customers are hesitant to transfer planning flexibility to the (network) operator. This is for several reasons, i.e. company policy, habituation, but also the pricing mechanism. Achieving planning flexibility requires persuading clients to allow flexible planning of their transportation orders. For that reason, studies into creating planning flexibility are required to answer the following research questions:

5. What is the value of planning flexibility for synchromodal networks?

As suggested by Lin (2014) and Wanders (2014), the market for inland container transportation can be segmented in groups of customers with different characteristics. These groups are sensitive to different *incentives* that may persuade customers to allow flexibility for planning purposes by the synchromodal transportation operator. For this, a revenue management (RM) model for container logistics is necessary, in order to balance customer demand and network transportation options, similar to revenue management problems in aviation (Barnhart *et al.,* 2003). Currently, only qualitative studies into customer preferences have been carried out for container transportation in North-West Europe, e.g. Lucassen *et al.* (2010), Palmer, *et al.* (2012) and Veenstra *et al.* (2012). One issue with developing a RM model in practice is the high number of stakeholders involved in a container transport. The decision on service level and price often has to be made between several stakeholders with conflicting incentives, such as the cargo owner, the container owner (shipping line) and the logistic service provider (Van der Horst and De Langen, 2008). Therefore, research on various topics is required. First of all, market research is necessary to gain insights in the incentives of different segments of transportation customers. Secondly, using the information from such market research, a method must be created for designing transportation products that encourage flexibility and thus synchromodal transportation. By designing transportation products properties according to customer preferences, customers can be targeted with different types of service level (delivery time, reliability), availability and other aspects. This allows addressing service needs more specifically, and enables pricing mechanisms that maximise revenue, by differential pricing (Barnhart *et al.,* 2003). Thirdly, a pricing strategy must be developed. Currently, transportation is priced per service, based on the mode (barge, rail) and the distance. This is typically *cost-plus pricing*. If the network operator is using a network planning approach to allocate containers to different modes or routes, this pricing mechanism is not suitable: a customer is not willing to pay a high price if his container is planned on an expensive route for the benefit of the entire network plan. The new pricing strategy must balance the need for flexibility in the order pool with maximising revenue. For instance, orders that allow flexible routing with flexible modes may incur a discount on the price. With a *value-based pricing model*, the price is based on the customer value of a transportation service. In this way a differentiated portfolio can be created, aimed for various customers groups that are willing to pay a certain price for a transportation product with a certain amount of flexibility.

Finally, such a new revenue management strategy in synchromodal transportation networks is different from other applications, such as aviation. With synchromodal networks, the network operator can use the flexibility in some products to attain a more efficient transportation plan. In this case the pricing strategy is strongly linked to the operations management: promoting planning flexibility is beneficial for the network if the flexibility can be used to achieve a more cost-efficient transportation plan. This is depicted in Fig. 1.2. While the operations management aims to assign transportation slots to a provided set of demand for minimum cost, the revenue management strategy aims to attain demand for a provided set of slots with maximum revenue. In our case, these two approaches are connected by the balance between flexibility and network utilisation. To optimise total profit, these two approaches must be optimised integrally to answer the following research questions:

6. How can the optimal fare class mix for a synchromodal corridor be found?
7. To what extent is it relevant to consider the synchromodal network structure when optimising the fare class mix?

For this new type of problem, we provide a framework for finding the optimal transportation service portfolio, the *Cargo Fare Class Mix problem*. Our proposed framework is based on the outcome of original market research, product design and a pricing strategy developed by EGS. The CFCM problem considers two transportation services with differentiated delivery lead times. We propose a method to find the revenue maximising balance between those two products. By this integral analysis of revenue and operations management, we aim to shown the value of planning flexibility in synchromodal container transportation. Furthermore, we propose an improved (faster) method for the single corridor problem, and use this to find lower and upper bounds for specific types of synchromodal networks.

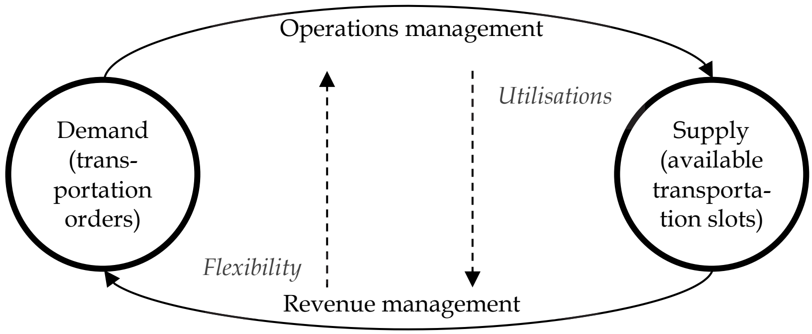

Fig. 1.2 Revenue management and operations management

1.5 Outline of the dissertation

In the next chapters, our research on these three topics is provided. Here, an outline of the remainder of this dissertation is provided. A schematic overview is provided in Fig. 1.3. Currently, the most important developments of synchromodal transportation occur in The Netherlands and focus on the Rotterdam hinterland. In this chapter we have provided a general overview of recent and current developments on the topic of operational implementation of synchromodal transportation. To support this transformation, our research focuses on three topics:

- Models for integrated network planning. In Chapter 2, the tactical level is assessed, for which we developed a new *service network design* method, answering research question 1. Chapter 3 considers the *impact and relevance of disturbances* in a synchromodal container transportation network on the operational level, and introduces the newly developed LCAT model, answering research question 2 and 3.
- Methods for real-time decision making for network transportation planning. In Chapter 4 a *real-time decision support system* is described, based on the LCAT model of Chapter 3. This chapter answers research question 4.
- Methods for optimising a differentiated portfolio of transportation services. In Chapter 5, a solution for finding the optimum in a single corridor case is provided by introducing the *Cargo Fare Class Mix (CFCM) problem,* answering research question 5 and 6. Finally, Chapter 6 extends the method towards synchromodal networks, answering research question 7.

The assumptions in the analyses differ between chapters. Since Chapter 2 and 3 mostly focus on the integrated planning of synchromodal networks, the planning conditions are modelled in more detail, whereas the specific customer demands are not in detail considered. In Chapter 5 and 6, the optimal combination of products in the portfolio is considered; therefore, these chapters put more emphasis on customer requirements, and less on planning conditions. Chapter 4 functions as a bridge between planning and practice, aiming to translate model information to real-time support in practice.

The results of our research are expected to have practical relevance, as all case studies are based on the network of EGS and the Rotterdam hinterland. Chapter 7 provides the overall conclusions and answer to the main research question. It also includes suggestions for future research and a description of the practical impacts of our research for EGS hitherto.

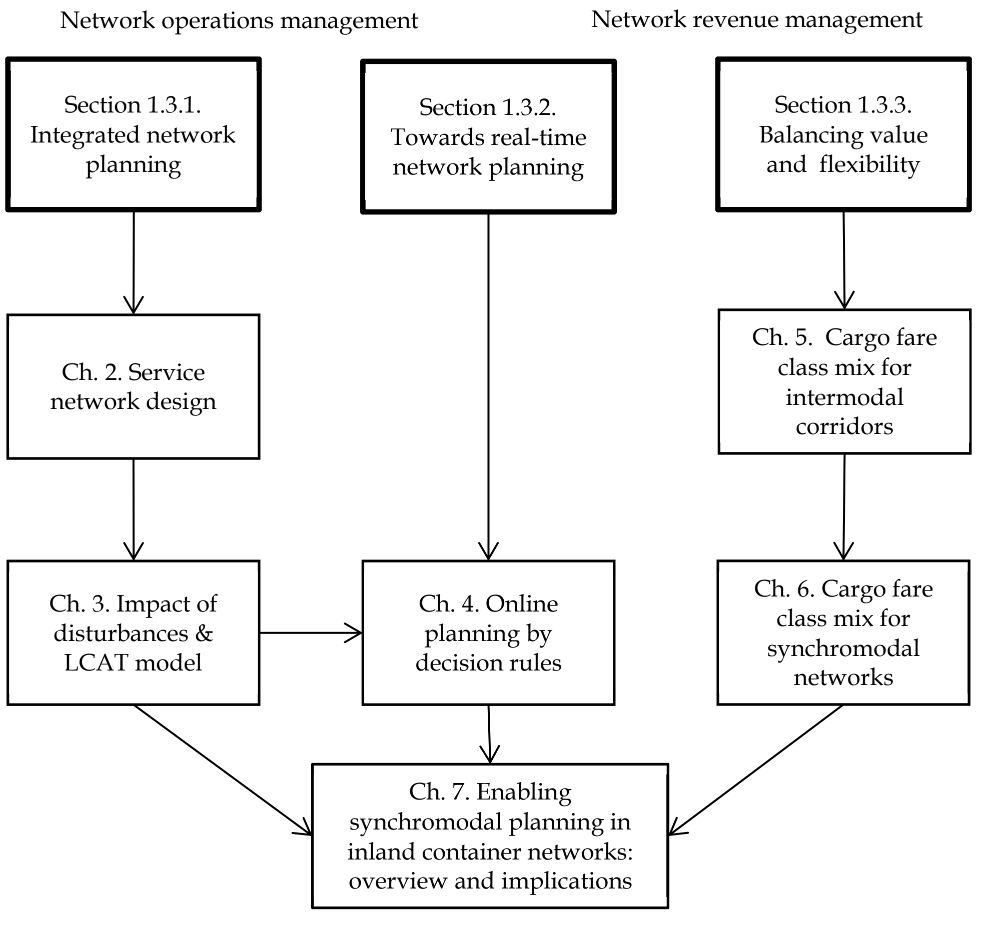

Fig. 1.3 Overview of the strucure of the research

2 Service network design for an intermodal container network

In the previous chapter, the concept of synchromodal transportation was introduced, as well as the case of EGS. To use this network cost-efficiently, a centralised planning of the container transportation is required, to be operated by the deep-sea terminal. In this chapter, a new mathematical model is proposed to determine the optimal service schedule between the given network terminals. The model introduces two new features to the intermodal network-planning problem. Firstly, overdue deliveries are penalised instead of prohibited. Secondly, the model combines self-operated and subcontracted slots. The model considers self-operated or subcontracted barge and rail services as well as transport by truck. In this chapter, we provide the answer to research question 1: "How must a service network design model accommodate for flexibility in overdue delivery as well as subcontracted and self-operated services?" In a case study of the EGS network, the benefit of using container transportation with intermediate transfers is studied. The results indicate that the proposed model is suitable for the service network design in modern intermodal container transport networks. Also, the results suggest that a synchromodal business model for the network transport and terminals is worth investigating further, as the transit costs can be reduced with lower transfer costs. This chapter is organised as follows. Section 2.1 provides an introduction to the problem addressed. Section 2.2 briefly reviews literature on service network design models. Section 2.3 introduces the proposed intermodal container network model. The case of EGS is used as an example for the intermodal container network model of this study in Section 2.4. The results of the experiments are discussed in Section 2.5. Section 2.6 concludes the chapter and proposes further research.[2]

Keywords: *Service network design; container logistics; intermodal transportation; hinterland transportation; flexible due times; subcontracted transport*

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[2] This chapter is based on the following publication with small modifications: Van Riessen, B., Negenborn, R. R., Dekker, R. and Lodewijks, G. (2015). Service network design for an intermodal container network with flexible transit times and the possibility of using subcontracted transport. *International Journal of Shipping and Transport Logistics*, 7(4), 457-478. The final publication is available via https://doi.org/10.1504/IJSTL.2015.069683.

2.1 Introduction

2.1.1 Development of container networks

In Section 1.1 an overview of recent developments in container networks was presented. A tendency of more integrated supply chains has sparked initiatives in North-West Europe to create transportation networks for containers (Groothedde *et al.*, 2005, Lucassen and Dogger, 2012, Rodrigue and Notteboom, 2012, Port of Rotterdam, 2011). In Fig. 1.1 the network of European Gateway Services (EGS) is depicted, a subsidiary of Europe Container Terminals (ECT), with three deep-sea terminals in Rotterdam and seven hinterland terminals. In this chapter, the service network design of such container networks is considered. For organising the transportation, a network operator such as EGS does not own barges and trains. It uses a combination of long-term contracts for a fixed amount of services per week (self-operated services) or it uses slots on existing services on a per-slot-basis (subcontracted transport). A long term contract comes with the risk of not fully loading the available capacity that is already paid for, but it also brings economies of scale. For subcontracted transport the network operator incurs no risk of unutilised space, but this comes at a higher price. For both types, a transport operator carries out the actual transport. Based on these observations, we propose a service network design model with several new aspects. First, the next section provides relevant definitions.

2.1.2 Definitions: intermodal and synchromodal

This study focuses on the transportation from the seaport terminal to a hinterland terminal (import) or vice versa (export), organised by the deep-sea terminal. This is called *hinterland transportation*. Final drayage to a customer is excluded. In the network, transport is carried out by three different *modes*: barge, rail and truck. Hence, as different modes can be selected, the transportation in the network is considered *multimodal transportation*. At terminals, containers can be switched from one transport mode to another. In this chapter, an exchange at a terminal is called a *transfer*. Fig. 2.1 shows a schematic view on three terminals. The figure shows five mode-specific *corridors* by which the terminals are directly connected. As multiple modes connect two terminals, multiple corridors exist. Terminal A and C are indirectly connected via terminal B, and transport is possible using the corridors to B and then to C. Each of the transport steps from one terminal to another is called a *leg*. The two consecutive legs are referred to as a *connection* between A and C. The specific itinerary of a container, i.e. the services used, is called a *path*. Each of the used corridors is referred to as a *leg* of the container transport. The *service* on a corridor between terminals is the movement of a vehicle from one terminal to another, travelling on a specific time and route. The number of services per time period on a certain corridor is called the *service frequency*. In this study, the frequency denotes the number of services *per week* on a corridor.

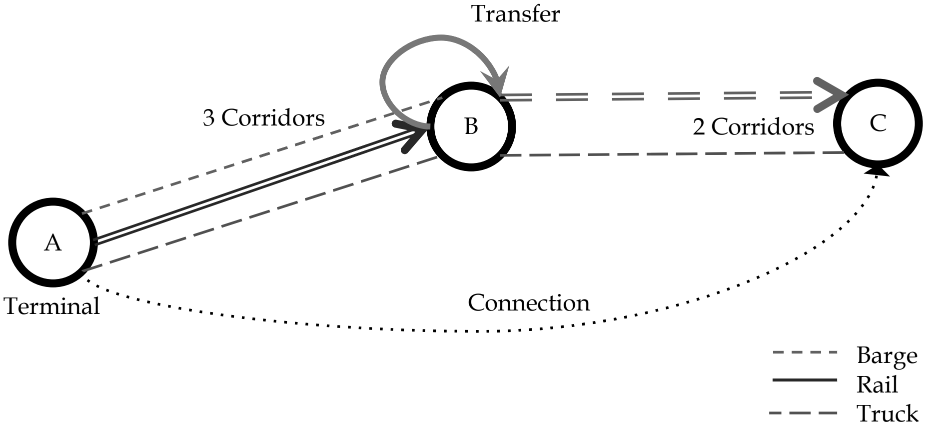


Fig. 2.1 Container transport (schematic)

Intermodal transportation is defined as 'Multimodal transport of goods, in one and the same intermodal transport unit by successive modes of transport without handling of the goods themselves when changing modes' (UNECE *et al.*, 2009, Section G.I-01). With *intermodal network planning*, the routing of containers with multiple consecutive services is possible, using *intermediate transfers* of the containers at network terminals. A container that has an itinerary with two services uses such an intermediate transfer.

On top of that, a network with centrally planned transportation can use *real-time switching* (Lucassen and Dogger, 2012). Real-time switching refers to changing the container routing over the network in real-time to cope with transportation disturbances, such as service delays or cancellations. The combination of intermodal planning with real-time switching is often referred to as *synchromodal planning*, as introduced in the agenda of the Dutch research platform for logistics (Topsector Logistiek, 2011). In this chapter, synchromodality is considered as *intermodal planning with the possibility of real-time switching between the modes* or online intermodal planning. As network transport orders with specific delivery time requirements are accepted, the use of synchromodal planning is essential for the network performance. This chapter focuses on creating the initial plan in a synchromodal setting: the use of intermediate transfers in the intermodal planning. For that reason, the service network design is assessed, considering additional corridors between inland terminals and container transportation over paths with multiple consecutive legs and intermediate transfers.

2.1.3 New aspects of the proposed model

In this chapter we propose a new mathematical model for the tactical service network design of intermodal container networks. Existing intermodal planning models do not suffice for this purpose for two reasons:

1. Current models use strict time restrictions for delivery. The extended gate network accepts network orders with time restrictions, but the daily practice in the container transportation (at EGS) is that planners and customers agree in mutual consultation on delivery times. Depending on the circumstances (transportation volume, disturbances) they are flexible in their negotiations. This cannot accurately be modelled by strict due time restrictions.
2. Moreover, existing service network design models focus on operating self-owned services in the network, often including a balanced routing of the vehicles over multiple stops. For the type of container transportation network studied here, this does not apply. Instead, the network operator uses a combination of self-operated services and subcontracted slots. Both types operate on dedicated corridors from A-B.

In the case of self-operated services, the network operator pays for the entire barge or train and incurs no additional transportation costs per TEU (twenty feet equivalent unit, a standardised container size measure). In the case of subcontracted transportation, transportation is paid for per TEU. Nonetheless, the loading and unloading of containers (handling costs) does have a cost per TEU for both cases. The service network design model proposed in this study introduces two new aspects to the service network design problem:

1. Overdue delivery is not restricted, but penalised by a penalty for overdue delivery.
2. The model allows for a combined use of self-operated and subcontracted slots.

2.2 Literature overview

In academic literature, three levels of network planning are distinguished (Crainic and Laporte, 1997; Macharis and Bontekoning, 2004): strategic, tactical and operational planning. The exact boundary between these levels often depends on the point of view of the planning. In general, strategic planning focuses on long-term network design, such as locations of terminals or transport hubs (e.g. Ishfaq and Sox, 2010, Meng and Wang, 2011-b). With tactical planning is referred to the mid-term decisions about optimally allocating the resources, e.g. designing the service network (Crainic, 2000). Operational planning focuses on the day-to-day planning of network transportation (e.g. Jansen *et al.*, 2004, Ziliaskopoulos and Wardell, 2000). Service network design consists of the following aspects as described by Crainic (2000): the selection and scheduling of the services to operate, the specification of the terminal operations and the routing of freight. Network design models are often mixed-integer problem-based formulations of a network structure where nodes represent terminals and arcs represent services (Crainic, 2000). The service network design is studied in detail for liner shipping networks, generally resulting in routes consisting of a sequence of port visits (multi-port calling problem), e.g. Meng and Wang (2011-a), Brouer *et al.* (2013). However, in this study we focus on intermodal networks consisting of services that operate on a dedicated A-B corridor. When multiple modes can travel between the same network terminals, multiple arcs are used to represent these corridors. Both the assignment of cargo to routes and the number of services on each corridor are considered simultaneously. In the existing literature about intermodal container transportation networks, several service network design models have been proposed. Two types of models can be distinguished:

- Link-based network flow models (LBNF)
- Path-based network design models (PBND)

Some LBNF models distinguish between multiple commodities. A commodity, or equivalently cargo class, is used to denote a set of containers that have equal properties, such as weight and delivery time. In PBND models the cargo classes also specify the origin and destination of a container set. Both types of models are able to consider capacitated flow. Table 2.1 shows examples of existing service network design models.

Table 2.1 Examples of existing service network design models

	Link-based network flow (LBNF)	*Path-based network design (PBND)*
Single commodity	Ziliaskopoulos (2000) Holmberg and Hellstrand (1998)	
Multi-commodity	Crainic and Rousseau (1986) Crainic (2000) Ishfaq and Sox (2010, 2012) Meng and Wang (2011-b)	Crainic and Rousseau (1986) Crainic and Laporte (1997) Crainic (2000)

LBNF models have the possibility of flexible routing of cargo over various links in the network. Also, explicit constraints on the link capacity can be set. However, the main disadvantage is the number of decision variables for multi-commodity, multi-mode formulations. A variable is required for each cargo class on each arc. For applications with many origin-destination pairs, weight categories and delivery times, the number of decision variables becomes too high for practical computation times. For PBND type of models, the possible paths for each cargo class are predetermined. A path is the exact route of a container using subsequent services and terminals. This reduces the number of decision variables substantially, provided that the number of possible paths is kept at a low enough number. However, with the traditional PBND formulations, the capacity of services travelling on each arc cannot be restricted directly, as multiple paths for the same or different cargo classes coincide on single services. The model proposed in the next section uses a formulation that combines the arc capacity restrictions with the routing of containers over predetermined paths, as suggested by Crainic (2000).

Some of the existing tactical service network formulations use strict constraints on delivery time (Ziliaskopoulos and Wardell, 2000) or no due time restrictions (e.g. Crainic, 2000). Strict constraints do not accurately model the flexibility that transportation planners have in consultation with customers. No time restrictions at all neglect the existing time pressure in the container transportation. The proposed model uses an alternative formulation that better suits the flexible delivery time restrictions.

Several models use formulations that model the economies of scale that occur when cargo is consolidated on an arc (e.g. Ishfaq and Sox, 2012). These abstract formulations of economies of scale cannot directly represent the current situation. The current practice in intermodal container networks is that multiple service and terminal operators cooperate and in this perspective, the network operator can exploit the economies of scale of its transportation volume by negotiating long term contract for fixed services dedicated to the network (self-operated services). Alternatively, the network operator can use subcontracted transport, without any risk, but at a higher cost. The difference in cost structure between these two cannot be modelled in the existing formulations for the economies of scale. Some studies refer to charter slots in a similar sense as the subcontracted slots mentioned here, but those models are not directly applicable to our case, e.g. Feng and Chang (2008) consider charter slots only for repositioning of empty containers, and Meng and Wang (2011-a) used it in a multi-port calling problem. Hence, the proposed model allows for a combined use of self-operated and subcontracted slots.

2.3 Proposed model

To solve the service network design problem, the optimal number of services on all corridors in the network must be determined, referred to as the service schedule in the remainder of this chapter. Note that a service schedule would also require determining the departure times during the week, but that is out of scope in this model. Determining the optimal service schedule is done by the central network operator and is evaluated every couple of months. The objective is to create a single weekly service schedule that minimises the weekly transportation costs for the expected demand. Demand is defined as the number of containers that must be transported between all origin-destination pairs in the network. The demand for one period (a week) is described as a demand pattern. For finding the optimal single service schedule, the model determines the service frequency between all nodes while considering multiple demand patterns Q. The demand patterns can be based on forecasts, or – as in our approach – on analysis of historic data. A *cargo class* is a group of containers with equal *origin* and *destination*, the same weight class and with the same period for delivery (due time). Each pattern $q \in Q$ consists of an expected transportation volume for each cargo class $c \in C$. The expected transportation volume of cargo class c in demand pattern q is denoted by $d_{c,q}$ (in TEU). For each cargo class c the parameters w_c and t_c denote the weight and due time of that cargo class, respectively.

The model is formulated as a mixed-integer linear programing problem with a linear objective and linear constraints. It combines aspects of the LBNF and PBND formulations described in the previous section (e.g. by Crainic, 2000). Moreover, two aspects are added: the possibility for overdue delivery, at the cost of a penalty, and the possibility of using self-operated and subcontracted transportation. The objective minimises the weekly transportation costs consisting of four cost terms:

- The cost of operating the self-operated services
- The cost of subcontracted transportation
- Transfer costs (loading and unloading containers)
- Penalties for overdue delivery

A *path* is a possible route for a container to travel from origin to destination, denoted by a sequence of services. The possible paths in the network for each cargo class must be predetermined. This can be done in various ways, such as using the expert knowledge in existing networks, or by an automated path generation method as is used in the case study of the next section. For path p, the number of transfers is denoted by F_p, with a minimum value of 1 for a path with only 1 service. The set of all possible paths is denoted by P. The subset of feasible paths for each cargo class c is denoted by P_c. In this study a path is considered feasible for cargo class c if the origin and final destination coincide.

The model uses five sets of decision variables. The integer service frequencies y_{ijm} denote the number of self-operated services between terminal i and j with mode m, defined as *corridor* (i, j, m). The set of available corridors is denoted by A. The amount of TEU of cargo class c on self-operated or subcontracted slots on corridor (i, j, m) in pattern q is denoted by the flow variables $z_{ijm}^{c,q}$ and $\zeta_{ijm}^{c,q}$, respectively. The path selection variable $x_p^{c,q}$ denotes the number of TEU of cargo class c transported on path p in pattern q. Finally, the auxiliary variable τ_p^c denotes the total number of overdue days of all planned containers of cargo class c on path p. The objective of the model is to minimise the following objective function J:

$$J = \sum_{(i,j,m)\in A} f_{ijm}\, y_{ijm} + \sum_{(i,j,m)\in A} \sum_{(c,q)\in C\times Q} c_{ijm}\, \zeta_{ijm}^{c,q} + c_F \sum_{p\in P} F_p \sum_{(c,q)\in C\times Q} x_p^{c,q} + c_\tau \sum_{(c,p)\in C\times P} \tau_p^c, \tag{2.1}$$

where

- f_{ijm} and c_{ijm} denote the costs of operating a service or subcontracting one TEU on corridor (i, j, m), respectively,
- c_F is the cost per transfer,
- F_p is the number of transfers on path p;
- c_τ denotes the cost per TEU for each day late delivery.

Hence, the first term of the objective represents the cost for the selected services to operate self; the second term sums all costs for subcontracted transports in all patterns q; the third term denotes the costs for transfers and the fourth term is the penalty cost for overdue delivery.

The minimisation of objective function J is subject to constraints: all transportation demand must be fulfilled, while meeting the capacity restrictions of the selected services. The TEU-capacity and maximum weight of a service on corridor (i, j, m) is denoted by u_{ijm} and m_{ijm}, respectively. Besides, the allocation of containers to paths, $x_p^{c,q}$, must be translated to the allocation of containers to services, denoted by the flow variables $z_{ijm}^{c,q}$ and $\zeta_{ijm}^{c,q}$. This mapping of selected paths to the flow variables is done with δ_{ijm}^p, which is 1 if the corridor (i, j, m) is on path p and zero else. The constraints of the model are formulated as follows:

$$\sum_{p \in P_c} x_p^{c,q} = d_{c,q} \qquad \forall (c, q) \in C \times Q \tag{2.2}$$

$$\sum_{p \in P} \delta_{ijm}^p x_p^{c,q} = z_{ijm}^{c,q} + \zeta_{ijm}^{c,q} \qquad \forall (i, j, m) \in A;\ \forall (c, q) \in C \times Q \tag{2.3}$$

$$\sum_{c \in C} z_{ijm}^{c,q} \leq u_{ijm} y_{ijm} \qquad \forall (i, j, m) \in A;\ \forall q \in Q \tag{2.4}$$

$$\sum_{c \in C} w_c z_{ijm}^{c,q} \leq m_{ijm} y_{ijm} \qquad \forall (i, j, m) \in A;\ \forall q \in Q \tag{2.5}$$

$$\sum_{q \in Q} x_p^{c,q} \left(T_p - t_c\right) \leq \tau_p^c \qquad \forall (c, p) \in C \times P \tag{2.6}$$

$$y_{ijm} = y_{jim} \qquad \forall (i, j, m) \in A \tag{2.7}$$

$$x_p^{c,q} \geq 0 \qquad \forall (c, q) \in (C \times Q);\ \forall p \in P \tag{2.8}$$

$$\tau_p^c \geq 0 \qquad \forall (c, p) \in C \times P \tag{2.9}$$

$$z_{ijm}^{c,q} \geq 0, \zeta_{ijm}^{c,q} \geq 0 \qquad \forall (i, j, m) \in \mathrm{A};\ \forall (c, q) \in C \times P \tag{2.10}$$

$$y_{ijm} \in \mathbb{N} \qquad \forall (i, j, m) \in A \tag{2.11}$$

Here, constraints (2.2)-(2.5) contain the transportation plan for each of the demand patterns $q \in Q$. constraint (2.2) ensures that all transportation demand is met in all patterns. The allocation of the demand to the paths is mapped to the flow variables by Constraint (2.3). This mapping depends on the used services (self-operated or contracted) in the predefined paths. Constraints (2.4) and (2.5) are the capacity constraints on each corridor. They must hold for the transportation plan for each demand pattern $q \in Q$. The maximum capacity of self-operated transport is limited by the selected number of services (denoted by y_{ijm}). Note that the capacity on subcontracted slots is considered unlimited in this formulation. Constraint (2.6) ensures that the auxiliary variable τ_p^c equals the total number of overdue time for all TEU of cargo class c on path p, by measuring the difference in the available delivery period t_c and the predetermined path duration T_p. The penalty increases linearly with the amount of time a container is overdue. The path durations are predetermined in this formulation, but the expected path durations will in practice depend on the selected service frequencies for the self-operated services and the frequencies of available subcontracted networks. In the current model, this dependency is not taken into account. In the case study a fixed transfer time is used and the due times of the cargo classes are adjusted to compensate for the negligence of waiting times at terminals. This approach is suggested by Ishfaq and Sox (2011). The model could also be applied iteratively to match path durations and service frequencies. If cargo class c is on time using path p, Constraint (2.9) ensures that τ_p^c is equal to zero. Constraint (2.7) is the balance equation for the used equipment for self-operated services: it ensures the same number of self-operated services back and forth on a corridor, to keep the equipment balanced over the network. Finally, Constraints (2.8) and (2.10) ensure the nonnegativity of the other variables and Constraint (2.11) restricts y_{ijm} to the integer set of natural numbers.

2.4 Case study of service network design in the EGS-network

2.4.1 Network and paths

The model is applied to the real-world case of the network transportation in the EGS network. The EGS network has been continuously growing with terminals and connections (European Gateway Services, 2012). This study's focus is on the network situation of June 2012: it consists of three ECT deep-sea terminals in Rotterdam (Delta, Euromax and Home) and seven inland terminals in the Netherlands, Belgium and Germany, i.e. Moerdijk, Venlo, Willebroek, Duisburg, Dortmund, Neuss and Nuremberg. All terminals can accommodate barge, rail and truck services, with a few exceptions: Willebroek and Moerdijk cannot accommodate train services; Dortmund and Nuremberg do not have a barge terminal.

Before the model can be applied to the service network design for this network, suitable paths must be predetermined. The number of possible paths could grow exponentially with the number of terminals in the network. However, in order to solve the model in a reasonable amount of time, a specifc path selection was applied to restrict the number of possible paths. Suitable paths between all locations are predetermined using the *k-shortest path* method by Yen (1971). This method is able to select shortest paths without loops in a network, based on Dijkstra's algorithm. In this study, the number of selected paths was restricted using the following three rules, all based on practical experience at the EGS planning department:

- Paths are selected based on the geographical length of the network arcs, up to a length of three times the length of the shortest path. Longer paths are considered unrealistic for use in practice, and did not show further cost reduction (Van Riessen, 2013). The geographical length of a network arc is measured as the length of the truck route on that arc.
- Subsequently, omitting all paths that consist of more than three transportation legs reduces the number of paths further. More than two intermediate transfers are not considered in this study.
- Then, paths that have a detour of more than 10% in any of the transportation legs are omitted. This detour is measured as the difference in distance to the destination from both ends of a leg. Let T_{kD} denote the trucking distance from node k to the destination. Then, a path is considered to make a detour if $T_{iD} \geq 1.1T_{jD}$ in any of its legs (i, j). This rule is added to prevent paths with unrealistic detours, while a little detour is allowed, though.

All of the remaining paths describe a geographic route with one to three transportation legs in the network. The final step of the path generation is to generate all intermodal possibilities of such a route, based on the possibility of barge and train corridors between the network locations. Truck is only considered for the last (first) leg before (after) the hinterland destination (origin), as it does not make sense to do truck transfers. E.g. a route Rotterdam Delta → Venlo → Nuremberg results in four paths, with a transfer in Venlo (see Fig. 2.2):

- Delta $\xrightarrow{barge}$ Venlo $\xrightarrow{rail}$ Nuremberg,
- Delta $\xrightarrow{rail}$ Venlo $\xrightarrow{rail}$ Nuremberg,
- Delta $\xrightarrow{rail}$ Venlo $\xrightarrow{truck}$ Nuremberg,
- Delta $\xrightarrow{barge}$ Venlo $\xrightarrow{truck}$ Nuremberg,

where both Delta and Venlo have a rail and barge terminal, but Nuremberg does not have a barge terminal. The direct paths Delta → Nuremberg by truck or rail have been omitted in the figure for simplicity, but will be considered in the case study. Note that the truck mode is only considered for the last leg. With each path p is associated a travel time T_p and a number of transfers F_p. As this study aims for a fixed number of services, operating in a schedule, the travel time T_p includes loading and unloading windows and is constant, independent of the loading rate of a vehicle. In the EGS case study, this method of path selection between all network terminals results in a set of 13977 paths.

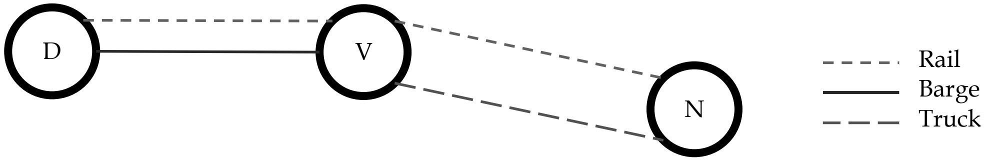


Fig. 2.2 Four intermodal paths on Delta → Venlo → Nuremberg (schematic)

2.4.2 Costs and transportation demand

The cost parameters in the study are based on the actual costs in the current operation of the EGS network. To protect the confidentiality of the data, all costs in this chapter are masked by a confidentiality factor.

The corridor costs per service (f_{ijm}) and per TEU (c_{ijm}) are modeled with a linear approximation of the actual network costs and the corridor length d_{ijm}, i.e. $c_{ijm} = \alpha d_{ijm} + \beta$. For each transfer a cost of $c_F = 24$ is used. In the network's current cost structure, the costs do not differ for different transfer types, as the terminals charge a single tariff. The cost of overdue delivery per TEU per day is $c_\tau = 50$. For the experiments carried out, also the CO_2-emissions are estimated, based on the STREAM report by CE Delft (Den Boer *et al.*, 2008). The CO_2-emissions are included in the model as a part of the costs, using a price of €8 per tonne CO_2, based on the price of an EU emission allowance for 1 tonne CO_2 as reported by Bloomberg in August 2012 (Bloomberg, 2012). A more detailed description of the costs and emissions per service can be found in Appendix 2.A, adapted from Van Riessen (2013).

For this case study, the expected demand is determined based on the historic transportation volumes. An analysis of the transportation on the EGS network in the period of January 2009 - June 2012 did not show significant periodic behaviour, so periodic demand fluctuations can be neglected. The weekly transportation volumes are tested for normality. As the transported volume grew fast in 2010, the weekly demands were further analysed based on the period January 2011 - June 2012. Using Pearson's χ^2 Goodness-of-fit test (Cochran, 1952), the hypothesis of normality of the distribution of the weekly volume was accepted with a p-value of 0.93.

Hence, the expected demand patterns for all cargo classes are based on the estimated normal distribution of transportation volumes in the period January 2011 – June 2012. The parameters of the normal distribution of the weekly volume are determined for each cargo class, i.e. for each weight category and for each origin-destination pair. With this, ten 10-percentile subsets of the normal distribution are generated for each cargo class. These demands are used as ten patterns q in the proposed model. The model will determine the optimal service frequencies simultaneously, optimised for all ten 10-percentile sets. Table 2.2 provides the average weekly in- and outbound volume per terminal and standard deviation as per 2013. For confidentiality reasons, the particular demand between origin-destination pairs has not been provided and the data has been normalised to the total network volume.

Table 2.2 Total demand per network location in 2013 (normalised)

Network location	*Company name*	*Average total demand (Standard deviation)*	
		Outbound	*Inbound*
Delta terminal *	DELTA	0,409 (0,175)	0,264 (0,100)
Euromax terminal *	EMX	0,117 (0,081)	0,078 (0,001)
Home terminal *	HOME	0,056 (0,042)	0,054 (0,097)
Moerdijk	MCT	0,097 (0,108)	0,130 (0,143)
Dortmund	CTD	0,000 (0,001)	0,000 (0,066)
Duisburg	DeCeTe	0,118 (0,062)	0,176 (0,037)
Neuss	NSS	0,001 (0,003)	0,001 (0,003)
Nuremburg	NUE	0,003 (0,012)	0,003 (0,012)
Willebroek	TCTB	0,017 (0,022)	0,051 (0,026)
Venlo	TCTV	0,181 (0,069)	0,244 (0,091)
* Rotterdam, sea port	Total	1	1

2.5 Computational Experiments

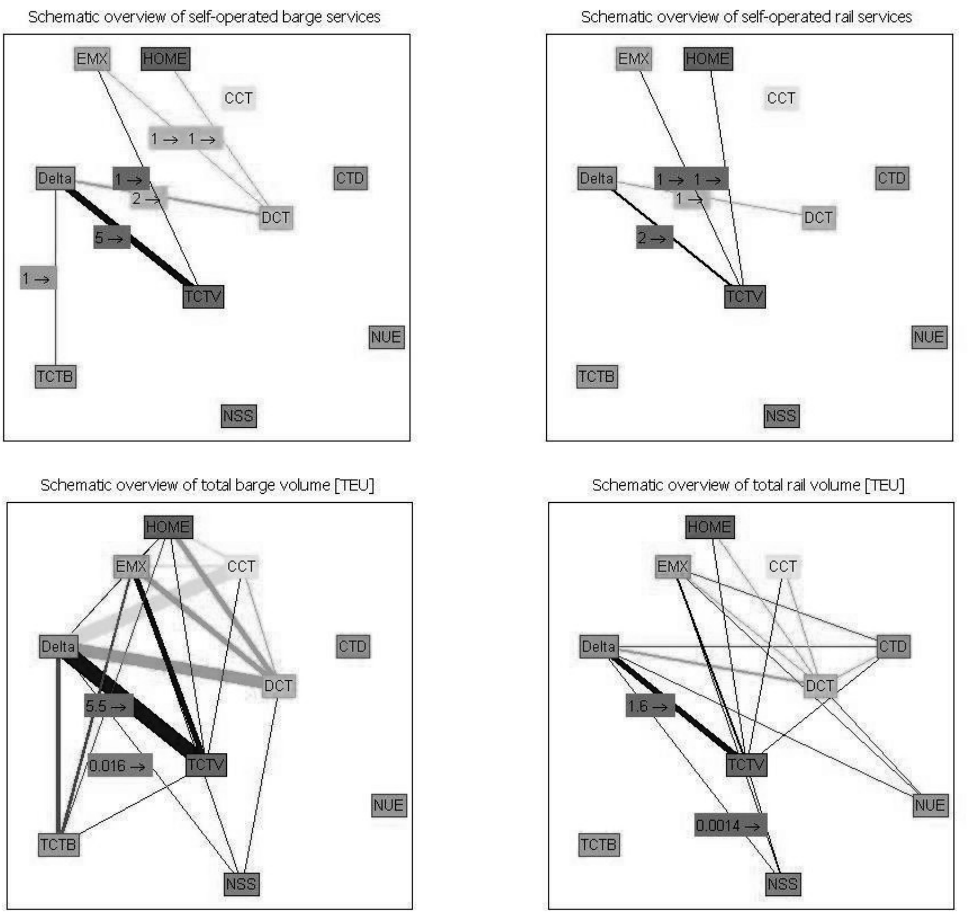
2.5.1 Scenarios

The model is solved for the EGS-case with AIMMS 3.12, using CPLEX 12.4, on a MacBook Pro with a dual core 2.66GHz processor and 8GB of RAM memory. Four categories of experiments are carried out. The service network design of the current EGS situation is considered the *basic scenario*. In comparison to that, three sets of additional experiments are carried out to assess the importance of the different aspects of the current model:

1. *Basic scenario:* For the scenario, the optimal solution of the service network design problem is computed without any further restrictions. As described, the proposed model considers both self-operated services and subcontracted transport, and it allows for overdue delivery at a penalty cost. In the basic scenario, the handling costs are set to 24 and the overdue delivery is set at 50 per day.
2. *Self-operated or subcontracted transport:* The value of combining self-operated transport with subcontracted transport is assessed. A situation in which the model can only use subcontracted transport is compared to the case in

which only self-operated services can be used. This shows the importance of using subcontracts along with self-operated network services.

3. *Transfer costs*: In the basic scenario, the model allows for intermediate transfers for transporting a container. With a series of experiments with different transfer costs, we investigate the relation between transfer costs and the amount of intermediate transfers used in the optimal solution. With the experiments, the transfer costs are varied between 0 and 40.
4. *Overdue delivery penalty*: The proposed model introduces the use of flexible due times. So, the final set of experiments considers different levels of the overdue delivery penalty to evaluate the impact of this aspect on the results. The overdue penalty is varied between 0 and 200, to compare with the penalty of 50 per day in the basic scenario.



The link colour corresponds to the inland terminal's colour

Fig. 2.3 Service schedule in basic case

2.5.2 Results

Fig. 2.3 shows the results of the basic case scenario. The top pictures show the selected number of self-operated barge and rail services per corridor. The bottom pictures show the selected subcontracted transports. The minimum and maximum flows are indicated, shown in a masked unit to protect the confidentiality of the data. Table 2.3 shows the objective costs and the costs for CO_2 emission for the basic scenario and 6 extreme cases. Also, the computation times to carry out the experiments are shown. With experiments 2a and 2b, the influence of the cost structure is studied: either only self-operated or only subcontracted transport are used in these experiments. In Section 2.1.1 it was described that the network operator can obtain economies of scale by negotiating long-term contracts for a service. As the physical transportation is carried out by transport operators, it is assumed that no further economies of scale apply for an increased number of self-operated services. The results show that the network operator can benefit from the economies of scale by selecting self-operated services for some connections, but not for all. From Table 2.3, the importance of combining subcontracted transport with self-operated transport can be seen directly: the scenarios where only one of both types is considered show substantial higher costs.

Table 2.3 Resulting costs of the EGS case study

Scenarios	*Total cost*	*Self-operated*	*Sub-contracted*	*Transfers*	*Over-due*	*CO2*	*Comp. time [s]*
1. Basic scenario	1149	223	163	632	122	9	119
2a. Only self-operated	1433	636	0	634	153	9	4067*
2b. Only subcontracts	1346	0	574	624	122	25	112
3a. No intermed. transfers	1151	223	173	624	122	9	82
3b. Free transfers	466	179	157	0	122	9	228
4a. No due times	955	206	103	638	0	9	87
4b. Strict due times+	>1513	203	670	632	-	8	91

* A solution within 2% of the optimal solution was found within 600 s.

+The case with strict due time constraints is infeasible for the used demand patterns. Hence, instead a case is taken where the overdue delivery penalty is very high. Hence, the overdue costs cannot be calculated, but will be larger than zero.

Then, Table 2.3 also shows that a large part of the weekly network transportation costs are for the handling of containers (transfer costs). The experiment with no intermediate transfers (3a) results in almost the same total cost as the basic scenario (1), in which it was allowed to use intermediate transfers. Hence, not many intermediate transfers were used in the solution of scenario 1. Presumable, the high costs for transfers are the reason for that; in experiment 3b we studied the hypothetical case in which transfers are free. The drop in total costs for this experiment is not only due to zero transfer costs, but also due to a substantial drop in *transit costs*, the costs for self-operated or subcontracted transportation. Likely, more efficient routing is possible if transfer costs are lower. A more detailed analysis follows in the remainder of this section.

Finally, experiments 4a and 4b show that the due time restriction has substantial results on the solution. Also, this aspect is studied in more detail further in this section.

The effect of the transfer cost on the solution is important for the following reason. Currently, the model considers an integral optimisation of transporting containers, but the operation of the terminals is not included, apart from a fixed fee for transfers. This is coherent with the situation in practice. However, the EGS network has the opportunity to include the terminals in the network operation in the future. In such an integral approach, latent capacity at inland terminals can potentially be leveraged for more efficient transportation, reducing transit costs. Considering this within the scope of the currently proposed model, costs per transfer will effectively become lower, since fixed costs are shared with a larger number of transfers. For that, it is interesting to consider how the network optimisation will change under various transfer costs. Fig. 2.4 shows the transit cost per transport type and per mode for a range of transfer costs c_F. The transfer cost has no influence on the amount of truck usage. Apart from that, it can be seen that the total transit costs increases with transfer costs for all types, except subcontracted rail. It also shows that transit costs will go down already for a small decrease of the transfer cost. Fig. 2.5 shows that the number of additional (intermediate) transfers is small in the region of the current transfer price, but that 48% additional transfers will be used if the transfer costs were zero. This suggests expanding the model with a more detailed specification of transfer costs in the network.

Finally, we consider the influence of the overdue penalty. Fig. 2.6 shows the transit cost per transport type and per mode for a range of values for the overdue penalty c_τ. For a higher overdue penalty than used in the basic scenario, the costs for truck increase rapidly. Fig. 2.7 shows the number of overdue days for the range of overdue penalties. This number of overdue days is masked by a confidentiality factor. The figure shows that the current overdue penalty results in a high number of overdue days. But with a small increase of the penalty, the model will select more truck delivery and overdue delivery will go down fast. Hence, the model can be tuned by adjusting this parameter to deliver the desired results w.r.t. transit costs and overdue delivery.

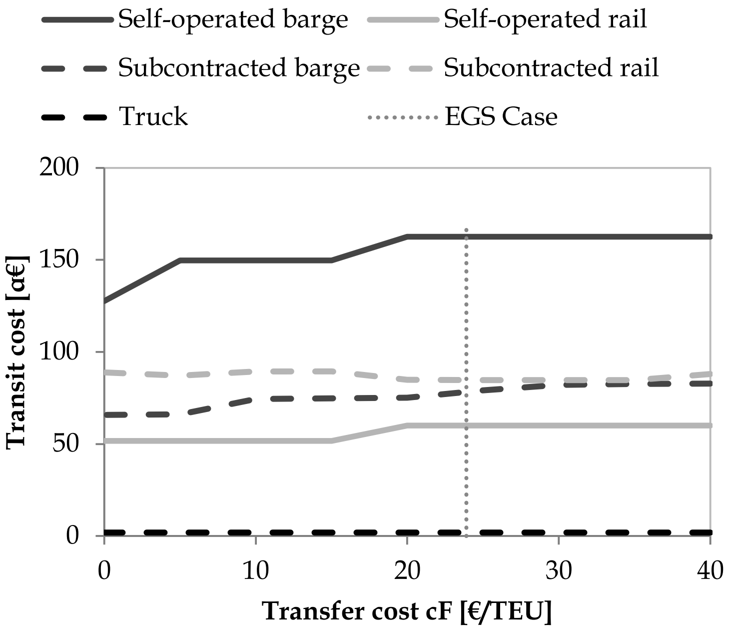


Fig. 2.4 The costs per mode of transport depending on transfer costs

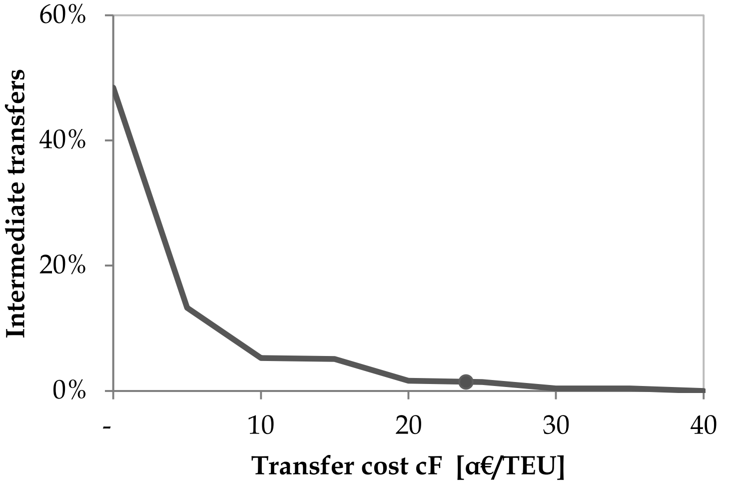


Fig. 2.5 Relative number of additional (intermediate) transfers depending on transfer costs

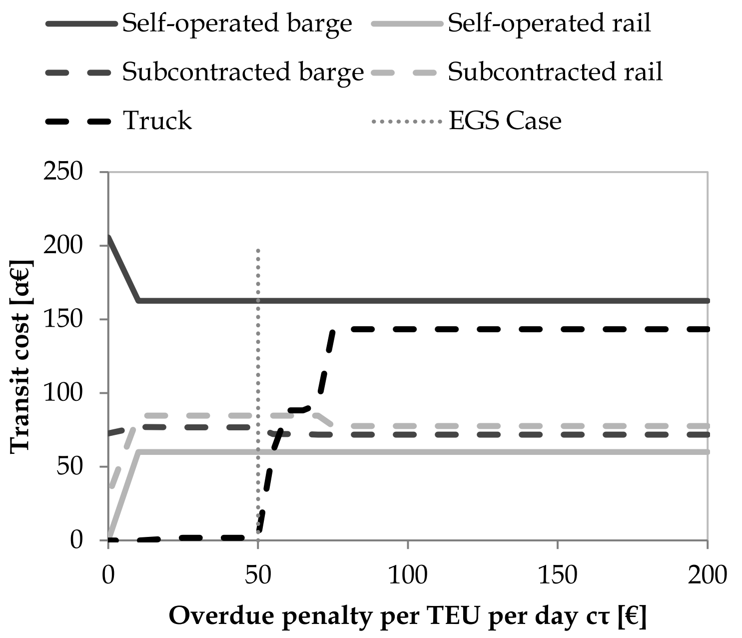


Fig. 2.6 The costs per mode of transport depending on overdue penalty

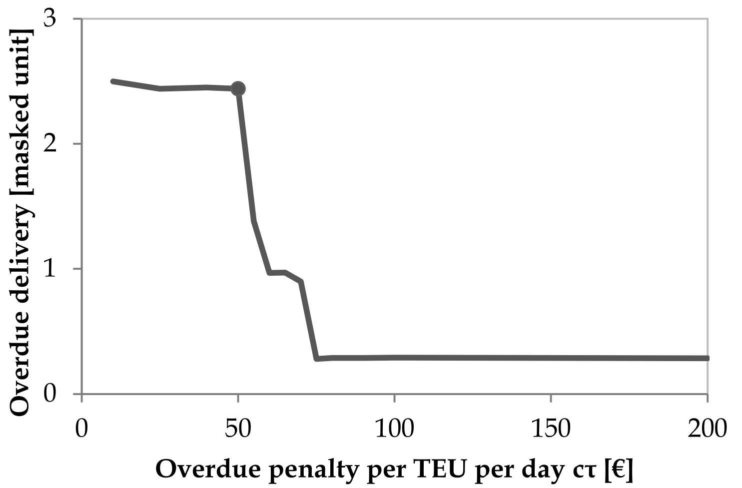


Fig. 2.7 Average number of overdue days depending on overdue penalty

2.5.3 Discussion

The importance of the combination of self-operated and subcontracted transports is shown in Table 2.3 by the scenarios with only self-operated services or only subcontracted transports. In these scenarios transit costs go up with 65% and 49% respectively, compared to the basic scenario. Even then, the number of late containers increases with 25% in the case with only self-operated transports.
The results of the experiments with varying transfer costs suggest that the network operator must look into the combined business model of services and terminals. As the network operator operates both the terminals and the services, it may be beneficial to decrease transit costs with additional intermediate service. For instance, terminals with a (temporarily) low utilisation of the available capacity can easily handle intermediate transfers, and in that way help reducing network transportation costs.
The scenario in which due times are omitted shows a reduction of transit costs, with 22%. Hence, in the studied base case 22% of the transportation costs are made in order to deliver on time. On top of that, in the basic case the model 'accepts' a fictional penalty of 10.6% for late delivery. Still, the number of overdue days decreases if a slightly higher overdue penalty is used. This shows the high sensitivity of the model around the selected overdue penalty and the importance of selecting a suitable overdue penalty for a specific situation. It also shows how important flexibility in timing is for the cost and on-time performance of the network. This validates the introduction of the overdue delivery flexibility in the model.
The proposed intermodal container network model was able to solve the various experiments fast in most scenarios. Computation times were below 2 minutes, except for the case in which no subcontracts were allowed. Solving that hypothetical case took more than an hour. The regular solution time of minutes makes the model suitable for the service network design of the current problem instance. An acceptable solution time is not guaranteed for larger problem instances, but it is expected that the solution method behaves well for regular cases. The size of regular problems is expected to be relatively small: most container networks will focus on the industrial zones supplied from a certain seaport. Such a network will often comprise a limited set of terminals, such as in the case of EGS. The number of paths (and path-related variables $x_p^{c,q}$ and τ_p^c) could increase exponentially, but smart path generation based on experience or other insights can be applied to restrict the number of paths. This will depend on the specific case, though. If, however, a studied network is very large, it will often be possible to split the network in independent sub-problems with no loss of generality. This option will depend on the specific geographical situation though.
Hence, it is expected that the model will perform well for regular problem sizes; and using smart path generation, the method is also expected to work well enough for larger problem instances. Regardless, the model is relevant from a theoretical

point of view, e.g. it illustrates the importance of transfer costs and overdue delivery flexibility in the case study.

2.6 Conclusions

In this chapter we have proposed a new model for the service network design of intermodal container networks, in order to answer research question 1, "How must a service network design model accommodate for flexibility in overdue delivery as well as subcontracted and self-operated services?". The model combined aspects of MNCF and PBND formulations and introduced two new aspects to the service network design: flexibility for overdue delivery and the use of subcontracted transport alongside self-operated services. With this model we assessed the benefit of intermediate transfers in the container transportation paths. In a case study of the EGS network, the following conclusions are drawn for intermodal container networks:

- Considering intermediate transfers is not beneficial in the current setting, as the cost reduction is negligible.
- A reduction of transfer costs will also result in a reduction of transit costs, by the use of intermediate transfers. This suggests that a combined business model for network terminals and transportation provides opportunities for reducing transportation costs.
- By using an overdue penalty, the model can be adjusted to result in the desirable balance between overdue delivery and transportation costs.
- The results show the importance of flexibility in timing for the cost and on-time performance of the network.
- The proposed model is suitable for the service network design in a modern intermodal container transport network where self-operated services are used in combination with subcontracted transport.

Furthermore, the results show that the proposed model results in substantial lower costs, compared to alternatives in which either subcontracted or self-operated transportation is considered, as well as compared to a model with strict due times. Although the results are based on a case study, sensitivity analysis shows that the proposed model is suitable for instances with various settings. In the next chapter, we consider the same new aspects (overdue delivery flexibility and combining subcontracted with self-operated transport) at the operational level. Based on the results in this chapter, we propose an operational intermodal network planning model for studying the effect of disturbances.

Appendix 2.A Network transport cost estimation and CO_2 emissions

Adapted from Van Riessen (2013, Appendix A)

To be able to analyse the transportation in an EGS-type of network, general cost formulas are estimated. The general cost structures are based on the available costs in the EGS network. The cost structures are introduced per mode in the following sections. All costs reported in this appendix are masked by a confidentiality factor, to protect the confidentiality of the data.

Costs of self-operated services
Two types of barges and two types of trains are recognised. Table 2.4 provides the estimated operation costs per week (for barges) and per km (for both barges and trains). For barges, the weekly costs must be split over the number of trips per month. For the sake of simplicity, we will use the following estimated number of services of a piece of equipment per connection to determine the cost per trip. This assumption is considered acceptable from a planning point of view, as the actual planning of equipment is not part of the research. The number of trips is based on a 12km/h barge travel speed and 9 hour stop per terminal. Although this is a rough estimate, the numbers of services correspond to the actual number of trips on the corridors that are already in use.
As an example, the resulting costs per trip of the services from and to the Delta terminal are shown in Table 2.5.

Table 2.4 Self-operated service costs

Barge type	*Rhine-barge*	*Benelux-barge*
Total fixed cost	8784/wk	7083/wk
Fuel per km	4.73/km	1.79/km
	Electric train	Diesel train
Costs per km	11.43/km	7.60/km

Table 2.5 Example: Transportation costs from Delta to hinterland (and v.v.)

Terminal	*Distance from Delta [km]*	*Barge type*	*Barge costs [€/trip]*	*Train type*	*Rail costs [€/trip]*
EMAX	5	Benelux	573	Electric	46
HOME	31	Benelux	776	Electric	266
MCT Moerdijk	58	Benelux	694	Diesel	562
CTD				Electric	3396
DeCeTe	242	Rhine	3340	Electric	2790
NSS	280	Rhine	3520	Electric	2938
NUE				Electric	8094
TCT Belgium	166	Benelux	1476		
TCT Venlo	215	Benelux	1564	Diesel	1528

Subcontracted transportation costs (per TEU)
The costs for subcontracted transportation are estimated from available EGS cost data as a linear function of the transportation distance. The results are reported Table 2.6.

Table 2.6 Costs for subcontracted transport

Mode	*Cost (per TEU)*
Barge	$0.14d$
Rail	$1.53 + 0.16d$
Truck	$76.4 + 1.04d$

Table 2.7 CO_2-emission in intermodal transport.

Based on STREAM-report (den Boer et al., 2008)

	Well-to-Wheel [g CO2/tonkm]	*Energy usage [MJ/km]*	*CO_2 in energy W2T/T2W [g CO_2/MJ]*	*Mean utilization [-]*	*CO_2-emission [tonne CO_2 / km / service]*
Truck (2 TEU)	98	10	14.2 / 73	0.33	0.88
Electric train (90TEU)	25	77	170 / 0	0.87	13
Diesel train (90 TEU)	32	188	14.2 / 73	0.87	16
Rhine barge (380 TEU)	34	363	14.2 / 73	0.65	32
Benelux barge (push convoy) [160TEU]	34	883	14.2 / 73	0.65	77

3 Impact and relevance of transit disturbances on planning in intermodal container networks

Chapter 2 introduced a new service network design model for intermodal container networks at a tactical level. The model includes some flexibility by allowing overdue delivery, and is able to combine subcontracted and self-operated services. In this chapter, we translate this to an operational level model, for the purpose of operations in North-West European hinterland networks, in order to address research question 2: "How can optimal transportation plans be created for synchromodal networks?" The network operations consist of allocating containers to available inland transportation services, i.e. planning. For adequate planning it is important to adapt to occurring disturbances. The proposed model, the Linear Container Allocation model with Time-restrictions (LCAT), is used for determining the influence of three main types of transit disturbances on network performance: early service departure, late service departure, and cancellation of inland services. In answer to research question 3, "How can the effect of disturbances in synchromodal networks be quantified?", the influence of a disturbance is measured in two ways. The impact measures the additional cost incurred by an updated planning in case of a disturbance. The relevance measures the cost difference between a fully updated and a locally updated plan. With the results of the analysis, key service properties of disturbed services that result in a high impact or high relevance can be determined. Based on this, the network operator can select focus areas to prevent disturbances with high impact and to improve the planning updates in case of disturbances with high relevance. Section 3.1 provides an introduction to the problem. In Section 3.2, the LCAT model is presented. In Section 3.3 the methodology to determine the disturbance impact and relevance is introduced. The use of this method in a case study of the EGS network is subject of Section 3.4. The general implications of the case study are considered in Section 3.5. Finally, Section 3.6 gives the conclusion of the study.[3]

Keywords: *Intermodal, synchromodal planning, container transportation, disturbances*

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[3] This chapter is based on the following publication with small modifications: Van Riessen, B., Negenborn, R. R., Lodewijks, G. and Dekker, R. (2015). Impact and relevance of transit disturbances on planning in intermodal container networks using disturbance cost analysis. Maritime Economics & Logistics, 17(4), 440-463. The final publication is available via https://doi.org/10.1057/mel.2014.27.

3.1 Introduction

In this chapter, the effects of disturbances on the operational planning of container transportation in an intermodal network are studied. The *impact* is proposed as a measure for the severity of a disturbance. It measures the additional cost incurred by an updated planning because of the disturbance. Based on the properties of services with high impact, the network operator can focus on these types of services to prevent disturbances with high impact. The *relevance* measures the cost difference between a fully updated and a locally updated plan. Disturbances that show a high relevance must be handled with full updates as much as possible, whereas in the case of disturbances with low relevance, a local update of the planning suffices. These measures will be used to assess transit disturbances in a case study of the EGS network in North-West Europe. Section 1.1 provided an overview of developments of container networks and in Section 2.1 an overview of planning in intermodal networks is provided. In this section, the planning of intermodal container transportation at an operational level will be considered in more detail.

3.1.1 Planning of container network transportation

A driver for the development of transportation networks is to reduce cost by consolidating containers on intermodal services. Crainic and Laporte (1997) signal that apart from low tariffs, customers also demand a higher quality of service. This quality of service consists of three parts: on-time delivery, delivery speed and the consistency of these aspects. The network operator aims to create the most cost-effective transportation plan that fulfils the demand while meeting the quality requirements. The transportation plan is the allocation of all containers onto the available inland services. Creating the transportation plan is referred to as *intermodal network planning*. Typically, this plan is created for transports up to one week ahead. The routing of containers with multiple consecutive services is possible, using intermediate transfers of the containers at network terminals. In this study the term *intermodal transfer* is used for a transfer between different modes. A container that has a path with two services uses such an intermodal transfer. As disturbances occur while executing the transportation, the transportation plan requires continuous adaptation.

As in Chapter 2, in this research, synchromodality is considered as *intermodal planning with the possibility of real-time switching between the modes* or online intermodal planning. In this chapter we study costs of disturbances, which indicate the value of using real-time switching. Occasionally, multiple services are disturbed simultaneously, e.g., because of snow, high water levels or strikes. However, this chapter focuses on the more frequently occurring disturbances of single services: early, delayed or cancelled departures, e.g., a train that is delayed because of shunting. Dealing with this kind of disturbances is daily practice for network

planners. What type of disturbances must be prevented and how should containers be re-planned in case of a disturbance?
Few models for the routing of containers in intermodal networks are available (Ziliaskopoulos and Wardell, 2000, Macharis and Bontekoning, 2004, Cho *et al.*, 2012). Most approaches consider the routing of containers as a part of the more general network design problem. These models focus on static versions of the planning problem and do not have the possibility to incorporate real-time changes to the planning problem, nor do they allow us to measure the effect and size of a disturbance. This chapter presents an alternative method that is able to quantify the effect of several types of disturbances. We propose the Linear Container Allocation model with Time-restrictions (LCAT) to find the most cost-effective solution of the container transportation planning problem in the network. Based on this, we propose a method to assess the effect of disturbances on operational planning. This effect is quantified using two new measures: impact and relevance. The *impact* measures the inevitable additional cost due to the disturbance; a high impact indicates a disturbance that must be prevented. The *relevance* measures the avoidable costs of a disturbance. This is measured as the difference in cost between an optimal planning update and a specific kind of local planning update; a high relevance indicates a disturbance that requires a full update of the transportation plan. For example, a delay for which we find zero impact and a high relevance will result in no additional costs if the network transportation plan is fully reconsidered. However, if the plan were only repaired with local changes, high additional costs would arise.
We focus on the operational planning of the network operator: the allocation of containers to inland services in a predefined service schedule. The network operator creates the plan up to 1 week ahead. Ideally, the network operator can allocate each container to alternative inland services at any point in time. In practice however, some restrictions regarding the possible real-time changes in planning exist. Because of customs and port procedures, changes in the assignment of containers to a service can be made only up to 6–9 h before departure of that service.

3.1.2 Literature overview

This section briefly reviews the relevant models in existing literature on the transportation planning of container networks (see Table 3.1). Several studies have been performed to find shortest or cheapest paths on a single container basis. The network is not optimised in general, but per order. Boardman *et al.* (1997) use a method that selects the cheapest path per container on a real-time basis. Ziliaskopoulos (2000) propose a model that selects the least-time path, considering dynamic travel and transfer times. Cho *et al.* (2010) use a weighted constrained shortest path problem to minimise time and cost of transport between two network nodes. These methods do not allow the network operator to do network-wide optimisations. Other studies use a network-wide optimisation approach by modelling the transportation demand as flows through the network. Guelat *et al.* (1990) propose a very general multi-commodity, multimodal network flow model. There, a commodity represents a group of containers with the same origin and destination. Crainic and Rousseau (1986) also propose a multimodal, multi-commodity network formulation. Caris *et al.* (2012) use a specific version to design a barge service network. In that model, the goal is to select the optimal barge round trips between the port and the hinterland terminals, but their work is focused on small problem sizes (up to 3 inland terminals). Crainic and Kim (2007) provide a model for fleet management, addressing the problem of balancing empty containers. In these methods the transportation planning is a static sub-problem of the network design and incorporating real-time disturbances is not considered. Some studies explicitly focus on the real-time influences on the operational planning, by incorporating these into the model. E.g., Ishfaq and Sox (2012) consider the effect of time-delays at hubs on network performance, but their approach does not provide methods for real-time planning updates. Our approach does not only measure the effect of a disturbance, but also provides the updated planning. In this study we compare the disturbance effects for two update methods: an optimal full update and a simple local update.

Table 3.1 Overview of existing container network models

	Objective	*Method*	*Flows*	*Timing*	*Level*
Boardman et al. (1997)	Lowest cost path per order	*k* cheapest paths (analytical)	Path	Pre-process *k* cheapest paths. Assign orders in real-time	Operational
Caris et al. (2012)	Minimise cost	Enumeration	Path	Offline	Tactical
Cho et al. (2010)	Lowest cost or shortest time	Dynamic programming	Arc	Offline	Operational
Crainic and Rousseau (1986)	Minimise cost	Optimal	Path	Offline	Strategic/ tactical
Crainic and Kim (2007)	Minimise cost	-	Arc	Rolling horizon	Strategic/ tactical
Guelat et al. (1990)	Minimise cost	Linear approx.. approach	Path	Offline	Strategic
Ishfaq and Sox (2012)	Minimise cost	Heuristic	Arc	Offline	Strategic
Ziliaskopoulos and Wardell (2000)	Least-time route per order	Optimal	Path	Pre-process all shortest paths. Assign orders in real-time	Operational

3.2 Proposed model

In this chapter we propose a linear programming model that can be used to create an optimal solution of the container transportation planning problem in a network.

The LCAT model is based on results from Chapter 2 (Van Riessen, *et al.*, 2015-a) and has the following key characteristics: the model combines the allocation of containers to paths with capacity constraints on all corridors; the model allows for overdue delivery at a penalty cost; and, the model combines the use of committed services with uncommitted capacity for transport. The network operator has long-term contracts with barge and rail operators for weekly services that provide committed capacity to the network operator, with a fixed cost per service and no additional costs per used slot. Alternatively, the network operator can use services from third parties with uncommitted capacity at a slot cost per TEU.

LCAT is solved offline, for a week of given demand of container transportation and a predefined service schedule. The demand of container transportation is categorised in container classes $c \in C$, each class represents a group of containers with the same origin, destination, weight category W_c, the time the container is available at the origin $t^c_{\text{available}}$ and the due time at the destination t^c_{due}. The origin-destination pair is referred to as the connection. The container weight is discretised in categories W_c.

For each connection, a set of suitable paths P_c is predetermined. Each path in P_c describes a sequence of 1 or more consecutive services that can move a container of class c from the origin to the destination. The method to predetermine paths is independent of the mathematical model. Suitable paths could be determined by listing all alternatives, by using expert knowledge or by another method. In this study an automated path generation method is used, based on a space-time graph of the service schedule, as described later in Section 3.3.1. For each path p, the transit cost per TEU c_p equals the slot cost of the uncommitted services on path p and the number of transfers F_p equals the number of services on path p, as a loading and a discharge handling per service are required. The time of departure T^p_D of a container on path p equals the scheduled departure of the first service on the path and the arrival time T^p_A is the scheduled arrival time of the last service on the path.

LCAT uses two sets of decision variables: the number of TEU of container class c that is assigned to path p, denoted by x^c_p, and the number of TEU of container class c that is transported by a direct truck transport, denoted by v^c . Besides this, two sets of auxiliary variables are used: the number of TEU of container class c on service s, denoted by z^c_s, and the combined number of days that containers of container class c transported on path p are overdue, denoted by τ^c_p. With LCAT the objective J is formulated as:

$$J = \sum_{p,c} x^c_p\left(c_p + c_F F_p\right) + c_\tau \sum_{c,p} \tau^c_p + c^c_{dt} \sum_c v^c, \tag{3.1}$$

where the first summation represents the sum of all transit costs c_p and all transfer cost $c_F F_p$ for the container classes c on path p, the second summation represents penalty cost of c_τ per TEU per day overdue, and the third term denotes the cost of

direct trucking of container class c, with c_{dt}^{c} the cost per TEU of direct trucking container class c.
The total demand of container class c is denoted by d^c. This demand must be transported on one of the feasible intermodal paths or by direct truck. The allocated number of TEU x_p^c is mapped to the number of TEU per service by a mapping parameter δ_s^p, which is equal to 1 if service s is part of path p or 0 otherwise. The maximum capacity of service s is denoted by u_s (TEU-capacity) and m_s (weight-capacity).

Objective J has to be minimised taking into account the following constraints:

$$v^c + \sum_p x_p^c = d^c \qquad \text{for all } c \tag{3.2}$$

$$z_s^c = \sum_{p \in P_c} \delta_s^p x_p^c \qquad \text{for all } c, s \tag{3.3}$$

$$\sum_c z_s^c \leq u_s \qquad \text{for all } s \tag{3.4}$$

$$\sum_c W_c z_s^c \leq m_s \qquad \text{for all } s \tag{3.5}$$

$$x_p^c T_D^p \geq x_p^c t_{\text{available}}^c \qquad \text{for all } c, p \tag{3.6}$$

$$x_p^c \left(T_A^p - t_{\text{due}}^c\right) \leq \tau_p^c \qquad \text{for all } c, p \tag{3.7}$$

$$x_p^c, \tau_p^c, v^c, z_s^c \geq 0 \qquad \text{for all } c, p, s \tag{3.8}$$

Here, constraint (3.2) ensures that all demand is met. By constraint (3.3), the auxiliary variable z_s^c is created. By constraints (3.4) and (3.5), the total number of TEU of the services is restricted to the available capacity. Constraint (3.6) ensures that a container is only planned on paths that depart after the time that the container is available: if the paths departure time $T_D^p \geq t_{\text{available}}^c$, then x_p^c can be any positive number. However, if $T_D^p < t_{\text{available}}^c$, than x_p^c has to be zero. Note that this time constraint is hard. Constraint (3.7) is the soft constraint for on-time delivery: τ_p^c measures the total number of days that containers of container class c on path p are late. Finally, constraint (3.8) is the nonnegativity constraint for the four sets of variables.
The next section will introduce the method in which the proposed model is used to determine the impact and relevance of disturbances in the network.

3.3 Method to determine disturbance impact and relevance

The model proposed in the previous section is used in this chapter to measure the effect of a disturbance on the operational planning. Three categories of disturbances are studied: late arrival, early arrival and cancellation of a network service. An experiment to determine the impact and relevance of a single disturbance consists of six steps (as seen in Fig. 3.1):

1. Initialise experiment setting
2. Generate the sets of suitable paths P_c
3. Solve equations (3.1)-(3.8) for an initial planning without any disturbances
4. Introduce a single disturbance and update the sets of suitable paths P_c
5. Solve the updated model twice: a full update and a local update
6. Determine *impact* and *relevance* of the introduced disturbance

The methodology used in step 2, path generation, and in step 5, solving the updated model, is described in more detail in Sections 3.3.1 and 3.3.2, respectively. Subsequently, the six step method is applied to determine the effect of disturbances in the EGS network in Section 3.4.

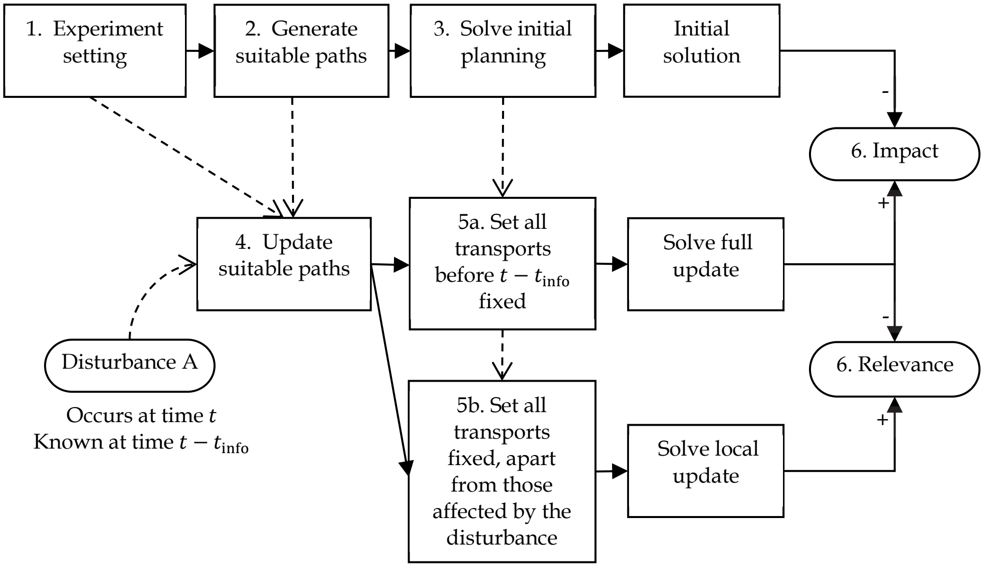

Fig. 3.1 Schematic overview of the experiment setup

3.3.1 Path Generation

For the proposed model, we require paths in the space-time expansion of the network and the service schedule. It is important that we do not miss relevant paths in our pre-selection, but the set must also be as small as possible, in order to limit the problem size and computation time. Several approaches could be used for generating the set of relevant paths: in existing networks, expert planners could denote all suitable container routes based on their practical knowledge. Or the model could use a list of all possible paths in the used service schedule. Alternatively, we propose to use an automated method to generate a relatively small set of paths P_c for each container class $c \in C$, using the following assumptions, similar to Chapter 2.

a) Only paths with a maximum of 3 legs are considered, as paths with more legs proved irrelevant in Van Riessen *et al.* (2013).
b) Paths with a detour of more than 10% in any of the transportation legs are ignored. This detour is measured as the difference in distance to the destination from both ends of a leg. Let T_{kD} denote the trucking distance from node k to the destination. Then, a path is considered to make a detour if $T_{iD} \geq 1.1T_{jD}$ in any of its legs (i,j). This rule is added to prevent paths with unrealistic detours; a little detour is allowed, though.
c) Only a leg directly to or from the hinterland terminal can be operated by truck. On intermediate legs containers can only be transported by barge or rail. This constraint is added, as it does not make sense to do truck transfers. Note that the proposed model can assign a direct truck delivery for containers in class c by variable v_c; therefore it is not considered in the path generation.
d) Paths have a maximum duration of 8 days. In the case study, only commodities with a due time of 7 days or less were allowed, so, containers with a due time of 7 days could still be delivered 1 day overdue.

To generate the set of paths, the k shortest path method (Yen, 1974) was applied to a space-time graph of the network. Each node represents a barge or rail service; each arc (i,j) represents a feasible transfer from service i to service j at a terminal in the network. Each arc (i,j) is assigned a value of $M + c_{\text{TEU},s}$, where $c_{\text{TEU},s}$ are the transit cost for one TEU on service s and M is a sufficiently large number. The method has generated all paths of three legs or less if the paths become larger than $4M$. After subtracting the multiple of M, the path lengths denote the transit cost. Subsequently, paths that do not comply with assumptions b)-d) are removed from the set and finally, the remaining paths are expanded with truck legs on the hinterland side, if feasible considering assumptions a)-d). For each path the transit cost per TEU c_p, the number of transfers F_p and the time of departure and arrival T_D^p and T_A^p are denoted. All container classes with the same origin and destination use the same set of suitable paths P_c; the time restrictions are ensured separately in the model.

3.3.2 Solve updated model: full update and local update

In this study we consider the planning for one week. The solution of the model for one week network transportation planning is referred to as the initial solution, schematically shown in Fig. 3.2a). The objective value of the initial solution as computed by (1) equals the cost of optimal operation of the network. This is denoted by $J^{\mathcal{I}}$ and the solution of the assigned containers is saved and referred to as $\acute{z}_s^c$.
In this study, we consider disturbances to barge and rail services: a late departure, an early departure or a cancellation. The estimated departure time of the service is denoted by t. A disturbance of service s is denoted by d_s. To handle an occurring disturbance, the planning has to be updated. This update can be calculated at the point in time where the information of the disturbance becomes available, denoted by $t - t_{\text{info}}$, where t_{info} denotes the *earliness of information*. The model can only consider cases where t_{info} is positive, i.e. where a disturbance is known in advance. The proposed model is aimed to solve the transportation plan for the network operator, which can plan containers on a service up to 6-9h before departure. Disturbances occurring after a service's departure can typically not be corrected by the network operator. So, cases of incomplete information, i.e. were t_{info} is negative, are not considered.
We use two update methods in order to determine the impact and relevance. For both update methods, the set of suitable paths is updated in the same way: all paths with the disturbed service are removed and new paths using the disturbed service are generated, if possible. First, we consider the case where this update is determined optimally. This is considered a *full update*. To get the full update, all transports z_s^c departed before $t - t_{\text{info}}$ are set fixed to the values of the initial solution $\acute{z}_s^c$, indicated by the accent over z. These transports have already taken place and cannot be rescheduled. This is shown schematically in Fig. 3.2c).

The objective value of the model with the fully updated plan represents the transportation cost of the fully updated plan, denoted by $J_{d_s}^{\mathcal{F}}$. However, in current practice full updates are not carried out, as transportation planners do not have the required software and expertise for fully updating the plan. Instead, only containers planned on the disturbed service are re-planned; this is considered a *local update*. To compute this local update with our model, again all transports z_s^c departed before $t - t_{\text{info}}$ are set fixed to the values of the initial solution $\acute{z}_s^c$. An additional constraint is added to ensure that all container classes c that are not planned on the disturbed service $\breve{s}$ are not updated. Let $C_{\breve{s}}$ denote the set of container classes and demand patterns that are planned on the disturbed service. Then the local update constraint is formulated as:

$$z_s^c \geq \acute{z}_s^c \qquad \forall c \notin C_{\breve{s}}\,, s \neq \breve{s} \tag{3.9}$$

where $C_{\breve{s}} = \{c \in C | \acute{z}_{\breve{s}}^c > 0\}$. Hence, only container classes from the disturbed service $\breve{s}$ can be re-planned; these must be re-planned on the remaining capacity in the network. This is indicated by Fig. 3.2b). The objective value of the model with the locally updated plan equals the transportation cost after the local update, denoted by $J_{d_s}^{\mathcal{L}}$.

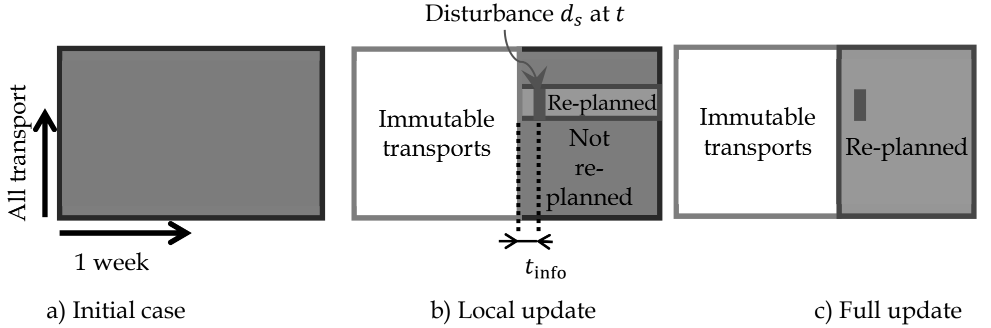

Fig. 3.2 Initial solution and two update methods using LCAT

3.3.3 Measuring disturbance impact and relevance

To measure the effect of a disturbance d_s, the cost impact of a full update is denoted by $\mathcal{F}_{d_s}$ and of a local update is $\mathcal{L}_{d_s}$. These are defined as follows:

$$\mathcal{F}_{d_s} = J_{d_s}^{\mathcal{F}} - J^{\mathcal{I}},$$

$$\mathcal{L}_{d_s} = J_{d_s}^{\mathcal{L}} - J^{\mathcal{I}}.$$

The possibly higher cost of a local update is measured by the cost relevance:

$$\mathcal{R}_{d_s} = \mathcal{L}_{d_s} - \mathcal{F}_{d_s}.$$

As the local update is also a feasible solution for the full update, by definition it holds that $\mathcal{L}_{d_s} \geq \mathcal{F}_{d_s}$ and $\mathcal{R}_{d_s} \geq 0$. If $\mathcal{R}_{d_s}$ equals zero, it means that the full update does not result in a better solution than the local update. If $\mathcal{R}_{d_s}$ is positive, it indicates the value of using a full update instead of a local update for disturbance d_s.

The impact measures as defined here denote the absolute value of the additional cost after the update. Two additional measures are introduced to report the impact relative to the cost and volume per service:

$$\mathcal{F}_{d_s}^{\mathcal{C}} = \frac{\mathcal{F}_{d_s}}{c_{\check{s}}},$$

$$\mathcal{F}_{d_s}^{\mathcal{V}} = \frac{\mathcal{F}_{d_s}}{V_{\check{s}}},$$

where $c_{\check{s}}$ and $V_{\check{s}}$ denote the cost contributed to and the volumes assigned to the service $\check{s}$ in the initial solution, respectively. These are defined as

$$V_s = \sum_c \acute{z}_s^c,$$

$$c_s = V_s\left(c_{TEU,s} + c_F\right) + c_{f,s},$$

With $c_{\mathrm{TEU},s}$ the cost per TEU on service s, c_F the handling cost per TEU and $c_{f,s}$ the fixed cost for service s. In this study it is assumed that $c_{\mathrm{TEU},s}$ equals 0 for committed services and $c_{f,s}$ equals 0 for uncommited services. In both cases the transfer cost c_F apply, though. Hence, with the relative impact measures, the disturbance cost can be reported relative to the service cost or the service's transport volume.
In the next section we present a case study into the late arrival, early arrival, and cancellation of network services to show the use of the measures *impact* and *relevance*. Note that with this method it is also possible to study the effect of other changes in the set of feasible paths, as long as the part of operation carried out before the time of information does not change. Hence, the method can also be used to study the effect of changes in the expected transportation demand, changes in available capacity or delays at terminals.

3.4 Case study of disturbances in the EGS-network

The proposed model and method to study disturbances is applied to the real-world case of the EGS network (Section 1.2). The planning updates in case of disturbances are time-consuming and possibly sub-optimal. In this case study, the impact and the relevance of disturbances are determined. The results indicate what type of disturbance is the most costly and when a full update of the planning is most advantageous. In Section 3.4.1 the case is described. The results are reported in Sections 3.4.2-3.4.4.

3.4.1 Case description

In Chapter 2 (Van Riessen, *et al.*, 2015-a), we determined the optimal service frequency of rail and barge services on all corridors between the terminals in the EGS network, see Table 3.3. For this study, we created a service schedule based on the optimal service frequencies. In this schedule the departure times of services on a corridor are distributed evenly over the week. For those services that can be used consecutively, the schedule is created such that the possible transfer time at intermodal transfers is as short as possible (with a minimum of 4h transfer time). The schedule consists of 166 services per week in total, of which 38 are operated by EGS, and on 128 services uncommitted space is available. Uncommitted services are operated by third parties, and they have a scheduled departure and arrival time.

The network operator can use slots on these uncommitted services, but does not have committed slots on these services. I.e., a cost per used slot is incurred, while a committed service is paid for irrespective of the number of used slots.
The set of suitable paths is generated according to the method described in Section 3.3.1. The total set consists of 13,357 paths. Because of a confidentiality agreement, the cost parameters as reported here are multiplied with a confidentiality factor. As this effect is proportional, it does not impact the validity of the results. For the (un)loading of a container on a service, a transfer cost of $c_F = 24$ is used. The cost of overdue delivery per TEU per day is $c_\tau = 50$. The cost per path c_p is the sum of the cost per TEU ($c_{\mathrm{TEU},s}$) on all services in the path. On committed services no cost per TEU is used, but a fixed cost for the service. This fixed cost is not part of the operational planning problem. The cost of uncommitted capacity is modelled with a linear approximation of the actual network cost and the corridor length l_s, i.e. $c_{\mathrm{TEU},s} = \alpha l_s + \beta$. A more detailed description of the transit cost can be found in Appendix 2.A.
Table 3.2 provides for 2013 the average weekly in- and outbound volume per terminal and standard deviation. For confidentiality reasons, the demand data has been normalised to the total network volume.
The distribution of demand for all container classes is estimated as a normal distribution based on the transportation volumes in the period January 2011-June 2012. The parameters of the normal distribution of the weekly volume are determined for each origin-destination pair. With this, ten 10-percentile subsets of the normal distribution are generated for each container class. Subsequently, the subsets are split into 4 categories with different due according to the following fixed ratio: due in 1 day (20%), 2 days (40%), 4 days (30%) or 7 days (10%). This ratio was based on estimates from EGS planning experts: in practice, only the actual transportation time is recorded and no reliable records about the available window for transportation were available.

Once the initial solution is found, the impact and relevance of various disturbances is determined. The disturbances are considered one by one. All these experiments are also carried out for all 10 demand patterns. The impact and relevance are averaged over the 10 solutions to obtain the results. We distinguish two sets of experiments:

a) Cancellation of services
b) Out-of-schedule departures (early or late)

Table 3.2 Normalised demand per network location in 2013 (from Table 2.2)

Network location	*Company name*	*Average total demand (Standard deviation)* *Outbound*	*Inbound*
Delta terminal *	DELTA	0,409 (0,175)	0,264 (0,100)
Euromax terminal *	EMX	0,117 (0,081)	0,078 (0,001)
Home terminal *	HOME	0,056 (0,042)	0,054 (0,097)
Moerdijk	MCT	0,097 (0,108)	0,130 (0,143)
Dortmund	CTD	0,000 (0,001)	0,000 (0,066)
Duisburg	DeCeTe	0,118 (0,062)	0,176 (0,037)
Neuss	NSS	0,001 (0,003)	0,001 (0,003)
Nuremburg	NUE	0,003 (0,012)	0,003 (0,012)
Willebroek	TCTB	0,017 (0,022)	0,051 (0,026)
Venlo	TCTV	0,181 (0,069)	0,244 (0,091)
* Rotterdam, sea port	Total	1	1

Table 3.3 One-way service frequencies per week in the EGS case study

Corridor	*Committed barge*	*Uncomm. barge*	*Committed train*	*Uncomm. train*
MCT Moerdijk - DeCeTe Duisburg	1			1
MCT Moerdijk - TCT Venlo		1		1
CTD Dortmund - DeCeTe Duisburg				1
CTD Dortmund - TCT Venlo				1
DeCeTe Duisburg - Neuss		1		
DeCeTe Duisburg - Nuremburg				1
Delta - MCT Moerdijk		14		
Delta - CTD Dortmund				1
Delta - DeCeTe Duisburg	2		1	3
Delta - Euromax		1		
Delta - HOME		1		
Delta - Neuss		1		1
Delta - Nuremburg				2
Delta - TCT Belgium	1	2		
Delta - TCT Venlo	5	4	2	6
Euromax - MCT Moerdijk		3		
Euromax - CTD Dortmund				1
Euromax - DeCeTe Duisburg	1			2
Euromax - Neuss		1		1
Euromax - Nuremburg				1
Euromax - TCT Belgium	1			
Euromax - TCT Venlo	2		1	1
HOME - MCT Moerdijk		3		
HOME - DeCeTe Duisburg	1			2
HOME - TCT Belgium		1		
HOME - TCT Venlo		2	1	
Neuss - TCT Venlo				1
Nuremburg - TCT Venlo				1
TCT Belgium - TCT Venlo		1		
Total	14	36	5	28

The experiments in set a) are carried out 3 times for each service in the service schedule, i.e. for the cases in which the time of information is 6, 12 or 24h before departure time. Services that depart on the last day of the week are omitted because of end-of-horizon effects.

The results of experiment set a) allow us to distinguish between services with high impact and low impact. As the cancellation of a service is the most severe disturbance, the impact of a cancellation is the upper bound for the impact of out-of-schedule departures in experiment set b). Therefore, for this experiment set we will focus on the set of services with high impact. The following disturbances are evaluated one by one for these services (Table 3.4).

Table 3.4 Experiments set b)

	Out-of-schedule departure time	*Time of information*
Late departure	$\Delta t \in \{6,12,24\}$	$t_{\text{info}} \in \{6,12,24\}$
Early departure	$-\Delta t \in \{6,12,24\}$	$t_{\text{info}} \in \{6,12,24 \mid t_{\text{info}} \geq -\Delta t\}$

Note that experiments in which the time of information is later than the time of departure are not feasible, as the model does not support situations with incomplete information. Hence, the early departure experiments are only carried out for $t_{\text{info}} \geq -\Delta t$, where the minus sign indicates a departure before the estimated time of arrival.

3.4.2 Initial solution

First, the initial solution is determined for each of the 10 demand patterns. Table 3.5 provides the average normalised cost structure of the transportation plans for one week. Note that the fixed costs of committed services are not part of the operational problem. Table 3.6 shows the average modal split and service utilisation. In 2010, the modal split for the entire port of Rotterdam was 55/35/10% (trucking/barge/rail), and the fraction of trucking must be reduced, according to the Port of Rotterdam (2011). Although the demand patterns for the EGS network do not represent the entire port's throughput, the results show a sustainable modal split for the hinterland in the EGS network: barging amounts to two thirds of the transportation and rail transportation is used for 1 third. For both modes, committed services account for more than ¾ of the transportation. Naturally, the utilisation of committed services is much higher than of uncommitted services. Note that on these uncommitted services also transportation from other parties takes place.

The next sections assess the experiments with disturbances. The resulting impact and relevance of cancellations are presented first, followed by the impact and relevance of out-of-schedule departures.

Table 3.5 Average cost structure of initial solutions for 10 demand patterns

Uncommitted	*Transfers*	*Late*	*Direct truck*
21.3%	60.1%	17.5%	1.0%

Table 3.6 Average modal split and utilisation over 10 demand patterns

	Model split		*Utilisation*
Trucking		1.8%	-
Uncommitted barge	15.3%	65.7%	20%
Committed barge	50.5%		53%
Uncommitted train	6.6%	32.5%	17%
Committed train	25.9%		75%

3.4.3 Impact and relevance of service cancellations

In the first set of experiments, three experiments per service are carried out, for the 143 services departing on day 1 to day 6 of the week, amounting to a total of 429 experiments.

In Table 3.7, the average impact and relevance of the disturbance of just one service are shown as a percentage of the initial objective value in which costs of 143 services are taken into account. The disturbance with the most severe impact is the cancellation of a committed service. This disturbance results on average in 2.4% additional cost: the equivalence of the cost of about 4 average services. Secondly, disturbances on committed services have an impact that is higher than disturbances on uncommitted services. For barges, the impact of cancelling committed services is 8 times more costly than the cancellation of uncommitted services. Also, cancellations of committed services have a higher relevance than of uncommitted services. Table 3.7 also shows the relevance as percentage of the impact. This shows that the use of a local update results on average in 6-16% additional impact, depending on the type of service that is cancelled. However, the absolute value of the relevance is not very large with respect to the total transportation cost.

Table 3.7 Average impact and relevance of cancellation

	$\frac{\mathcal{F}_{d_s}}{J^{\mathcal{I}}}$	$\frac{\mathcal{R}_{d_s}}{J^{\mathcal{I}}}$	$\frac{\mathcal{R}_{d_s}}{\mathcal{F}_{d_s}}$
Uncommitted barge	0,30%	0,03%	10%
Committed barge	2,43%	0,19%	8%
Uncommitted train	0,43%	0,03%	6%
Committed train	0,68%	0,11%	16%

In Fig. 3.3, the impact of the cancellation of a service is presented with respect to the time of information. Fig. 3.4 shows the impact relative to the cost of the disturbed service, denoted as the cost factor. If a disturbance is identified earlier, the planning update is less restricted, and hence, the impact must decrease with increasing t_{info}. This is indeed the case in Fig. 3.3 and Fig. 3.4. However, barges show more cost reduction by early information than trains, especially for committed services. The absolute impact of committed barges is a lot higher than the impact of committed trains (Fig. 3.3). Fig. 3.4 shows the cost impact relative to the cost contribution of the disturbed service in the initial solutions. This relative impact is higher for barges than for trains.

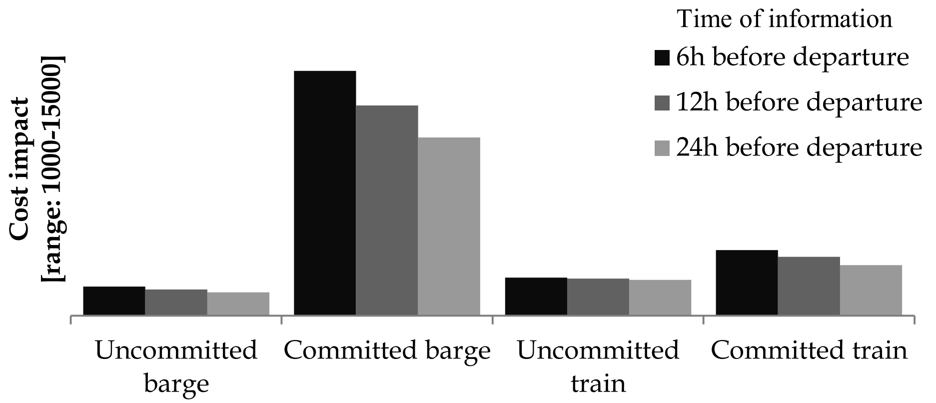

Fig. 3.3 Full impact $\mathcal{F}_{d_s}$ of cancellation (per type of service, exact numbers confidential)

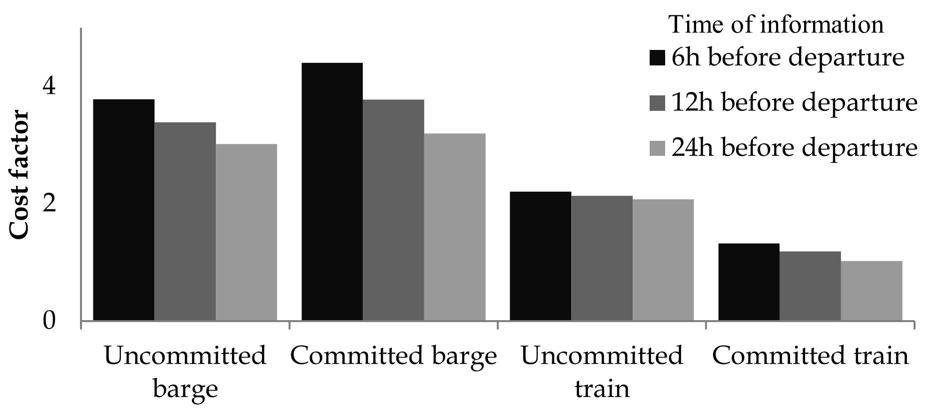

Fig. 3.4 Impact per service cost $\mathcal{F}^{C}_{d_s}$ of cancellation (per type of service)

3.4.4 Impact and relevance of early and late departures

From the experiments with service cancellations, we select 25 services that showed the highest impact per TEU, $\mathcal{F}_{d_s}^{v}$. Out of these 25 services, all services with an absolute cost impact $\mathcal{F}_{d_s}$ of less than 500 are omitted. By doing this, we focus on services of various sizes for which the planning update shows the largest differences. This results in a total of 17 services, for the second series of experiments. In the second series of experiments, 9 experiments for late departure and 6 experiments for early departure are carried out; a total of 255 experiments.
Fig. 3.5 shows the results of these experiments. It can be seen that the impact increases with more severe disturbances (earlier, later). The average impact of cancellation of these services was around 12,000. As can be expected, the impact of out-of-schedule departures is lower than the impact of the cancellation. The effect of departing too early or late is similar; however, early departure has a slightly larger impact than late departure. In practice, early departures of barges do occur: as barges decide last-minute on the route in the Rotterdam area (as they visit several terminals), they may arrive early or late compared to the times as expected several days in advance. The time of information has not much influence on average. The average impact is only slightly lower if the time of information is earlier.

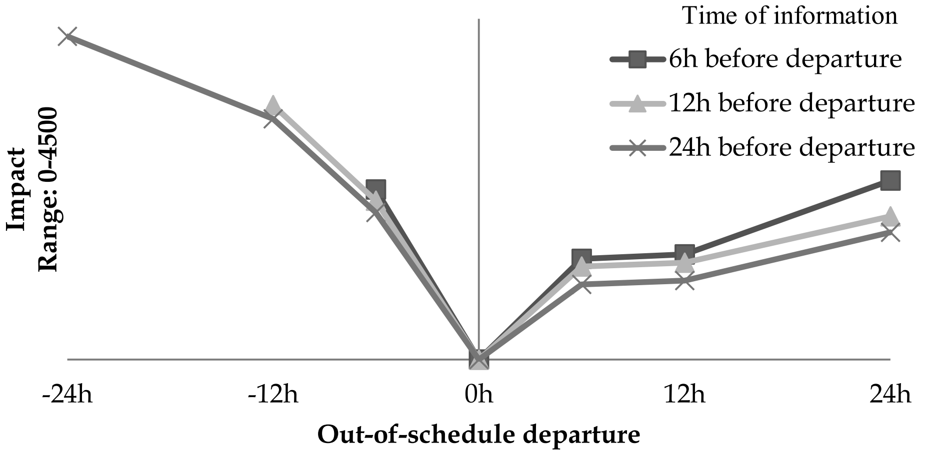

Fig. 3.5 Impact $\mathcal{F}_{d_s}$ of early and late departure of selected services

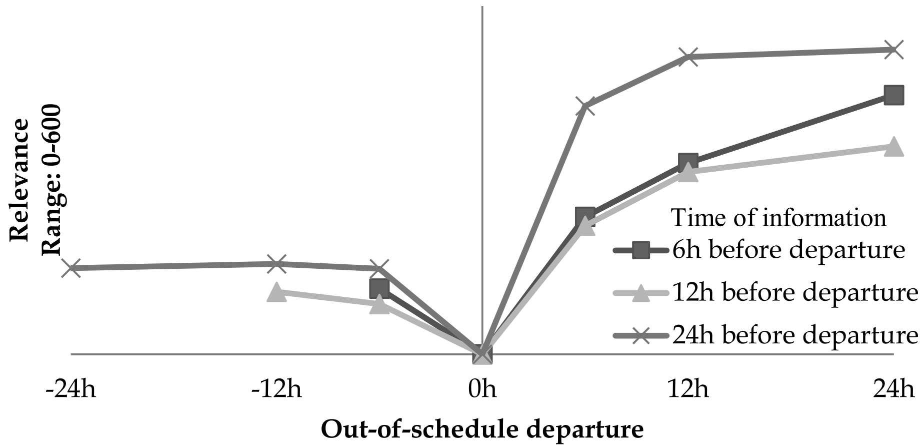

Fig. 3.6 Relevance $\mathcal{R}_{d_s}$ of early and late departure of selected services

Fig. 3.6 shows the relevance of full updates in case of out-of-schedule departure. Note that a negative relevance is impossible by definition: the solution of the local update is also a feasible solution of the full update. The relevance measures the cost savings of a network-wide full update compared with a local update. Clearly, a full update is more relevant in case of late departure than in case of early departure. Also, the relevance is not linear with the earliness of information. The relevance is highest for the case where the disturbance is known 1 day in advance. However, the case where $t - t_{\text{info}} = 6\text{h}$ shows a higher relevance than the case where $t - t_{\text{info}} = 12\text{h}$.

Table 3.8 shows the relevance as percentage of the impact of out-of-schedule departures and of cancellations for the selected services. Although the cancellation of a service often has a much higher impact than an early or late departure, the table shows that the relevance of a cancellation is only 1% of the impact. This indicates that a cancellation is costly, regardless of the update method. Table 3.8 also shows that the relative relevance is higher for delays than for early departures; i.e., a full update offers a larger cost reduction for delays than for early departures, relatively.

Table 3.8 Relevance compared to impact (selected services)

Disturbance	$\frac{\mathcal{R}_{d_s}}{\mathcal{F}_{d_s}}$
Cancellation (selected services)	1%
24h early	4%
12h early	5%
6h early	6%
6h late	28%
12h late	35%
24h late	25%

3.5 Conclusions

In this study the new LCAT model is proposed in answer to research question 2: "How can optimal transportation plans be created for synchromodal networks?". It adds two new aspects to existing models for operational planning: overdue delivery at a penalty cost and the combination of uncommitted and committed services. Truck transportation can be selected as fast alternative for the intermodal services, but is expensive. An automated method is proposed to find a relatively small set containing all suitable paths. This method is a good starting point to generate relevant paths in similar cases of a network between a sea terminal and several hinterland terminals. Furthermore, two new measures are proposed in the chapter to answer research question 3: "How can the effect of disturbances in synchromodal networks be quantified?". These new measures were introduced as impact and relevance. The impact measures the additional cost of a disturbance. The relevance measures the difference between the cost of a full or local update. A high relevance for a specific type of disturbance suggests the use of a full update if that type of disturbance occurs. A low relevance indicates that the local update method of this study performed almost as well as the full update.

We used a case study to illustrate the potential of the LCAT model for planning in an intermodal container network. It was used to assess the impact and relevance of disturbances of the network services. The inevitable costs, the impact, of a cancelled service can amount up to 15,000 for the network operator, and for out-of-schedule departures up to 4,500. The costs that can be avoided by using a full update of the transportation plan after a disturbance, the relevance, is found to be much lower: up to 600 for out-of-schedule departures.

Generally, the relevance is low, compared with the total transportation costs. Hence, the use of full updates does not result in large cost reductions compared with local updates. Full updates may be unwanted for other reasons. Full updates were not used in the EGS network at the time of the research and the development and implementation of real-time planning methods for full updates is costly. Secondly, during full updates, large amounts of containers may be rescheduled. In our method, it is assumed that the cost of reassigning containers to another service is negligible, so the costs of implementing an updated plan are not taken into account in this study. On the other hand, the local planning method in this study can be improved to give planning results even closer to the optimal full update. Further research is required to develop improved methods for partial updates, suitable for manual planners. With improved manual methods for partial updates, the relevance of disturbances can be further decreased. This eliminates the necessity of full updates and implementing automated planning methods. One improvement may be that the local update re-plans containers on all services on the disturbed corridor. The current local update can only change the paths of containers on the disturbed service. This extension of the local update will allow bumping, i.e. postponing containers planned on future services to allow containers of the disturbed service to arrive on time.

The case study was based on data from EGS. The results support the following managerial insights regarding the EGS network:

- Where possible, use fixed schedules for departures. This reduces the late schedule changes causing early and late departures compared with the initial planning. EGS tried to do this, for instance on the service to MCT Moerdijk. This research supports that effort.
- The network operator can use the results to identify disturbances that should be prevented Based on the results, the network operator must focus on preventing early departures, as these have the highest impact. A high impact indicates a disturbance with large additional costs that cannot be reduced with a full update of the transportation plan.
- Simultaneously, the planning department of the network operator must give additional attention to disturbances on barges or committed services. These showed high relevance; cost reduction can be attained with more elaborate planning updates, or even a full update.

Note the following practical limitations of the model. The model uses a linearised cost structure. Container transportation demand is represented as a continuous flow. Also, the historic demand may differ from the future demand. Several operational limitations at the terminal are not incorporated in the model, such as custom restrictions, available quay and crane capacity and security issues. The proposed method is suitable for studying the joint influence of multiple disturbances simultaneously, e.g., because of snow, high water or strikes. However, in this study such simultaneous disturbances were not considered.

In this chapter we considered an integral planning method for creating transportation plan. In the next chapter this model is used as a basis for creating a real-time decision support system for container transportation planning.

4 Real-time Container Transport Planning with Decision Trees

Chapter 2 and 3 considered integral planning methods for intermodal hinterland networks. For finding the answer to research question 4, "How can the results of the LCAT model be translated into a white box decision support method for human planning operators?", this chapter aims to consider the problem of real-time planning. We derive real-time decision rules for suitable allocations of containers to inland services by analysing the solution structure of the centralised optimisation method of Chapter 3. The resulting decision tree can be used in a decision support system (DSS) for instantaneously allocating incoming orders to suitable services, without the need for continuous automated planning updates. Such a DSS is beneficial, as it is easy to implement in the current practice of container transportation. Earlier proposed centralised methods can find the optimal solution for the intermodal inland transportation problem in retrospect, but are not suitable when information becomes gradually available. The main contributions are threefold: firstly, a structured method for creating decision trees from optimal solutions is proposed. Secondly, an innovative method is used for obtaining multiple equivalent optimal solutions to prevent overfitting of the decision tree. And finally, a structured analysis of three error types is presented for assessing the quality of an obtained tree. A case study illustrates the method's purpose by comparing the quality of the resulting plan with alternative methods.
This chapter is organised as follows. In Section 4.1 the problem is introduced and Section 4.2 provides an overview of relevant literature on real-time decision support and decision trees. Subsequently, Section 4.3 gives a formal description of the proposed method for obtaining and using the decision tree. In Section 4.4 methods for estimating the performance of the algorithm in general are described. In Section 4.5, the method is applied in a case study of an intermodal hinterland transportation corridor. Section 4.6 summarises the findings of the study and provides an outlook on future research.[4]
Keywords: *Intermodal planning, synchromodal planning, container transportation, decision support, decision trees.*

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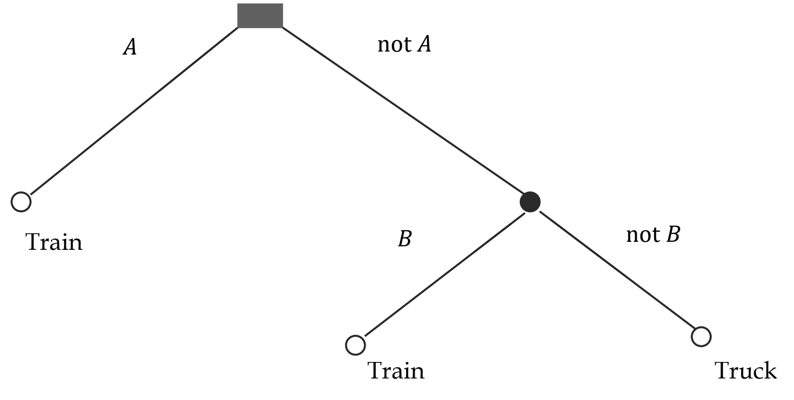
[4] This chapter is based on the following publication with small modifications: Van Riessen, B., Negenborn, R. R. and Dekker, R. (2016). Real-time container transport planning with decision trees based on offline obtained optimal solutions. Decision Support Systems, 89, 1-16. The final publication is available via https://doi.org/10.1016/j.dss.2016.06.004.

4.1 Introduction

Continuous growth of global container volumes puts increasing pressure on the inland road, water and rail connections, especially in developed countries with limited public support for infrastructural expansion. Simultaneously, shippers require more reliable inland connections because their supply chain demands for just-in-time delivery, and the environmental impact of the inland transportation is increasingly bound by restrictions from governments and from shippers themselves. In this study, we consider decision support for the planning of inland transportation. The problem is based on the situation of European Gateway Services (EGS), as introduced in Section 1.2. Although the inland network has sufficient capacity in general, temporary congestion occurs frequently on all inland modes: road, water, and rail connections. Most inland transportation of containers is carried out by operators that are dedicated to specific modes. In the light of these developments, an integral approach for the routing and planning of all inland container transportation is vital. In this study we propose a real-time DSS for providing improved planning support. In particular, we propose to use decision trees as method in the DSS. Decision trees are a way to represent rules underlying data with hierarchical, sequential structures that recursively partition the data (Murthy, 1998). In our method, the routing decision is made per container, by applying the tree to the properties of the container transportation order (i.e. booking). Fig. 4.1 gives an example of a decision tree supporting the routing decision for a container.



The first decision is based on whether or not the container has property A. If not, a second decision follows, based on whether or not the container has property B.

Fig. 4.1 Example decision tree for deciding on the mode of transportation for a container.

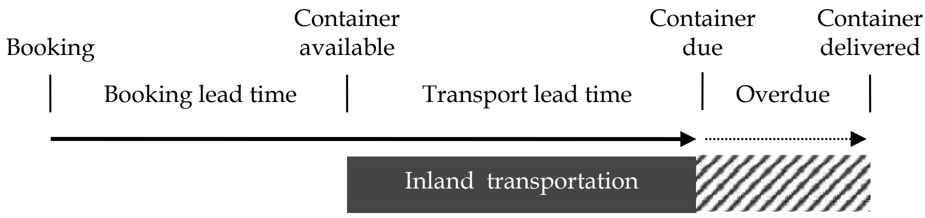


Fig. 4.2 Timeline of orders and inland transportation

4.1.1 Characteristic intermodal decision problem

For a particular corridor (i.e., the set of available transportation options between two locations), a set of inland services is available, characterised by the mode of transport (barge, rail or truck), cost per container, departure time, arrival time, and vehicle capacity (volume and weight). Naturally, the time between departure and arrival of a service depends on the mode's travel speed. Typically, speed and cost are high for trucking and low for barge transport. Volume capacity is high for barge transportation and low for a truck. The weight capacity for both barge and truck is mostly not restrictive. The mode train has intermediate levels for speed, cost and capacity, but typically has a restrictive weight capacity, especially in mountainous regions. In this setting, we consider scheduled barge and train services with fixed capacities, while trucks can be ordered at any time without limits. Generally, in a transportation setting, orders arrive sequentially at a transportation network planning department. Each order has several attributes, such as the client name, the number of containers for the order, the booking lead time, the transport lead time and the size and weight of each container in the order. The number of containers is measured in standard container sizes of Twenty feet Equivalent Units (TEU). The booking lead time is the time between the arrival of the order and the availability of the container; the transport lead time is the time between the availability of the containers and the due time at the destination (see Fig. 4.2). The planner's goal is to transport the containers at the lowest possible total cost, ideally before the due time of the containers, but often it is allowed to deliver a little later, indicated by the overdue time. In practice, overdue delivery can sometimes be negotiated with customers, in our modelling overdue delivery is allowed at a penalty cost for the network operator. The characteristics of this decision problem do not change over time, giving rise to periodicity, e.g. weekly. Therefore, analytics on historic information can be used to find patterns and create a decision tree (DT). Subsequently, this decision tree can be used for decision support in future periods.

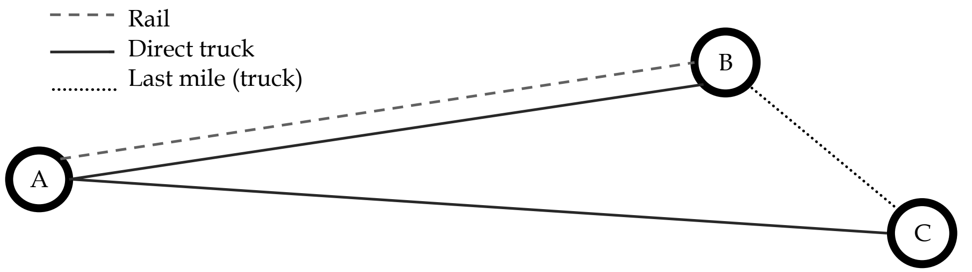


Fig. 4.3 Characteristic decision problem

Fig. 4.3 illustrates an example of the characteristic intermodal decision problem schematically. Compared to the more general intermodal picture in Fig 2.1, the focus here is on the choice between an intermodal (rail) connection, or using a direct truck. We consider 1 origin, A, and 2 destinations: B and C. Both destinations can be reached by using a truck (T) or, alternatively, a rail connection (R) for transport from A to B or from A to C via B. In the case of using rail transportation for containers with destination C, last mile trucking from B to C is required. In general, rail is cheaper than truck, but has limited capacity. Trucking capacity is abundant, and considered unlimited for this study. The train has a limited capacity, denoted by K. The costs for the four transportation options are denoted as c_{dm}, where d denotes the destination and m denotes the used mode, $d \in \{\mathrm{B}, \mathrm{C}\}, m \in \{\mathrm{R}, \mathrm{T}\}$. E.g., c_{BR} denotes the costs for transporting one unit from A to destination B by rail. Typically, the goal is to maximise the utilisation rate of the lower priced rail mode for the highest yielding destination. Because of different transportation restrictions between container classes and differences in costs, this decision problem is not straightforward.
For the planner, who must make decisions instantaneously for incoming orders, the question is how many slots to reserve for each destination, i.e., use a booking limit of K_{B} slots for containers to destination B and K_{C} slots for destination C, adhering to $K_{\mathrm{B}} + K_{\mathrm{C}} = K$.

4.1.2 Real-time intermodal planning problem

Nowadays, in real cases (according to our experiences with EGS) often a greedy approach or first come, first serve (FCFS) approach is used for planning the container transportation. In case of a greedy approach, a container transportation order is assigned to the cheapest feasible service at the time of order arrival, i.e. the cheapest service with free capacity that travels within the container's time restrictions. In an FCFS approach, a booking is assigned to the earliest available service. In both methods, an order is assigned instantaneously at the time of order arrival.

The problem addressed in this study is to allocate an incoming order immediately to the most suitable inland service, as part of the optimisation of the entire corridor. Existing scientific methods for real-time decision making for planning of inland container transportation focus on finding cheapest or shortest paths per transport order (Ziliaskopoulos and Wardell, 2000; Ayed et al., 2011). More advanced methods for solving the online problem require real-time automated data processing and are less insightful to human planning operators (Nabais, 2015, Li *et al.*, 2013). We propose a method for allocating orders to services based on optimal historical plans.

4.1.3 Proposed method for real-time decision support

In recent years, several studies have proposed optimisation methods for determining the optimal allocation of containers to all available inland transportation services, considering capacity, costs, lead times and emissions. The proposed methods are suitable for solving the *offline* planning problem, in which an optimal network plan is created for a batch of transportation orders collectively. In intermodal networks, such as the network of European Gateway Services, the implementation of a centralised offline approach is difficult for various reasons:

- Real-time decisions: The nature of the inland transport logistics requires a real-time approach, in which a customer can get immediate feedback on the selected mode, route, and most importantly, the estimated time of arrival. Consequently, updates in the planning of inland transportation have large influences on the subsequent production processes, possibly resulting in an undesired cascade of changes in earlier determined plans. An improved solution method must support real-time planning decisions, without continuous planning updates.
- Incomplete information: The operation of transportation systems is often not centralised, but depends on multiple cooperating decision makers, e.g. a logistics service provider and a transportation operator. The supply chain of container logistics lacks information integration (Van der Horst and de Langen, 2008). Capacity and/or demand information for future periods is often not fully available. However, existing centralised optimisation methods depend strongly on complete information from integrated and automated processes, both for terminals, as for other parts of the supply chain. They lack the flexibility to deal with incomplete information. A method must therefore be able to provide decision support even with incomplete information.
- Human-aware decision making: In relation to the previous aspect, planning operators manually gather information ad hoc, such as real-time information on capacity and delays. Delays are common as the workloads in container terminals have a stochastic nature and are distributed unevenly in time (Murty, 2005). For this, direct communication between

manual operators is essential (Douma, 2008). A transparent approach is required that allows the human operators to include manually obtained information in the decision process. We consider this the white box property of the desired solution method.

In this chapter, we propose a general method for a real-time DSS that addresses the aforementioned issues, by meeting three main requirements. Firstly, the proposed method allows real-time decision support for allocating incoming transport orders directly to available inland services, resulting in a stable solution and instant feedback to the customer without the necessity of continuous planning updates. Secondly, the method does not need complete information to provide decision support: The decision tree obtained by our method can be applied in real-time in daily practice without an automated decision system. Thirdly, the proposed method provides decision support in a white box system: The human planner responsible for a central network planning can check available capacity on a proposed service manually and include that in the decision process. In a case study, we will show how the proposed method adheres to these three characteristics while resulting in a solution closer to the optimum than the current practice, although some misclassifications are still to be expected. It is assumed that the problem is cyclical: the weekly service schedule and the distribution of demand are considered as constant in time.

4.1.4 Approach

The model we propose is based on an analysis of the solution space of an offline optimisation model, and translates the offline model's optimal solutions to a decision tree: a white box representation of decision rules. It will therefore more easily be accepted for use in daily practice. The method must operate well under various circumstances and therefore multiple historic order arrival patterns are used. The proposed approach is valid for a decision process with cyclical patterns, for which offline optima of historic data can be determined. The quality of the real-time decision support will depend on the problem structure. We introduce a method to assess that a priori (i.e. before applying it in real-time). In the remainder of this chapter, we focus on the problem of intermodal hinterland transportation. Nonetheless, the general method can be applied to other cases as well.
The approach is pictured schematically in Fig. 4.4. First, the data of historic demands are assembled, i.e. the historic container transportation bookings. Secondly, the optimal transportation plan is determined using the *linear container allocation problem with time restrictions* (LCAT) from Chapter 3 (Van Riessen *et al.*, 2015-b). The resulting optimal solutions for historical demand periods provide the baseline for real-time decision support and are used in the third step to find properties of an effective planning of a container considering the uncertainty in the demand. The relations between container properties and the planned mode and

route for that container in the optimal solution are determined. For this, we use a method of supervised learning for creating a decision tree based on the allocations in the optimal plans of the training sets. The supervised learning algorithm creates decision rules for the allocation of a container to a suitable service based on the container and order properties, such as the time of availability, the transportation lead time, and container weight. Subsequently, the set of rules can be used in a real-time setting as DSS: for each incoming order the DSS will provide a human planner with a set of suitable services in an understandable way.

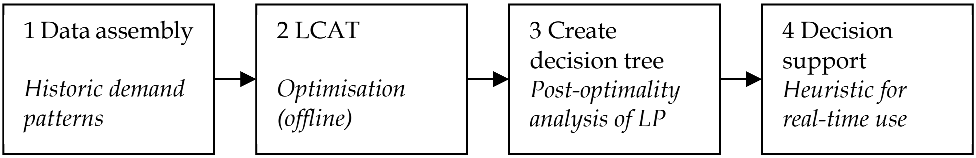


Fig. 4.4 Proposed methodology to obtain real-time decision support

It is expected that the performance of the proposed method is comparable to a low-level assignment strategy such as *first-come, first serve* for cases with orders that are entirely randomly distributed across the selected input features. If, however, historic information contains specific demand patterns, identifiable from the selected features, our method will capture those patterns without further detailed analysis. In this chapter we extend our previous work on real-time decision support based on offline optimisation (Van Riessen et al., 2014).

4.1.5 Contribution

The main contributions of the method are threefold. First, we propose a structured method for creating decision trees from optimal solutions. Secondly, we use a method for obtaining multiple equivalent optimal solutions to prevent overfitting of the decision tree. And finally, we develop a structured analysis of three error types for assessing the quality of an obtained tree and the expected error compared to the theoretical optimum.

4.2 Literature overview of real-time decision-making (using offline models)

4.2.1 Optimisation models for decision problems

In the literature, several methods have been proposed to deal with uncertainty in a combinatorial optimisation problem. Gal and Davis (1979) describe parametric analysis in linear programming (LP); Jenkins (1990) describes parametric analysis in (mixed) integer linear programming (MIP). His purpose is to study the sensitivity of the problem's objective for certain parameters. Greenburg (1998) gives an extensive overview of the more general concept of post solution analysis for both LP and MIP. He mentions the concept of *stability analysis:* finding the set of parameters for which a given solution remains optimal. However, Wallace (2000) illustrates that sensitivity analysis is only appropriate for deterministic problems and not suitable to support decision making under uncertainty. An alternative for parametric analysis of a solution is to develop a robust planning, that is optimal considering the uncertainty of all parameters. Since 2000, a large number of studies have been published on Robust Optimisation, see Bertsimas *et al.* (2011) for an overview. Both parametric analysis and robust optimisation assume a fixed set of decision variables. However, in our case, the number of decisions to take depends on the number of transportation orders. Branley *et al.* (1997) describe the concept of post-evaluation analysis. The purpose of such an analysis is to describe the decision surface, representing the value of the objective of the problem for a set of decision variables. Such a surface gives insight in the effect of certain decisions, but creating such a surface is computationally very demanding as all optimal solutions must be found. This problem belongs to the class of #P-complete problems and is as least as difficult as NP-complete problems (Valiant, 1979). In post-optimisation analysis, only a set of optimal solutions is studied, i.e., a subset of solutions with equal optimal objective value (Venkat *et al.*, 2003). Such post-optimisation analysis is often applied in multi-objective decision-making.

The intermodal decision problem can be considered as a specific type of multi-knapsack problem. The multi-knapsack problem is a well-known problem in literature, e.g. Rinnooy Kan *et al.* (1993), Pak and Dekker (2004) and Van Hentenryck and Bent (2009). The former two do not address decision support for real-time decisions. Van Hentenryck and Bent (2009) address a category of problems for which the uncertainty does not depend on the decision-making. Typically, the time-critical nature of the decisions in such a problem require online decision making. Online anticipatory algorithms (OAA) are used to solve this type of problems, by combining online algorithms and optimisation models. For making a decision at a given point in time a distribution of future events is assumed. If a predictive model is not available, sampling of historic data can be used. With OAA, an optimal policy that prescribes the required action in any state is not necessary, instead, only the decision provided the current situation and the expected future events are considered using optimisation models. An OAA can be used in an iterative manner, alternating between decision-making and incorporating new observations. However, in our proposed method we do not yet consider iterative learning. The distributions of inputs are sampled and learned independently from historic data of the underlying decision process (Van Hentenryck and Bent, 2009, Van Hentenryck *et al.*, 2010). Verwer *et al.* (2014) propose a method that can be seen as the inverse from our proposal: Their technique encodes optimisation models from learned decision trees, which can be used in auction settings. The method we propose uses a new approach for post-optimisation analysis. As no predictive model is available, generally, we propose a learning algorithm that translates historic optimal solutions of the offline problem into real-time decision support.

4.2.2 Decision Support Systems in container transportation

Steiger (1998) states that the purpose of a decision support system is to provide understanding to the decision maker. Apart from the solution to a model, this also requires insight in the model and model outcome. Giboney (2015) shows that the representation of a knowledge systems is crucial for user acceptance. In relation to container logistics, existing literature mostly focuses on modelling and finding solutions. Several DSSs have been developed that focus on the operational problem of container transhipment in container terminals (e.g. Murty *et al.*, 2005; Ngai *et al.*, 2007; Ursavas, 2014). Ursavas (2014) also mentions some works in literature that have proposed DSSs for container transportation problems. Some studies consider that demand is known in advance, such as Shen and Khoong (1995), who developed a mathematical model for planning the distribution of empty containers, suggesting specific options to the decision maker. Bandeira *et al.* (2009) propose a computer-based heuristic for solving a network flow model of both empty and full containers. After each time step, newly arrived future demand is considered. Jansen *et al.* (2004) describe an automated planning program for container trucking. Several studies considered a stochastic model using the expected future demand, e.g. Cheung and Chen (1998). However, because of the problem complexity and consequential computation time, this type of problems is impractical for application in real-time, as well as that no theoretical distribution of the future demand is available. More advanced methods for solving the online problem include Nabais (2015), who uses model predictive control to achieve a required modal split, and Li *et al*. (2013), who developed a sequential linear programming approach. All methods use computerised systems for providing proposed solutions to the decision maker.

Table 4.1 provides an overview of mentioned literature for decision support systems in real-time container transportation planning. For each of them is indicated to what extent they meet the 3 requirements for our problem as introduced in Section 4.1.3. From Table 4.1 we can see that all methods support decisions in real time to various extent. Several can deal with incomplete demand information, e.g. by using distributions of future demand. Most techniques require complete information on capacity, except for Ziliaskopoulos and Wardell's method, in which capacity is not considered. Also, none of the existing methods have a white box representation of the decision process. Therefore, our approach is compared with two simple heuristics that do meet all 3 requirements: a greedy approach and a FCFS approach.

Table 4.1 Overview of decision support techniques with respect to 3 requirements

Technique	*Real-time decision support*	*Level of information required* Demand	Capacity
Without white box principle			
Shen and Khoong (1995), Network flow	Periodically	Complete	Complete
Cheung and Chen (1998), Stoch. Progr.	Time restrictive*	Distribution	Complete
Ziliaskop. and Wardell (2000), Shortest p.	Instantly	Current order	Ignored
Janssen et al. (2004), Multi-step heuristic	Periodically (15m)	Active orders	Complete
Bandeira et al. (2009), Network flow	Periodically	Distribution	Complete
Nabais (2015), Model predictive control	Instantly	Distribution	Complete
Li et al. (2013), Sequential LP	Periodically	Complete	Complete
With white box principle			
Cormen et al. (1990), Greedy	Instantly	Current order	On request+
Ishfaq and Sox (2012), FCFS	Instantly	Current order	On request+
Proposed method, Decision Tree	Instantly	Historic orders	Historic+

* The proposed stochastic programming approach can be applied periodically, but may take very long to solve

+ With Greedy and FCFS the operator can request up-to-date capacity info per incoming order; this is also possible in our proposed method

4.2.3 Decision trees

We select decision trees as the classification approach for our study for several reasons. Firstly, decision trees provide direct insight into which rules and criteria lead to a decision. This is important for practical acceptance by the manual planning operators and is defined as a *white box* property. Secondly, decision trees can be trained using offline data. Subsequently, a decision tree can be used to distinguish between more than two classes, i.e., different inland services. Finally, the learning method must be suitable for using input parameters with categorical data, for instance, the customer type (Kotsiantis, 2007). Huysmans *et al.* (2011) describe several rule-based decision support methods: decision trees, decision tables and textual rule set descriptions. They performed empirical tests of users using these methods on various problems. For classification type problems, as in our case, decision tables result in slightly faster and more accurate results. However, as no direct methods for obtaining decision tables exist, decision trees are a suitable alternative.

The challenge is to create an accurate classifier. Only after the learning process the accuracy can be determined, i.e. by splitting the data in a training and test set, or by cross-validation techniques (Kotsiantis, 2007). In our method we use a test set to validate the performance of the classifier that was trained on a training set.

Decision tree classifiers are used as a method to structure complex decision-making. The decision is split up in multiple stages of simpler sub decisions. A decision tree can be represented by an acyclic directed graph, where a decision rule is associated with each node (Safavian *et al.*, 1991). To make a decision using a decision tree, the sub decisions per node are applied recursively to the parameters of the case. The decision rule at each node level defines what the next node of the decision process will be. This is called the child-node. Nodes without children are called leaf nodes and are associated with the final decision outcomes of the tree.

The generalisation error of a tree is defined as the misclassification rate over the input distribution (Rokach *et al.*, 2005). Typically, the goal for creating a decision tree is to find an optimal tree that minimises the generalisation error. Finding an optimal tree is an NP hard task, which is only feasible for small problem sizes (Rokach *et al.*, 2005). The topology of a decision tree and the decision rule at each node can be estimated empirically, using real-world data for which the intended outcome is known, i.e., supervised learning (Arentze and Timmermans, 2004).

Estimating a decision tree involves three aspects: design of the tree structure, the inference method for the decision rule at each node, and the selection of the feature set containing the input parameters (Safavian *et al.,* 1991). The tree structure and decision rules are determined using a learning heuristic, or *inference method*. Rokach *et al.* (2005) provide an overview of inference methods: Most often a top-down heuristic is used as inference method, although bottom-up inference methods also exist. The inference of the tree usually involves a growth phase followed by a pruning phase. In the growth phase, branches are added starting from the root of the tree while considering a splitting criterion. In the pruning phase, branch nodes are turned into leave nodes and the leaf nodes of that node are removed (Rokach *et al.*, 2005). According to Arentze and Timmermans (2004), the following are the most widely used learning heuristics: C4.5 (Quinlan, 1993), CART (Breiman, 1984) and CHAID (Kass, 1980). All methods consider a condition with a single input variable as splitting criterion and use a top down induction method. Chandra and Varghese (2009) mention two popular splitting criteria: the Gain ratio (Quinlan, 1993) and the Gini index (Breiman, 1984). Lastly, the set of input parameters must be determined. Often, this is carried out in a greedy way, by adding the input parameter that adds the most value to the classification accuracy iteratively, until no more improvement is made (Rokach *et al.*, 2005).

The induction of a decision tree via a learning heuristic requires a training set for the learning process and a test set to evaluate the quality of the induced tree in a cross-validation. If some observations are more important than others, it is possible to add observation weights to each observation.

4.3 Decision trees for real-time decision making in intermodal planning

4.3.1 Approach

This study focuses on developing a method that is suitable for operational usage in a real-time setting. The quality of the real-time method is compared with the quality of a theoretically optimal solution, obtained offline. In the method we propose in this study, we do not aim to formulate the online decision problem explicitly. Instead we aim to translate the results of an optimal model into rules for online application automatically. We do not pursue rule inference by interviewing operational planning experts, as it has two disadvantages. This approach typically results in a few rules per man day (Quinlan, 1986). An expert system that can provide decision support for container transportation planning may require a large amount of rules. As a result, the rule inference for an entire network may be time-consuming. Secondly, the quality of the transportation by the operational planning experts is unsure. For these reasons, we use a machine learning technique to infer the decision rules based on optimal planning solutions of the offline problem. The DSS is induced in a series of steps. The approach depicted in Fig. 4.1 is formalised in Algorithm 4.1. Sections 4.3.2 to 4.3.4 describe the steps 2 to 4 of Algorithm 4.1, respectively.

Algorithm 4.1 Obtain real-time decision support

1. Assemble N demand sets for training
2. Determine P optimal solutions for each demand set using the CLCAT model.
3. Infer decision tree T based on $N \times P$ solutions
4. Use decision tree T in a real-time setting on a per-container planning heuristic.

4.3.2 Finding *P* optimal solutions using the CLCAT model

The model we use to determine the optimal solution for the transportation planning is based on the LCAT model from Chapter 3 (Van Riessen et al., 2015-b). That model delivers optimal solutions for the planning of an entire network. For the characteristic intermodal problem studied in this chapter, we introduce the simplified formulation of minimising costs on a single corridor, the Corridor Linear Container Allocation model with Time restrictions (CLCAT).

The set of all cargo types that must be planned is denoted by demand set C and the set containing all services by S. The total number of TEU of cargo type c that must be transported is denoted as the demand d^c, this demand must be transported on one of the intermodal services or by direct truck. The set of services includes all available train and barge services, but not trucks, as trucks do not depart at predefined service schedules. Each service has a slot capacity u_s and a weight capacity of m_s, departs at time T_D^s and arrives at time T_A^s. Let x_s^c denote the number of TEU of cargo type $c \in C$ that is assigned to service $s \in S$. Each container of class c has a weight of W_c and must be transported in the time window from $t_{\text{available}}^c$ to t_{due}^c. The number of days that these containers are late is denoted by τ_s^c. The number of TEU of cargo class c assigned to a direct truck is denoted by v^c. No capacity or time restrictions are considered for trucking, as it is only used in exceptional cases. It is assumed that required trucking capacity is readily available. The transit costs of transporting one TEU on service s are denoted as c_s and the cost for direct trucking of a container of cargo class c is denoted as c_t^c. The objective of CLCAT is to minimise the total transportation costs of all containers, considering a penalty for overdue delivery of c_τ per day:

$$\min J_{CLCAT} = \sum_{s \in S} \sum_{c \in C} (c_s x_s^c + c_\tau \tau_s^c + c_t^c v^c), \tag{4.1}$$

subject to:

$$v^c + \sum_s x_s^c = d^c \qquad \forall c \in C \tag{4.2}$$

$$\sum_c x_s^c \leq u_s \qquad \forall s \in S \tag{4.3}$$

$$\sum_c W_c x_s^c \leq m_s \qquad \forall s \in S \tag{4.4}$$

$$x_s^c T_D^s \geq x_s^c t_{\text{available}}^c \qquad \forall c \in C, \forall s \in S \tag{4.5}$$

$$x_s^c (T_A^s - t_{\text{due}}^c) \leq \tau_s^c \qquad \forall c \in C, \forall s \in S \tag{4.6}$$

$$x_s^c, \tau_s^c, v^c \geq 0 \qquad \forall c \in C, \forall s \in S, \tag{4.7}$$

where the maximum capacity of service s is denoted by u_s (TEU capacity) and m_s (weight capacity). Constraints (4.2) ensure that all demand is met. By constraints (4.3) and (4.4), the total number of TEU on each service is restricted to the available capacity. Constraints (4.5) and (4.6) are the time constraints, where constraints (4.6) are for on-time delivery: τ_s^c measures the total number of days that containers of cargo class c on service s are late. Finally, constraints (4.7) are the nonnegativity constraints for the three sets of variables.

For most problems, multiple equivalent optimal solutions of (4.1) $-$ (4.7) exist, as each solution consists of specific assignments of cargo to a service. Often, some of these flows are fully exchangeable, e.g. because multiple services s are available with equal costs. In order to prevent overfitting on one optimal solution and to get decision rules that resemble all available optimal solutions as closely as possible, we need to determine a set of optimal solutions for demand set C. Finding all optimal solutions is a very difficult task (Valiant, 1979), so we use a new, innovative approach, aimed at finding a random subset of the set of optimal solutions. In order to generate such a random subset of optimal solutions, we solve the following problem P times:

$$\min \quad \sum \boldsymbol{rx} \tag{4.8}$$

subject to: $$(4.2) - (4.7) \tag{4.9}$$

$$\sum_{s\in S}\sum_{c\in C} c_s\ x_s^c + c_\tau \tau_s^c + c_t^c v^c = J_{CLCAT} \tag{4.10}$$

where $\boldsymbol{x} = [x_s^c, \tau_s^c, v^c]^{\mathrm{T}}$, a vector of all decision variables, and $\boldsymbol{r}$ is a row vector of the same length of random numbers from the standard uniform distribution (ranging from 0 to 1). By (4.10), all feasible solutions of (4.8) − (4.10) are optimal solutions of (4.1) − (4.7). The random vector $\boldsymbol{r}$ is introduced to get random subset of solutions out of the set of all optimal solutions, i.e., solving (4.8) − (4.10) P times corresponds to generating P random optimal solutions from the set of optimal solutions to (4.1) − (4.7). By definition, all these solutions have equal objective value J_{CLCAT}.

As mentioned in the introduction, a centralised offline optimisation method such as the CLCAT model is not useful in many practical situations for three reasons: it does not support real-time decisions; it would require extensive IT implementation to obtain all data form the transportation system; it requires complete information. In practice, real-time decisions require a heuristic provides decision support per incoming order anticipating unknown information, such as future demand. Current practical heuristics do not do that, but only provide solutions for available information. Below, we describe how the proposed DSS framework uses the optimal solutions on historic data in a learning algorithm to obtain a real-time DSS.

4.3.3 Decision tree inference

In order to obtain a decision tree that performs well under various circumstances and demand sets we use N demand sets for training. Historical data provides the distribution of attribute values; the sets can be demand sets from the last N weeks for instance. It is assumed that future demand will show a similar structure as the historic demand sets. Per demand set, P optimal solutions are determined using (4.8) – (4.10). In this study, we use $P = 50$ optimal solutions. In total, we use P plans for N demand sets, i.e. PN optimal plans. Each observation in this set of solution denotes the allocation of x_s^c containers of cargo class c to service s. Each plan can contain $|C||S|$ observations, resulting in $m = NP|C||S|$ observations in total for the inference process. For creating the tree, the importance of each observation is proportional to the number of containers x_s^c that is assigned, hence x_s^c is used as the observation weight. We aim to create a decision tree that predicts the allocated service, based on selected input features from the transportation booking. The inference of the decision tree is carried out using the CART method (Breiman *et al.*, 1984), with Gini's split criterion: This method is suitable for discrete and nominal input features, aims for splitting on the most distinguishing feature and is also suitable for small data sets. The CART method uses recursive partitioning and selects in each node the input feature that gives the least impurity of the child nodes, according to the Gini's index. The Gini index is denoted by (Rokach, 2005):

$$G(y, Z) = 1 - \sum_{c_j \in dom(y)} \frac{\left|\sigma_{y=c_j} Z\right|^2}{|Z|^2},$$

where y represents the target attribute, $|Z|$ represents the number of observations in the set and $|\sigma_{y=c_j} Z|$ the number of observations in the set with target value $y = c_j$. Hence, a pure node with just one class has only observations with $y = c_1$ and Gini index 0; otherwise the Gini index is positive. So the Gini index is a measure of node impurity. The recursive partitioning of nodes continues until in each node the stopping criterion has been reached; we choose to stop splitting a node that corresponds to less than 20% of the average allocation to a service, i.e. 20% of the number of observations m divided by the number of services s. Hence, the minimum node size is $\epsilon = 0.2\frac{m}{s}$. Further detailing the allocation would likely result in overfitting. With each leaf node, a table is associated containing the class distribution in that leaf node for all observations in the training sets. If a leaf node is pure and the Gini-index equals zero, the classification table for that node has only one entry: all observations in the training set associated with that node were assigned to a single inland service. For leaf nodes with some impurity, the largest class indicates the label of that leaf node.

The obtained decision tree classifies incoming transport orders by recursively making sub decisions until a leaf node is reached. A classification table is association with each leaf node, indicating the distribution of inland services used for bookings that end in that leaf node. A human planning operator can use this list for determining the actual allocation, while he considers the remaining capacity and other practical considerations. In the approach we describe in this chapter, we use a heuristic for the actual allocation, called the DT heuristic in the remainder of the chapter.

4.3.4 Applying the decision tree in a per-container planning heuristic

We introduce the DT heuristic to use the inferred decision tree for assigning incoming orders to inland services. It can be used on a per-container basis. For each order, the splitting criterion in subsequent nodes are applied. Orders for transporting multiple containers can be considered as one, without loss of generality as the decision tree gives the same results for each container. In practice, this process can be carried out by a human operator using the decision tree. In order to demonstrate our approach in a systematic way we use an automated heuristic to generate the transportation plan for our case study. Using the decision tree, an incoming transportation order is associated with one of the leave nodes. The DT heuristic will use the classification table of that node containing the distribution of services associated with that leaf node in decreasing order. The DT heuristic is provided in Algorithm 4.2, considering a previously obtained decision tree T. Note that the greedy strategy of step 4 in Algorithm 4.2 will select a direct truck if none of the available inland services has capacity left. The allocation process is repeated at the arrival of every transportation order. To clarify the process of the decision tree inference and application, the next section shows an explanatory example for the characteristic intermodal problem.

Algorithm 4.2 – Decision tree heuristic using decision tree T

1. Consider incoming container transportation order
2. Apply decision tree T to obtain the classification table of the resulting leave node
3. Assign containers to the services that have capacity left proportionally to distribution in the classification table
4. If none of the indicated services has capacity available, the container is assigned to a service according to a greedy strategy, i.e., the feasible service with minimum cost is selected.

4.3.5 Complexity of pre-processing steps and real-time operations

For real-time decision support, the running time of any DSS is critical. Our method supports real-time decisions by using a pre-processing step based on historic data. Here we show that the complexity of each step is polynomial, and that the pre-processing steps result in a significant reduction of complexity for the real-time decision process.

Without pre-processing, we could apply LP (4.1) − (4.7) to find the optimal plan. The average case complexity of solving LP (4.1) − (4.7) is determined using the result of Borgwardt (1982) for the average running time of the simplex method:

$$O\left(n^3 p^{\frac{1}{n-1}}\right), \tag{4.11}$$

in which n denotes the number of columns, i.e. the number of decision variables, and p the number of rows, i.e. the number of constraints. In our case, the number of decision variables $n = 2(|C||S|) + |C|$, with $|C|$ and $|S|$ denoting the number of cargo types and services, respectively. The number of constraints $p = 3|C||S| + |C| + 2|S|$.

Substituting n and p in (4.11), and observing that $n-1 \geq 2$, the average case complexity of LP $(4.1)-(4.7)$ is

$$O((|C||S|)^{3+\alpha}), \tag{4.12}$$

with $0 < \alpha \leq \frac{1}{2}$.

In the first pre-processing step, we consider LP (4.8) – (4.10), which also has average case complexity (4.12) as only 1 constraint is added in comparison to LP $(4.1)-(4.7)$. We solve this LP PN times (Section 4.3.2), i.e. for N historic periods and P repetition per period.

The second pre-processing step is the learning algorithm for the DT (Section 4.3.3). The complexity of the learning algorithm can be determined using the rationale of Su and Zhang (2006). In each node, containing a subset of $|Z|$ observations, one of l attributes must be selected as splitting criterion by considering each possible split for each candidate attribute. This operation has complexity of $O(|Z|l)$. For each level in the tree, the union of the subsets comprises all m observations. Hence, the complexity for each sublevel is of $O(ml)$, with $m = NP|C||S|$. Considering the minimum node size $\epsilon = 0.2\frac{m}{|S|}$, the maximum depth of the tree (the maximum number of levels) equals $\frac{m}{\epsilon} = 5|S|$. During the inference process, a maximum of $5|S|$ levels must be considered. Hence, the complexity of the entire inference operation is:

$$O(|C||S|^2 l). \tag{4.13}$$

From (4.12) and (4.13) we can see that the average running time of the pre-processing steps to obtain the tree is polynomial in the number of cargo types and the number of services considered in the problem. The algorithm can also be applied to larger scale problems.

Finally, we consider the problem of the real time decision problem as well (Section 4.3.4). The decision tree is used for each incoming order. The complexity of applying the tree only depends on the number of levels in the tree, so it has a complexity:

$$O(|S|). \tag{4.14}$$

Comparing (4.14) with (4.12), we see that the making decisions with the decision tree is much less computationally complex than solving the LP for the optimal solution. This supports our aim to derive a decision support system that can be easily applied in real-time in practice, leveraging information of historic optima.

4.3.6 Validation of the DT heuristic using the characteristic intermodal decision problem

In this section, we make a comparison between the optimal strategy and using our DT heuristic in the characteristic intermodal problem. For this problem, as depicted in Fig. 4.3, the question is how many slots to reserve for each destination. It is possible to determine an optimal strategy analytically; but even for such a simple problem it requires detailed analysis. Here we show that our DT heuristic is much more convenient to apply and results in results very close to the optimum. The purpose here is not to study a very realistic case, but merely to assess an example for which a comparison with the optimum is possible. In Section 4.4 we present a method for assessing the quality of the DT heuristic in more general cases, for which comparing to the optimum is not possible. This is also demonstrated in a more elaborate case study in Section 4.5.

In the characteristic intermodal decision problem, a planner has to decide between a lower priced, fixed capacity mode and a higher priced ample capacity mode. Two order types compete for the lower priced mode, in this case orders for two destinations, B and C. Containers for both destinations can go by a fixed capacity on rail, or using ample capacity of trucking, so we consider 4 transportation options: rail to B (BR), rail to C (BT), trucking to B (CR) and trucking to C (CT). For an optimal strategy, we need to determine the booking limits for rail slots toward B (K_{B}) and toward C (K_{C}), adhering to $K_{\mathrm{B}} + K_{\mathrm{C}} = K$, resulting in the lowest expected total cost. A detailed overview of determining these booking limits is presented in Appendix 4.A, here we provide the main results.

4.3.6.1 *Optimal slot reservation*

We assume independent distributions for the number of containers for destination B and C during a planning period, denoted by N_{B} and N_{C}, respectively. For each destination d and mode m, we consider the number of used slots (i.e. planned containers), denoted by S^{dm} with a cost denoted by c_{dm}. Note that the costs of transporting one unit from A to C via rail, c_{CR}, also include the costs for last mile trucking between B and C. In line with the characteristic intermodal problem, we consider the set of problems for which the trucking costs exceed rail costs for all destinations x, i.e., $c_{d\mathrm{T}} \geq c_{d\mathrm{R}}$. The optimal booking limit on the train for each destination can be found by minimising the total costs for all transports, denoted by J. The expected costs are a sum of the costs for all four transportation options:

$$\mathbb{E}(J) = c_{BR}\mathbb{E}(S^{BR}) + c_{BT}\mathbb{E}(S^{BT}) + c_{CR}\mathbb{E}(S^{CR}) + c_{CT}\mathbb{E}(S^{CT}), \tag{4.15}$$

where $\mathbb{E}(\cdot)$ is the expectancy operator. For a known booking limit K_{B} (and K_{C}), we can determine the expected utilisation on each mode and each destination. First, we determine the expected slots used for transportation to destination B. The expected number of train slots used for destination B is the sum of the conditional expectation if $N_{\mathrm{B}} \leq K_{\mathrm{B}}$ and of the case that $N_{\mathrm{B}} > K_{\mathrm{B}}$:

$$\mathbb{E}(S^{BR}) = \mathbb{E}(N_B \mid N_B \leq K_B)\mathbb{P}(N_B \leq K_B) + K_B\mathbb{P}(N_B > K_B), \tag{4.16}$$

where $\mathbb{P}(\cdot)$ denotes the probability of event $\cdot$, and

$$\begin{aligned}\mathbb{E}(N_B \mid N_B \leq K_B) &= \sum_{n\in\{1,2,\dots\}} n \frac{\mathbb{P}(N_B = n \cap n \leq K_B)}{\mathbb{P}(N_B \leq K_B)} \\ &= \sum_{n\in\{1,2,\dots,K_B\}} n \frac{\mathbb{P}(N_B = n)}{\mathbb{P}(N_B \leq K_B)}.\end{aligned} \tag{4.17}$$

By substituting (4.17) in (4.16), we get the expected number of rail slots used for destination B:

$$\mathbb{E}(S^{BR}) = \sum_{n\in\{1,2,\dots,K_B\}} n\mathbb{P}(N_B = n) + K_B\mathbb{P}(N_B > K_B) \tag{4.18}$$

The results for the other transportation options are shown in Appendix 4.A. Substituting (4.4) and from Appendix 4.A (4.37) – (4.39) in (4.15) gives the expected costs for a given value of K_B (and $K_\mathrm{C} = K - K_\mathrm{B}$). The optimal booking limit for rail slots used for destination B, i.e., the optimal value of K_B is then determined by solving for the mimimum of total expected costs c_T

$$K_\mathrm{B}^* = \underset{K_\mathrm{B}}{\operatorname{argmin}}\ \mathbb{E}c_T$$

This is valid for any independent distributions of N_B and N_C. Here, we will determine the optimal value K_B^* for a uniform distribution of the demand to destinations B and C. E.g., for uniform distributions $N_\mathrm{B} \sim U(b_1, b_2)$, $N_\mathrm{C} \sim U(c_1, c_2)$, that allow a total demand exceeding the train capacity, i.e., $b_2 + c_2 > K$, the expected number of rail slots used for destination B can be estimated using (4.18) as

$$\mathbb{E}(S^{BR}) = (K_B - b_1)\frac{b_1 + K_B + 1}{2(b_2 - b_1)} + K_B\frac{b_2 - K_B}{b_2 - b_1}$$

$$\mathbb{E}(S^{BR}) = \frac{{K_B}^2 + {b_1}^2 - 2K_B b_2 + b_1 - K_B}{2(b_1 - b_2)}. \tag{4.19}$$

The results for the other transportation options are presented in Appendix 4.A. By using $K_\mathrm{C} = K - K_\mathrm{B}$ and finding the minimum of (4.15), we can find the analytical optimal value for $K_\mathbf{B}$:

$$K_B^* = \frac{\left(c_2 - K + \frac{1}{2}\right)(c_{CR} - c_{CT})(b_1 - b_2) + \left(b_2 + \frac{1}{2}\right)(c_{BR} - c_{BT})(c_1 - c_2)}{(b_1 - b_2)(c_{CR} - c_{CT}) + (c_1 - c_2)(c_{BR} - c_{BT})} \tag{4.20}$$

The optimal value K_B^* is the upper limit for slots that can be used for transporting containers to destination B by rail. Next, we will compare the result of the proposed decision tree method with the analytical optimum.

4.3.6.2 *Comparing DT heuristic to optimal solution for the characteristic intermodal problem*

Now, we will use some specific instances to compare the performance of the DT heuristic with the analytical optimum for this problem. We assume a capacity of $K = 40$ for the train and we consider three demand scenarios. Table 4.2 shows the hypothetical costs and demand scenarios. The cost for the more expensive mode, trucking, is equal in both cases. The rail connection that is available travels directly to destination B, omitting the need for a last-mile trucking leg. Hence, this is the lowest priced transport. Using the rail connection to destination C requires a last-mile truck delivery. For this transport an intermediate cost is assumed. The three demand scenarios all result in a conflict between planning containers for destination B or C on the train. We determine the optimal booking limits (i.e. slot reservations) using (4.20). The resulting limits for destination B and C are denoted in Table 4.3. For all three instances, we applied Algorithm 4.1 to obtain decision trees. As the first step, we assemble data patterns for training: we generate 20 sets of demand volumes for destination B and C using N_{B} and N_{C}, with a specific arrival sequence. For the real-time application of the DT heuristic, the sequence of bookings is relevant. Secondly, we find the optimal solution for each of these 20 demand sets using the CLCAT model. Thirdly, we use the results to train the decision tree on, with the following features for a container transportation order j: the destination D_j and the amount of containers with destination C that has already been ordered d_C^j before order i.

As the decision tree inference method is based on the demand set, we repeated the process 3 times, creating 3 decision trees per demand scenario, using independent demand sets. Fig. 4.5 shows the resulting decision trees. If we inspect the decision trees for scenario 1, we observe that the trees shown in Fig. 4.5a and Fig. 4.5b result in a maximum of 3, resp. 4, train slots for destination C. This is remarkably close to the optimum of 4. However, Fig. 4.5c shows a tree that only uses 1 rail slot for destination C, which is too conservative, compared to the optimum. For demand scenario 2, the decision trees shown in Fig. 4.5d and Fig. 4.5e result in a maximum of 10, resp. 11, train slots for destination C, which is close to the optimum of 12. Fig. 4.5f shows a very simple decision tree, that allocates all incoming orders to the train. This results in the optimum in most cases (e.g. if $N_{\mathrm{B}} + N_{\mathrm{C}} \leq 40$), but in some extreme case may allow too many slots be used for destination C (e.g. if a large number of orders for destination C arrives early). Finally, for demand scenario 3, we obtain three very similar trees, in which 16 – 18 train slots are used for destination C (Fig. 4.5g-i). This is again close to the optimum of 18 slots for destination C. The results for all scenarios show that the proposed method can identify the structure of the problem from the historic demand and provides a decision tree close to the optimal solution in most cases for this characteristic intermodal problem. In the next section, the DT heuristic will be applied to several variants of the characteristic intermodal problem with a range of parameters to validate the method for the more general situation.

Table 4.2 Cost matrix and three demand instances of the characteristic decision problem

Destination	*Train*	*Truck*	*Demand (1)*	*Demand (2)*	*Demand (3)*
B	$c_{\mathrm{BR}} = 2$	$c_{\mathrm{BT}} = 4$	$N_{\mathrm{B}} \sim U(30{,}40)$	$N_B \sim U(20{,}30)$	$N_B \sim U(15{,}25)$
C	$c_{\mathrm{CR}} = 3$	$c_{\mathrm{CT}} = 4$	$N_C \sim U(0{,}20)$	$N_C \sim U(0{,}20)$	$N_C \sim U(15{,}25)$

Table 4.3 Optimal slot reservations for characteristic decision problem instances

Destination	K_B^*	K_C^*
Demand (1)	36	4
Demand (2)	28	12
Demand (3)	22	18

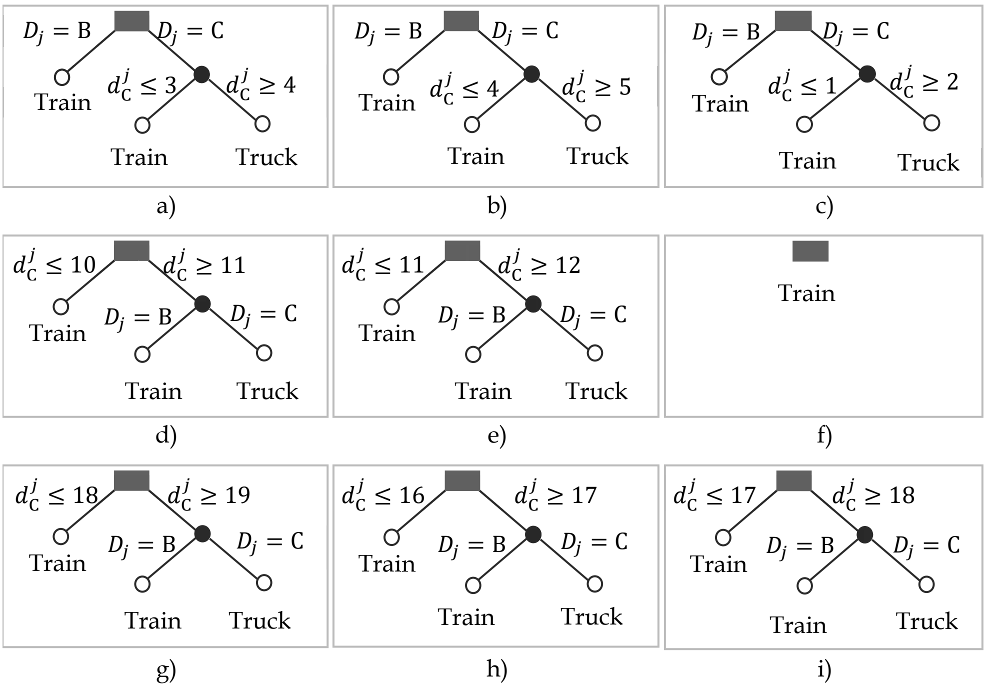


Fig. 4.5 Decision trees obtained from Algorithm 4.1 for scenarios 1 (a-c), 2 (d-f) and 3 (g-i)

4.3.6.3 *Evaluation of the DT heuristic applied to variants of the characteristic intermodal decision problem*

The previous section looked in detail into several examples of generated trees. To validate the approach more generally, we apply it to a larger set of scenarios of the characteristic intermodal problem. For this, we determine multiple input values for the cost parameters and demand interval. Each combination of input parameters is considered as a separate instance. The demand intervals are defined as

$$N_B \sim U(b_1, b_1 + w_b);\ N_C \sim U(c_1, c_1 + w_c)$$

The parameters used are indicated in Table 4.4. Taking all combinations results in a total of 2187 scenarios. For each scenario, plans are created for 50 test instances using 4 methods: the theoretical optimum (obtained offline using the CLCAT model), the DT heuristic, the Greedy approach and the FCFS approach. For comparison, we use the competitive ratio of the objective costs of the heuristics and the optimal objective value. The competitive ratio is determined as the ratio of the optimal objective value and the objective value of the heuristic's results (Borodin and El-Yaniv, 1998). The optimal objective value can be obtained offline using the CLCAT model. By this definition, the competitive ratio of the CLCAT solution is always equal to 1, and for the heuristics always ≤ 1. A high competitive ratio indicates a good plan. As a benchmark, the quality of the Greedy algorithm is considered in more detail in Appendix 4.B.

For each scenario and for each method, the mean and standard deviation of the competitive ratio is determined over 50 test instances. The averages over all scenarios are shown in Table 4.5. Further detail can be seen in the boxplots of Fig. 4.6. The box plots consists of the median in a box from the 25th to 75th percentile. The whiskers denote the minimum and maximum competitive ratio, truncated at a whisker length of 1.5 times the length of the box. Results exceeding the whiskers are plotted as outliers. This shows that the DT heuristic performs generally better than the alternatives. Furthermore, we look in more detail into the differences in competitive ratio per scenario. Fig. 4.7 shows the competitive ratio of the DT heuristic over the alternatives, in ascending order. The competitive ratio $\eta_{\mathrm{G,DT}}$ of the DT heuristic over the Greedy algorithm is defined as the ratio of the total costs of using these methods, denoted as J_{DT} and J_{G}, respectively:, and similarly with the costs of FCFS, denoted by J_{FCFS}:

$$\eta_{\mathrm{G,DT}} = \frac{J_{\mathrm{G}}}{J_{\mathrm{DT}}};\ \eta_{\mathrm{FCFS,DT}} = \frac{J_{\mathrm{FCFS}}}{J_{\mathrm{DT}}}.$$

A number higher than 1 indicates that the DT heuristic outperforms the other method. The DT heuristic outperforms the Greedy algorithm in roughly half of the scenarios and the FCFS in most. More precisely, the competitive ratio of the DT heuristic is as least as good as the Greedy algorithm in 1746 (80%) scenarios and as least as good as the FCFS approach in 1838 (84%) scenarios.

Table 4.4 Values of input parameters

Parameter	*Values*	*Parameter*	*Values*
c_{BR}	0	b_1, c_1	0, 10, 20
c_{BT}	1, 2, 3	w_b, w_c	20, 30, 40
c_{CR}	2, 3, 4	K	40
c_{CT}	2, 3, 4		

Table 4.5 Resulting mean and st. dev. of competitive ratios over 2187 instances

	DT	*Greedy*	*FCFS*
Mean	98.5%	94.7%	82.1%
Standard deviation	2.0%	3.6%	5.1%

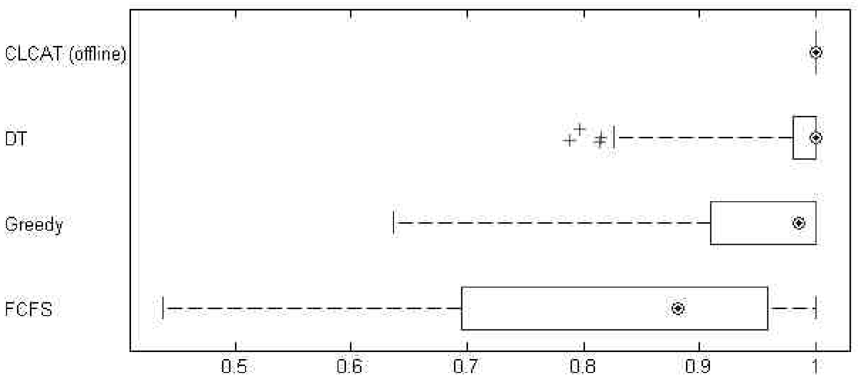


Fig. 4.6 Average competitive ratios over 50 test sets for 2187 instances

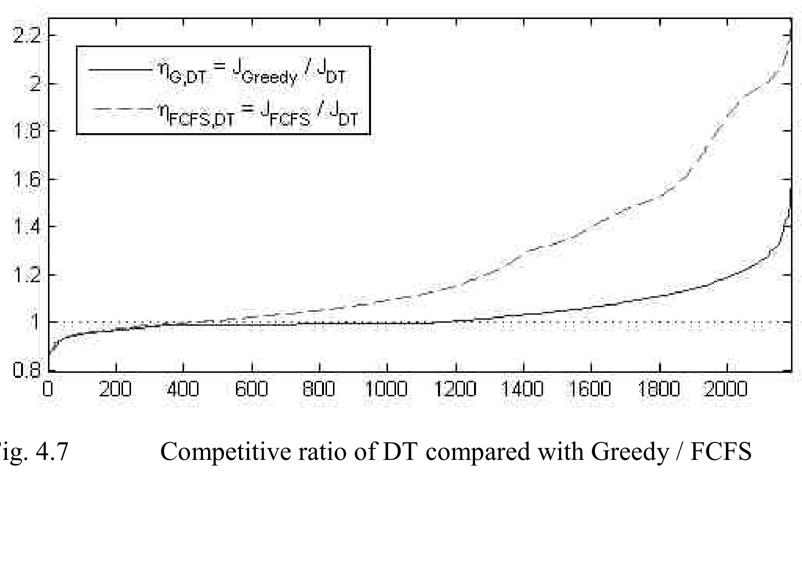


Fig. 4.7 Competitive ratio of DT compared with Greedy / FCFS

The results of this section and the previous one show that in most cases the DT heuristic is preferable compared to the alternative heuristics, Greedy and FCFS. However, in some cases, the DT heuristic underperforms. The intuition for this is as follows. The DT heuristic uses a classification mechanism of optimal assignments in historic data sets and applies that to incoming orders. Optimal assignments are classified based on the order properties used in learning the tree. For those problem variants in which the optimal allocations follow a specific structure with a repetitive nature, the DT is capable of finding and exploiting that structure. As expected, due to stochasticity in the demand, some assignments might be misclassified. Generally, the benefit of following the DT assignment outweighs the cost of occasional misclassification. However, in problem variants with limited structure, the benefit of the DT heuristic diminishes, and the DT assignments may result in a higher costs than the alternative algorithms, due to misclassification. Considering the 20% of variants in which the DT underperforms the Greedy algorithm (as seen in Fig. 4.7), we found this occurs predominantly if the rail corridor was not beneficial for destination C ($c_{\mathrm{CR}} > c_{\mathrm{CT}}$) or if the corridor is less beneficial for destination C than for destination B ($c_{\mathrm{CR}} < c_{\mathrm{CT}}$ and $c_{\mathrm{CT}} - c_{\mathrm{CR}} < c_{\mathrm{BT}} - c_{\mathrm{BR}}$). In these cases, structure of the problem is such that the DT provided too little benefit to compensate for some misclassifications.

Therefore, it is vital to measure the quality of an obtained tree in any scenario *before* applying it in practice. The next section provides an analysis method of the algorithm in order to determine the quality of a tree in advance, by assessing the misclassification error and two other sources of error.

4.4 Algorithm analysis

As shown in the previous section, the proposed DT heuristic provides an improvement over existing heuristics in most cases, but not in all. Therefore, in the following, we will address the performance of the DT heuristic by estimating the gap between the solution of the DT heuristic and the optimal solution. This algorithm analysis allows to address the expected quality of the DT directly after obtaining it, before applying it in practice. If the algorithm analysis results in an acceptably low error, the DT can be used in practice. If not, we can reiterate the learning process, for instance with a different feature set.

The purpose of the decision tree heuristic is to find solutions as close as possible to the optimum. We use some notation to distinguish between several sets of solutions. We denote the set of all possible demand patterns by Δ and the set of all optimal solutions for all demands sets by Ω. During the decision tree inference, we use a subset of optimal solutions $Z, Z \subset \Omega$, the solutions to the training set of historic data. Also we have a set of solutions to an independent test set of historic data, denoted by $Y, Y \subset \Omega$. To find an estimate of the optimality gap of the DT heuristic, we consider each service in the service schedule separately. Let us consider service $b \in \{1,2,\dots\}$. A solution $s_i \in \Omega$ consists of a list of allocations of containers to services

$b \in \{1,2, \dots\}$. For each service b, we denote the number of available slots as K_b. Let n_b^i denote the number of slots of service b that are in use in optimal solution s_i. The average number of slots in use on service b over all optimal solutions $s_i \in \Omega$, is denoted by $\overline{n_b^\Omega}$. The average number of slots in use on service b over the subset of optimal solutions $s_i \in Z$ is denoted by $\overline{n_b^Z}$. If decision tree T is applied to a subset of demand patterns, we obtain a set of solutions R'. We denote a solution in this set as $r'_k \in R'$. For service b the number of used slots in this solution is denoted by n'^k_b and the distribution of number of used slots is denoted as $n_b^{R'}$, with mean $\overline{n_b^{R'}}$. We use the accent to indicate the results of applying the tree directly, without the heuristic of Algorithm 4.2. Note that applying the decision tree directly may result in overbooking on a service, as no capacity limits are considered. Hence, finally, we consider the set of solutions R, obtained by applying Algorithm 4.2, the DT heuristic. A solution $r_k \in R$ denotes the heuristic's solution to demand set k. For service b the number of used slots in solution r_k is denoted by n_b^k and the distribution of used slots is denoted as n_b^R, with mean $\overline{n_b^R}$.

The cost on a slot of service b is denoted by c_b, and the total cost for all slots of service b in a solution s_i is $c_b n_b^i$. The DT heuristic aims to find the optimal number of used slots for each service b, but an error in finding the optimal number results in a different total cost for the found solution. For each service b, we distinguish between 3 error types:

Error type α. *Historic data error.* The decision support system is trained on historic data set Z. The target value of allocations to a service is based on the expected number of used slots of service b from the historic data. The error in determining this target value from the historic data is denoted as error type α. This error type represents data inaccuracy, rather than an error of the algorithm.

Error type β. *Misclassification error.* Secondly, the decision tree must represent a classification that results in assigning the correct target number of containers to service b. The misclassification of containers in service b is denoted as error type β.

Error type γ. *Capacity-restriction error*. Finally, error type γ consists of misclassification due to the capacity limits of service b. Due to the stochastic nature of new demand patterns, the actual number of containers allocated to service b by the decision support system is variable. Because of the maximum capacity of service b, the expected value of containers allocated to this service is lower than the number would be in a case without capacity limits.

Below, we elaborate on how the size of all three error types can be estimated during the inference process, before the decision tree is used for real-time decision support.

4.4.1 Error type α, historic data error

First we look at error type α, the *historic data error*. This error measures the accuracy of the average number of used slots for service b in the historic data. We compare the set of available optimal solutions Z with the set of all possible optimal solutions Ω. In practice, not all demand patterns Δ are known, and not all optimal solutions Ω can be computed in advance. Instead, we can use only a subset of all optimal solutions $Z \subset \Omega$. The average number of used slots of service b is estimated using subset Z, using $\overline{n_b^Z}$ and variance ${\sigma_{b,\alpha}}^2$:

$$\overline{n_b^Z} = \frac{\sum_{i \in Z} n_b^i}{|Z|},$$

$$ {\sigma_{b,\alpha}}^2 = \frac{\sum_{i \in Z}\left(n_b^i - \overline{n_b^Z}\right)^2}{|Z|} \tag{4.21}$$

Error type α denotes the difference in the allocations between subset Z and complete set Ω:

$$e_{b,\alpha} = \mathbb{E}\left(\overline{n_b^Z} - \overline{n_b^\Omega}\right).$$

A positive value $e_{b,\alpha}$ denotes an overestimation of the number of containers assigned to service b. According to the Central Limit Theorem, the difference $\overline{n_b^Z} - \overline{n_b^\Omega}$ is normally distributed with mean 0 and standard deviation $\sigma_{b.\alpha}/\sqrt{n}$. This gives $\mathbb{E}\left[e_{b,\alpha}\right] = 0$ and a 95% confidence interval for $e_{b,0}$ of

$$0 \pm 2\frac{\sigma_{b.\alpha}}{\sqrt{|Z|}}. \tag{4.22}$$

4.4.2 Error type β, misclassification error

Secondly, we determine the size of error type β, the *misclassification error* of the tree. Let us consider decision tree T that is able to provide a perfect classification, i.e. with a node purity of 100%. The probability of a container allocation to service b is a property of this decision tree, denoted by Pr_b. For this perfect decision tree, it holds that $Pr_b\overline{n^Z} = \overline{n_b^Z}$, with $\overline{n^Z}$ the average total number of containers in the solutions of the training set. However, in practice, the decision tree will not be perfect and $Pr_b\overline{n^Z} \neq \overline{n_b^Z}$, due to some misclassification errors. This is error type β. For estimating the size of error type β, we use the empirical distribution $n_b^{R'}$, denoting the number of slots of service b used in the tree's solutions r'_k. This empirical distribution n_b has a mean of

$$\overline{n_b^Z} = Pr_b\overline{n^Z} \tag{4.23}$$

and a variance of

$$\sigma_{b,\beta}^2 = \sum_{i \in Z} \frac{\left(n_b^i - \overline{n_b^Z} \right)^2}{|Z| - 1}. \tag{4.24}$$

For a given tree, the size of error type β can be determined directly after creation, by identifying:

$$e_{b,\beta} = \overline{n_b^Z} - \overline{\mathcal{n}_b^Z},$$

with a variance equal to (4.24) and a 95% confidence interval of:

$$e_{b,\beta} \pm 2 \frac{\sigma_{b.0}}{\sqrt{|Z|}}. \tag{4.25}$$

The value of $e_{b,\beta}$ denotes the average number of containers that the tree assigns to service b in excess of the optimum. A positive value of $e_{b,\beta}$ denotes that more containers are booked on service b than in the optimum; a negative value denotes that less containers are booked on service b than in the optimum.

4.4.3 Error type γ, capacity-restriction error

Finally, we consider error type γ, the *capacity-restriction error*. For assessing the quality of the online solution with this decision tree, we consider a set of new demand instances, test set D. If we apply the tree directly, we obtain a set of solutions R. We compare these with the set of solutions H, obtained by applying Algorithm 4.2.

The distribution of used slots on service b in solution $r_k \in R$ is denoted by $n_b^{r_k}$. We denote the distribution of $n_b^{r_k}$ by n_b^R. The number of containers classified in service b may be higher than its capacity K_b. On the other hand, we have $n_b^{h_k}$ the number of containers assigned to service b in solution $h_k \in H$, which is obtained by the DT heuristic. Hence, the capacity restrictions are adhered to. We denote the distribution of $n_b^{h_k}$ by n_b^H. Error type γ estimates the difference between the solutions r_k and h_k. The theoretical distributions of n_b^R and n_b^H are not known, as they depend on the structure of tree T. In order to assess the size of this capacity-restriction error, we can use an empirical distribution of containers assigned to b, based on the distribution of n_b^R and n_b^H in the solutions for test set D. Now, the size of error type 2 for service b is determined by the expected difference in number of containers assigned to service b:

$$e_{b,2} = \mathbb{E}(n_b^H - n_b^R). \tag{4.26}$$

We obtain the variance of error γ also by using the empirical distributions:

$$\sigma_{b,\gamma}^2 = Var(n_b^H - n_b^R) = \sum_{k \in D} \frac{\left(\left(\overline{n_b^R} - \overline{n_b^H}\right) - \left(n_b^{r_k} - n_b^{r_k}\right)\right)^2}{|R| - 1}. \tag{4.27}$$

This gives a 95% confidence interval for error type γ of:

$$e_{b,\gamma} \pm 2\frac{\sigma_{b,2}}{\sqrt{|R|}}. \tag{4.28}$$

4.4.4 Total error estimate

Finally, to estimate the total error in cost, we take the sum of all errors multiplied by the respective slot costs.

$$e = \sum_b c_b\left(e_{b,\alpha} + e_{b,\beta} + e_{b,\gamma}\right). \tag{4.29}$$

Note that a positive error value denotes additional costs compared with the optimal solution. For individual services, an individual error component can be negative, for instance, when Algorithm 4.2 allocates less containers to a specific service than in the optimal solution. Assuming that the error types α, β and γ for each service b are independent, the variance for the total error is:

$$\sigma^2 = \sum_b c_b\left(\sigma_{b,\alpha}^2 + \sigma_{b,\beta}^2 + \sigma_{b,\gamma}^2\right). \tag{4.30}$$

Assuming independence is conservative. In practice, the errors may have dependencies, resulting in a lower variance because of cross-correlations between the error terms. Determining these cross-correlations in general will be difficult and we will use (4.30) to determine the error variance.

4.5 Case study of real-time decision support in an intermodal corridor

In Section 4.3.5 we compared the proposed method with the optimal strategy in a small example. In this section, we will apply the DT heuristic to a more elaborate case study, and we will use the analysis method of Section 4.4 to determine a confidence interval for the obtained results. In our experiments, we will compare three online heuristics and the optimal offline plan in a series of simulations. As before, we use the competitive ratio to compare the objective costs of the heuristics and the optimal objective value, obtained offline using the CLCAT model. A high competitive ratio indicates a good plan.

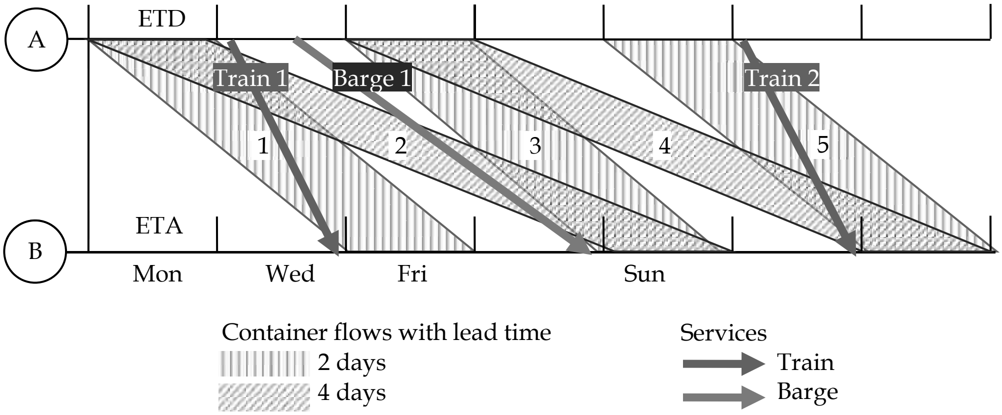


Fig. 4.8 Transport orders and service schedule for the case study

Table 4.6 Inland services for the case study

	Capacity *[TEU]*	*[tonnes]*	*Costs* *[per TEU]*
Train 1 and 2	90	1,000	100
Barge 1	200	10,000	50
Trucking	-	-	285

4.5.1 Scenarios

We compare two scenarios with identical service schedules, but different demand patterns. In Scenario 1 the demand is distributed randomly across the input features and in Scenario 2 a specific demand pattern is considered. First we consider Scenario 1. Fig. 4.8 shows a service schedule for a week with the Estimated Time of Departure (ETD) and Estimated Time of Arrival (ETA) of three services from A towards B. Trucks can always be used, and are therefore not shown. As our model is aimed at operators of intermodal networks, trucking is only used as a last resort, e.g. in case of disruptions or peak demands. Hence, the incidental demand for trucking is generally easily met by available capacity. The trucking capacity does not have to be modelled. For generating the tree, we use the container's time of availability ($t^c_{\text{available}}$), the transport lead time ($t_L = t^c_{\text{due}} - t^c_{\text{available}}$) and the container weight W_c.

Also, five transport demand flows are indicated. These flows have some variability; for obtaining the demand, we use a normal distribution with a mean of 50 TEU and a standard deviation of 12.5 TEU, rounded to integers. We assume a weight per TEU of 10 t. The $t^c_{\text{available}}$ and t^c_{due} of these flows are indicated by the shaded bands in Fig. 4.8. E.g., flow 1 is available at A at some point during Monday and is expected two days later at B. The only service suitable for this flow is Train 1, as it departs after the containers are available and arrives at B before the due time of flow 1. Alternatively, high priced trucks could be selected. Table 4.6 provides details on the services.

For this scenario, the optimal solution can be easily found by reasoning: Flow 1 and 2 must be fully assigned to Train 1 and Barge 1, respectively. Flow 3 is fully transported by trucks, as no suitable service is available. Then finally, flow 4 and 5 share service Train 2 up to its full capacity, however, the expected number of containers in flow 4 and 5 is 100 TEU, which is larger than the TEU-capacity for Train 2 (90 TEU), so some trucks must be used. The same solution is found by applying the learning method proposed in the previous section. The trees inference process was implemented using the CART implementation of the Statistics toolbox of MATLAB R2012a and the experiments were carried out using an AMD Athlon II X2 3.0 GHz processor. The resulting decision tree for scenario 1 is shown in Fig. 4.9: the optimal solution is mapped entirely by the tree. Fig. 4.9 also exemplifies three important characteristics of the method. Firstly, the tree can be used as decision support per incoming container transportation order. Hence, immediate feedback can be provided to the customer after processing the order. Secondly, the decision tree is presented in a comprehensible manner to human planners. If, because of some disruption, Barge 1 is late, the planner can make a manual decision on an alternative routing for affected containers. Thirdly, apart from the order information the human planner does not need anything else to apply the decision tree. Subsequently, he can manually check if the proposed allocation is suitable. No real-time information exchange is required.

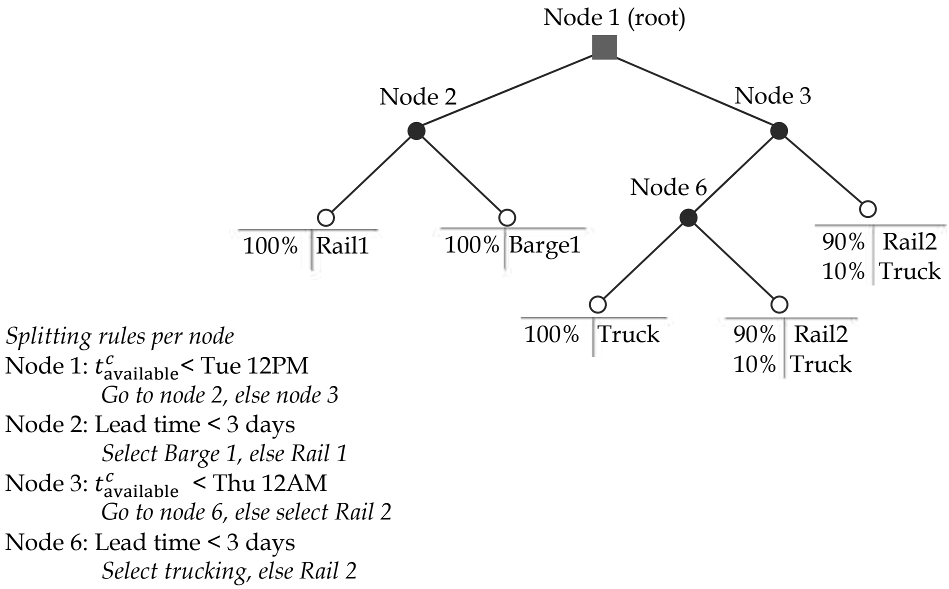


Fig. 4.9 Tree obtained from the learning method (for Scenario 1)

Table 4.7 Estimation of error types 0,1 and 2 for scenario 2 (50 test sets)

Service	c_b	$e_{b,0} \pm \sigma_{b,0}$	$e_{b,1} \pm \sigma_{b,1}$	$e_{b,2} \pm \sigma_{b,2}$	$e_b \pm \sigma_b$
Train 1	100	0±1.6	0±0	1±0.3	1±1.6
Train 2	100	0±1.2	-5±13.9	-2±15.7	-7±21.0
Barge	50	0±2.0	0±0	1±0.3	-1±2.1
Truck	285	0±2.6	5±13.9	1±15.3	6±20.8

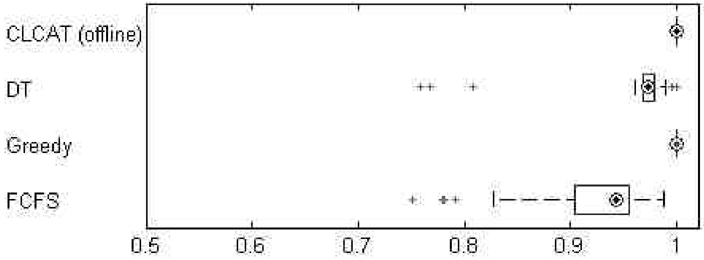
Scenario 2 is identical to Scenario 1, except for one property: we now assume that all containers of flow 4 have a weight of 25 t (all other flows remain 10 t per TEU). If the solution of Scenario 1 would be applied to this scenario, Train 2 will most likely not be used to its full TEU capacity as the weight limit is reached well before that. So, for this scenario the optimal solution is slightly different: all containers of flow 5 must be planned on Train 2, while the containers of flow 4 are planned on Train 2 if possible. The remaining containers of flow 4 must be transported by trucks. With this solution, Train 2 can be used to its full TEU capacity. The corresponding tree for Scenario 2 was generated in a similar way as in Scenario 1 (depicted in Appendix 4.C). Using (4.22), (4.25) and (4.28), we determine the expected error types α, β and γ for of applying this tree for scenario 2 in an online setting. Table 4.7 provides the expected error for the number of assigned containers to all four services including standard deviations. This results in a 95% confidence interval for the total error costs of [277, 1917] in excess of the estimated total cost of 36,807. This corresponds to a 95% confidence interval for the expected competitive ratio between 95.1% and 99.3% using the tree in Appendix 4.C.

4.5.2 Experiments

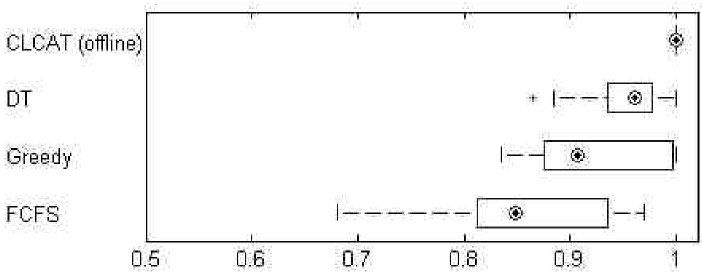
In order to test our method, we apply our DT heuristic to both scenarios described, as well as a greedy and a FCFS heuristic. In the greedy heuristic, every incoming order is assigned to the available slot with the lowest price, whereas the FCFS heuristic selects the earliest available slot. We compare using the competitive ratio. Hence, we compare three online heuristics and the optimal offline plan in a series of simulations.

We generate $N = 20$ new demand sets of a week for both scenarios. The sets for both scenarios are equal, except for the weight of flow 4: 25 t per TEU instead of 10 t. For each of these sets $P = 50$ optimal solutions are computed offline using (4.8) – (4.10) and the results are used by the learning algorithm to generate the decision tree. Subsequently, we similarly generated 50 test sets for both scenarios and applied the four methods. Fig. 4.10 shows boxplots of the competitive ratios of the 50 test sets for both scenarios. The box plots consists of the median in a box from the 25th to 75th percentile. The whiskers denote the minimum and maximum competitive ratio, truncated at a whisker length of 1.5 times the length of the box. Results exceeding the whiskers are plotted as outliers. In Scenario 1, both the DT heuristic and the greedy heuristic found the optimum in all 50 test sets. The FCFS heuristic performed much worse with a competitive ratio of 0.92. From Fig. 4.8 we can deduct that a FCFS heuristic will allocate orders of flow 2 to Train 1, and requires the use of trucks for flow 1 when Train 1 is full. This results in additional costs and a lower competitive ratio.

In Scenario 2, all heuristics have an average competitive ratio lower than 1. On average, the DT heuristic outperformed the other heuristics with a competitive ratio of 95.4% compared with 92.5% (greedy) and 86.1% (FCFS). A Wilcoxon signed-rank test was used to test the measured results for significance. This showed that the solution of the Greedy approach and the optimal solution in scenario 1 did not differ significantly. All other methods in scenario 1 and 2 resulted in significantly different competitive ratios. The results are in accordance with our expectations: with randomly distributed demand, the DT heuristic performs comparable with the low-level greedy heuristic as in Scenario 1. However, if the demand follows specific patterns, as in Scenario 2, the DT heuristic outperforms the other heuristics. Also, we see that the resulting competitive ratio is within the 95% confidence interval we have determined for the tree. This shows that our method performs as expected.



a) Boxplots of competitive ratios of 50 test sets (scenario 1)



b) Boxplots of competitive ratios of 50 test sets (scenario 2)

Fig. 4.10 Experiment results of case study

4.6 Conclusions

In this chapter we proposed a new approach for decision support using information of offline optimal solutions of container transportation problems in an online setting. With the proposed method, we aim to answer research question 4: "How can the results of the LCAT model be translated into a white box decision support method for human planning operators?". Three problems concerning existing optimisation methods are addressed with this new method:

- The method provides instant decisions for an incoming order, for direct feedback to the customer. The method does not use additional planning updates after the first allocation, allowing the customer to align the container transportation with the subsequent steps in his supply chain.
- The method does not need the level of automation and standardised communication protocols for information exchange that centralised planning optimisations methods need. In our method optimisation can be carried out offline for historic data.
- The method provides a white box decision tree representation of decision rules, useful and acceptable for human operators in logistics as indicated by Huysmans *et al*. (2011).

We have selected decision tree classifiers as the supervised learning method, as this method can use offline input, it is suitable for classifying into multiple classes and it allows for categorical attributes. A general four step method is proposed: historic data assembly, optimisation of historic sets, decision tree inference, applying the decision tree in real time. In this chapter, we have used a container transportation setting to develop these steps. The proposed method uses an offline optimal planning method (CLCAT) to get optimal results of historic transportation problems. The results are translated into a decision tree with the CART inference method. Also, we used a mathematical model for obtaining multiple offline optima with equivalent objective value as input for the learning algorithm. Finally, we proposed an analysis to assess the quality of the tree using three error types: the historic data error, the misclassification error and the over-capacity error. By determining the size of the errors, the quality of the obtained decision tree can be estimated before applying it in practice.

The proposed DSS framework shows that traditional manual planning can be improved without extensive IT development. The DT heuristic uses optimal solutions and translates that to real-time decisions. Managers responsible for operational planning should consider such an approach as an alternative for costly, time-consuming and/or infeasible system integration projects. In a case study we found that the DT approach could reduce inefficiency, as measured by the competitive ratio, by half, amounting to a 3% reduction of transportation costs compared with a Greedy approach. Secondly, our tools for the algorithm analysis in Section 4.4 will support management in assessing the expected benefits before applying it in practice. Specifically for the case of intermodal transportation providers, our case study results show that this approach improves the quality of the plan significantly in comparison with every day practices such as Greedy or first come, first serve.

With the decision tree method it is possible to exploit specific demand patterns in historic data. We showed that the proposed method was able to identify a specific pattern automatically, such as a categories of containers with specific weights.
Some limitations should be taken into account. Firstly, if no specific patterns exist in the historic demand, the method will give results comparable to alternative low-level heuristics, such as first come, first serve or a greedy heuristic. It is important to use the proposed algorithm analysis for each case, to identify whether significant improvement can be expected from using the DT approach in comparison with alternatives. Secondly, in this chapter, we used the DT heuristic to model the human operator using the decision tree. In practice, this method supports the human operator by indicating suitable services for an order, while the operator is still able to incorporate his specific knowledge into his decisions.
Finally, the applicability of the DT approach is restricted by the problem size of the historic optimisation problems. Although our method results in a real-time DSS with a low complexity, by carrying out the more complex optimisation of historic data and the DT inference process offline, the problem size may be restrictive if it is not feasible to find historic optima at all. In that case an alternative approach for finding good solutions for the historic data may be used.
Applying the DT approach is only relevant for situations in which multiple options exist. As described in Chapter 1, the network operator is often faced with a lack of planning freedom if all transportation orders have a fixed route, mode and departure time. Chapter 5 will focus on an optimal fare class mix that balances planning flexibility and revenue.

Appendix 4.A Results on optimal slot reservation in a characteristic intermodal problem

A.1 Optimal slot reservation

For a known demand pattern, the booking limit that results in the highest expectation of used slots can be determined. We assume independent distributions for the number of containers for destination B and C during a planning period, denoted by N_B and N_C, respectively. For each destination d and mode m, we consider the number of used slots (i.e. planned containers), denoted by S^{dm}. The optimal booking limit on the train for each destination can be found by minimising the total costs for all transports, denoted by c_T. The expected costs are a sum of the costs for all four transportation options:

$$\mathbb{E}(c_T) = c_{BR}\mathbb{E}(S^{BR}) + c_{BT}\mathbb{E}(S^{BT}) + c_{CR}\mathbb{E}(S^{CR}) + c_{CT}\mathbb{E}(S^{CT}), \tag{4.31}$$

where $\mathbb{E}$ is the expectancy operator. For a known booking limit K_{B} (and K_{C}), we can determine the expected number of slots used on each mode and each destination. First, we determine the expected slots used for transportation to destination B. The expected number of train slots used for destination B is:

$$\mathbb{E}(S^{BR}) = \mathbb{E}(N_B \mid N_B \le K_B)\mathbb{P}(N_B \le K_B) + K_B\mathbb{P}(N_B > K_B), \tag{4.32}$$

where $\mathbb{P}(\cdot)$ denotes the probability of event $\cdot$, and

$$\begin{aligned}\mathbb{E}(N_B \mid N_B \le K_B) &= \sum_{n\in\{1,2,\dots\}} n\frac{\mathbb{P}(N_B = n \cap n \le K_B)}{\mathbb{P}(N_B \le K_B)} \\ &= \sum_{n\in\{1,2,\dots,K_B\}} n\frac{\mathbb{P}(N_B = n)}{\mathbb{P}(N_B \le K_B)}.\end{aligned} \tag{4.33}$$

By substituting (4.33) in (4.32), we get the expected number of rail slots used for destination B:

$$\mathbb{E}(S^{BR}) = \sum_{n\in\{1,2,\dots,K_B\}} n\mathbb{P}(N_B = n) + K_B\mathbb{P}(N_B > K_B) \tag{4.34}$$

The expected number of units that is transported to destination B by truck is computed as

$$\begin{aligned}\mathbb{E}(S^{BT}) &= \mathbb{E}(N_B - K_B \mid N_B > K_B)\mathbb{P}(N_B > K_B) \\ &= \left(\mathbb{E}(N_B \mid N_B > K_B) - K_B\right)\mathbb{P}(N_B > K_B)\end{aligned} \tag{4.35}$$

with

$$\begin{aligned}&\mathbb{E}(N_B \mid N_B > K_B) \\ &\quad = \sum_{n\in\{1,2,\dots\}} n\frac{\mathbb{P}(N_B = n \cap n > K_B)}{\mathbb{P}(N_B > K_B)} = \sum_{n\in\{K_B+1,K_B+2,\dots\}} n\frac{\mathbb{P}(N_B = n)}{\mathbb{P}(N_B > K_B)}.\end{aligned} \tag{4.36}$$

Again, by substituting (4.36) in (4.35), we get the result:

$$\mathbb{E}(S^{BT}) = \sum_{n\in\{K_B+1,K_B+2,\dots\}} n\mathbb{P}(N_B = n) - K_B\mathbb{P}(N_B > K_B) \tag{4.37}$$

The results for the expected number of slots used for transportation towards destination C are determined in a similar way as (4.32) – (4.37):

$$\mathbb{E}(S^{CR}) = \sum_{n\in\{1,2,\dots,K_C\}} n\mathbb{P}(N_C = n) + K_C\mathbb{P}(N_C > K_C) \tag{4.38}$$

$$\mathbb{E}(S^{CT}) = \sum_{n\in\{K_C+1,K_C+2,\dots\}} n\mathbb{P}(N_C = n) - K_C\mathbb{P}(N_C > K_C) \tag{4.39}$$

Substituting (4.34) and (4.37) – (4.39) in (4.31) gives the expected costs for a given value of K_B (and $K_C = K - K_B$). The optimal booking limit for rail slots used for destination B, i.e., the optimal value of K_B is then determined by solving

$$K_B^* = \underset{K_B}{argmin}\, \mathbb{E}(c_T).$$

In the next section, we will determine the optimal value K_B^* for a uniform distribution of the demand to destinations B and C.

A.2 Optimal slot reservation for uniformly distributed demand

For known distributions of N_B and N_C, the value of K_B that results in the lowest expected costs can be computed. E.g., for uniform distributions $N_B \sim U(b_1, b_2), N_C \sim U(c_1, c_2)$, that allow a total demand exceeding the train capacity, i.e., $b_2 + c_2 > K$, the expected number of rail slots used for destination B can be estimated by rewriting (4.34) as

$$\mathbb{E}(S^{BR}) = (K_B - b_1)\frac{b_1 + K_B + 1}{2(b_2 - b_1)} + K_B \frac{b_2 - K_B}{b_2 - b_1}$$

$$\mathbb{E}(S^{BR}) = \frac{{K_B}^2 + {b_1}^2 - 2K_B b_2 + b_1 - K_B}{2(b_1 - b_2)}. \tag{4.40}$$

The expected number of units transported to destination B by truck can be determined by rewriting (4.37) as

$$\mathbb{E}(S^{BT}) = (b_2 - K_B)\frac{b_2 + K_B + 1}{2(b_2 - b_1)} - K_B \frac{b_2 - K_B}{b_2 - b_1}$$

$$\mathbb{E}(S^{BT}) = -\frac{K_B^2 + b_2^2 - 2K_B b_2 + b_2 - K_B}{2(b_1 - b_2)}. \tag{4.41}$$

Similarly, we can rewrite (4.38) and (4.39) as

$$\mathbb{E}(S^{CR}) = \frac{{K_C}^2 + {c_1}^2 - 2K_C c_2 + c_1 - K_C}{2(c_1 - c_2)}, \tag{4.42}$$

$$\mathbb{E}(S^{CT}) = -\frac{K_C^2 + c_2^2 - 2K_C c_2 + c_2 - K_C}{2(c_1 - c_2)}. \tag{4.43}$$

Combining and rewriting (4.31), (4.40) – (4.43) gives

$$\mathbb{E}(c_T) = c_{BR}\mathbb{E}(S^{BR}) + c_{CR}\mathbb{E}(S^{CR}) + c_{BT}\mathbb{E}(S^{BT}) + \quad c_{CT}\mathbb{E}(S^{CT}). \tag{4.44}$$

By using $K_C = K - K_B$ and finding the minimum of (4.44), we can find the analytical optimal value for $K_{\mathbf{B}}$:

$$K_B^* = \frac{\left(c_2 - K + \frac{1}{2}\right)(c_{CR} - c_{CT})(b_1 - b_2) + \left(b_2 + \frac{1}{2}\right)(c_{BR} - c_{BT})(c_1 - c_2)}{(b_1 - b_2)(c_{CR} - c_{CT}) + (c_1 - c_2)(c_{BR} - c_{BT})} \quad (4.45)$$

The optimal value K_B^* is the upper limit for slots that can be used for transporting containers to destination B by rail. Next, we will compare the result of the proposed decision tree method with the analytical optimum.

Appendix 4.B Theoretical bound of the Greedy algorithm

In this section we will consider the quality of the Greedy algorithm. Reusing an approach by Van Hentenryck and Bent (2009), we consider this from a profit persepective. Considering a profit per slot, we provide the proof that the Greedy algorithm is 2-competitive. That is, the total profit of the optimal solution is never more than twice the profit of the solution of the Greedy algorithm.

Consider instance ξ of the arrival process of containers. Let $\mathcal{O}(\xi)$ denote the series of optimal allocations of the arriving containers in ξ, and $w\big(\mathcal{O}(\xi)\big)$ the total revenue of the optimal solution. We denote the generic OAA algorithm by $\mathcal{A}(\xi)$, and the optimal policy for all states by $\pi^*(s_0)$. Van Hentenryck and Bent (2009) show that

$$\mathbb{E}_{\xi \epsilon \mathcal{I}}\, \omega\big(\mathcal{A}(\xi)\big) \leq \mathbb{E} \;\; \pi^*(s_0) \leq \mathbb{E}_{\xi \epsilon \mathcal{I}}\, \omega\big(\mathcal{O}(\xi)\big),$$

denoting that the expected profit of the optimal online algorithm on the expected future inputs is less than or equal to the optimal policy which is less than or equal to the a posteriori optimal solution. Without losing generality we assume that each container c arrives alone and the network operator must make a decision directly. The set of arriving containers is denoted by O. The ith element is the ith container to arrive. For simplicity, the time of arrival t_i is denoted by $t_i = i$ and the container arriving at that time by c_i. All incoming containers can be transported by available inland services. Each inland service q has a departure time t_q which restricts the set of containers that can be transported by that service, denoted by $O_q\colon \{c \in O | t_c \geq t_q\}$. Each service q has n_q slots available. Without losing generality we only consider slots in the remainder of this section. For each slot $s \in S$ we have a set of feasible containers $O_s\colon \{c \in O | t_c \geq t_s\}$, if a slot s is used, a profit per slot of f_s applies. A solution to the corridor transportation problem is denoted by x_{cs}, that is equal to 1 of container c is assigned to slot s or 0 otherwise. If a container is not assigned to a slot $s \in S$, it is assigned to the dummy set $\perp$, with unlimited capacity and zero profit. The optimal solution $\mathcal{O}(\xi)$ is the solution that transports all containers $c \in O$ with maximum profit. The series of slots used for containers 1 to t in the optimal solution is denoted by γ^*. The total profit of these slots is denoted by $\omega(\gamma^*)$. The series of used slots in the solution of the OAA algorithm is denoted by $\gamma^{\mathcal{A}}$ with profit $\omega(\gamma^{\mathcal{A}})$. Then set U is defined as the set of slots included in the optimal solution but not in the solution of the online algorithm:

$$U = \{s \in \gamma^* | s \notin \gamma^{\mathcal{A}}\}$$

And similarly:

$$R \ = \{s \in \gamma^{\mathcal{A}} | s \notin \gamma^*\}$$

Let n_U and n_R denote the number of slots in U and R, respectively. Note that $n_U = n_R$ as the number of slots in $\gamma^{\mathcal{A}}$ and γ^* is equal to the number of containers $c \in O$.

For any algorithm $\mathcal{A}$, by definition of optimality, the following holds:

$$\omega(\gamma^*) \geq \omega(\gamma^{\mathcal{A}}).$$

And, because all slots of solution γ^* are included in the combined set of $\gamma^{\mathcal{A}}$ and U it holds that:

$$\omega(\gamma^*) \leq \omega(\gamma^{\mathcal{A}}) + \omega(U).$$

We consider the online greedy algorithm $\mathcal{G}$, which selects the feasible slot with maximum profit at each container arrival c_i. The sequence of slots selected by algorithm $\mathcal{G}$ is denoted by $\gamma^{\mathcal{G}}$, and $\gamma_i^{\mathcal{G}}$ denotes the ith slot of this sequence. Now, consider a slot $p \in U$ that was assigned to container c_i in the optimal solution at time i. Since $p \notin \gamma^{\mathcal{A}}$ slot p was also available for algorithm $\mathcal{G}$ at time i, hence it follows that $\omega\left(\gamma_i^{\mathcal{G}}\right) \geq \omega(p)$. Hence,

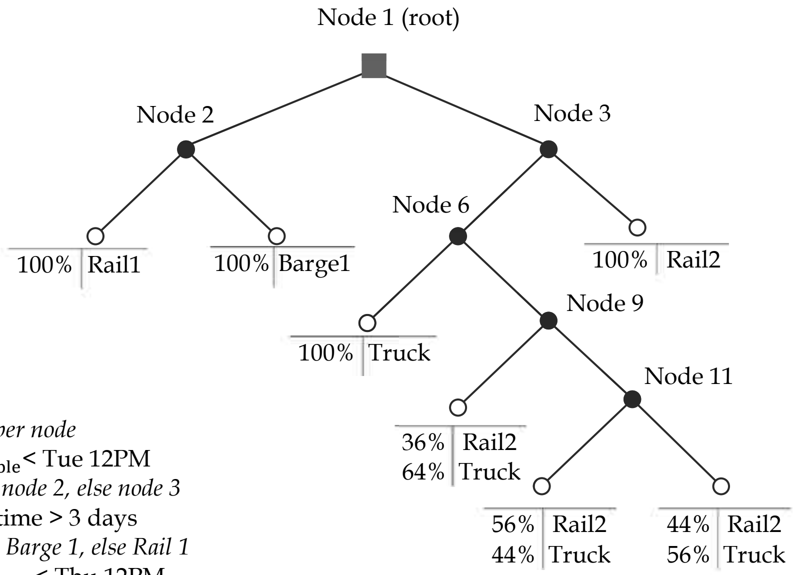
$$\omega(U) = \sum_{p \in U} \omega(p) \leq \omega(\gamma^{\mathcal{G}}).$$

From this we get:

$$\omega(\gamma^*) \leq \omega(\gamma^{\mathcal{A}}) + \omega(U) \leq 2\omega(\gamma^{\mathcal{G}}).$$

Hence, the Greedy algorithm is 2-competitive as the profit of the optimal solution is at maximum twice the profit of the solution obtained from the Greedy algorithm.

Appendix 4.C Decision tree for case study scenario 2



Splitting rules per node

Node 1: $t^{c}_{\text{available}}$ < Tue 12PM
Go to node 2, else node 3

Node 2: Lead time > 3 days
Select Barge 1, else Rail 1

Node 3: $t^{c}_{\text{available}}$ < Thu 12PM
Go to node 6, else select Rail 2

Node 6: Weight < 17.5 t
Select trucking, else go to node 9

Node 9: $t^{c}_{\text{available}}$ < Wed 6AM
Select trucking, else go to node 11

Node 11: $t^{c}_{\text{available}}$ < Wed 12PM
Select Rail 2, else trucking

5 The Cargo Fare Class Mix problem for an intermodal corridor

In Chapters 2 – 4 the optimal transportation planning in intermodal networks was considered. From this chapter onwards, we consider problem of optimising the intermodal service portfolio in such a network. This chapter first aims to answer research question 5: "What is the value of planning flexibility for synchromodal networks?", i.e. we study to what extent it is important to develop a balanced portfolio and transportation plan for optimal operation of synchromodal networks. Synchromodality aims to overcome the limited flexibility in intermodal planning by a new product structure based on differentiation in price and lead time. Each product is considered as a fare class with a related service level, allowing to target different customer segments and to use revenue management for maximising revenue. However, higher priced fare classes come with tighter planning restrictions and must be carefully balanced with lower priced fare classes to match available capacity and optimise network utilisation. We propose the Cargo Fare Class Mix problem to set limits for each fare class at a tactical level, such that the expected revenue is maximised, considering the available capacity at the operational level. The main purpose of the chapter is to show that using a limit on each fare class increases revenue and reliability, thereby outperforming existing fare class mix policies, such as Littlewood. After the introduction in Section 5.1, the chapter is structured as follows. Section 5.2 provides an overview of existing literature on intermodal networks and revenue management in freight applications. Section 5.3 proposes a classification structure for different variants of the CFCM problem and describes the corridor case. Section 5.4 proposes a solution method, in answer to research question 6: "How can the optimal fare class mix for a synchromodal corridor be found?". Section 5.5 presents a case study and results, showing the potential gains for this case. Section 5.6 concludes this chapter with an overview and outlook to future research.[5]

Keywords: *Intermodal planning, synchromodal planning, container transportation, revenue management, fare class sizes.*

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[5] This chapter is based on the following publication with small modifications: Van Riessen, B., Negenborn, R. R. and Dekker, R. (2017). The Cargo Fare Class Mix problem for an intermodal corridor: revenue management in synchromodal container transportation. *Flexible Services and Manufacturing Journal, 29*(3-4), 634-658. The final publication is available via https://doi.org/10.1007/s10696-017-9285-7.

5.1 Introduction

Section 1.1 highlighted the motivation for renewed attention to intermodal container transportation: optimisation is required to meet the modal split targets in deep-sea ports and to satisfy the need for a more integrated approach to hinterland transportation. Available network optimisation models mostly assume that all transportation orders can be scheduled with full flexibility, considering operational constraints and time windows. However, integral network optimisation models have limited value as long as no integral coordination is possible. The need for a differentiated product portfolio was described in Chapter 1 (Van Riessen *et al.*, 2015-c). Ypsilantis (2016, pp. 23–46) showed that container dwell times at terminals largely depend on shipper's actions, representing a varying need of urgency of further transporting containers. This relates to a high variation in the number of transports from day to day, as shippers generally order for transportation with a fixed mode, route and time. Such orders do not give the operator of an inland transportation network any flexibility for integral optimisation. Some flexibility, allowing the network operator to choose from multiple options per order, could be used to optimise the network transportation plan. Therefore, the network operator has an incentive to introduce a range of transportation services with varying levels of flexibility.

Such new product ranges have been studied at European Gateway Services (EGS) by Lin (2014) and independently by Wanders (2014). Their work is related to the development of differentiated product portfolios in practical applications in North West Europe, such as in the hinterland transportation network of EGS (see European Gateway Services, n.d.). EGS is considering to offer a differentiated portfolio to the market, starting with a single corridor in its network. Their goal is to increase both utilisation of inland trains and vessels, and to increase reliability of container transports arriving on time. In this chapter, we study their case to find the benefit of a new set of two products with a different degree of flexibility for a single corridor of container hinterland transportation. We compare corridors, based on differences in demand and price levels to support EGS in deciding which corridor is most promising. The new portfolio consists of two fare classes with varying delivery lead times and prices. This is a problem similar to the fare mix problem in aviation: how much available capacity must be reserved for each fare class? In a traditional capacity allocation model, typically the inferior fare class is limited, to reserve space for the superior fare class with high revenue (such as Littlewood 1972/2005). In the EGS case however, long-term commitments to customers with repetitive demand are made, and all incoming demand for a fare class within the commitment must be transported. To achieve an optimal balance between both fare classes, a limit for each fare class must be determined.

The main purpose of this chapter is to show how offering two fare classes can significantly increase revenue compared to alternative approaches. Also, we show that including limits for each fare class is not only necessary to prevent high costs of trucking excess cargo, it is even beneficial in terms of expected revenue compared to alternatives. We define these problems as the Cargo Fare Class Mix (CFCM) problem. This class of problems is based on differentiated service portfolios in intermodal networks, but it is also relevant for applications in parcel delivery services and inventory management in online retail. We provide a framework to distinguish between different variants of the problem and we provide analytical solution methods for a single corridor. We propose a model and exact solution method for the special case of the CFCM problem with two products in an application with 1 intermodal route, multiple destinations and a horizon of 2 delivery periods. We demonstrate the model and solution method in a case study of many different parameter settings comparing different hinterland transportation corridors. This case study supports European Gateway Services in introducing such a differentiated portfolio. Finally, we show by numerical experiments that the increase in expected revenue by considering a longer delivery horizon is limited.

5.2 Literature overview

5.2.1 Intermodal networks

In Section 1.1, intermodal transportation was introduced. Generally, container hinterland transportation is organised per corridor between a deep-sea terminal and a hinterland destination, although integral network operators are arising, such as EGS (Section 1.2). E.g., the approach towards offering hinterland transportation services is changing. Franc and Van der Horst (2010) studied the motivation of shipping lines and terminals for the integration of the hinterland in their service. In Chapter 1 (Van Riessen, *et al.*, 2015-c), we described that synchromodality can only really provide an advantage if the intermodal planning problem is considered in conjunction with the product portfolio offered to customers. Related to this, some researchers have studied the pricing problem of intermodal inland services. Ypsilantis (2016, pp. 47-82) proposed a model for jointly determining prices for transportation products and designing the transportation network. Li *et al.* (2015) study the problem of pricing a differentiated portfolio in a cargo network based on expected realised costs, considering the network state. These works have not looked into the optimal fare class mix of offered transportation services yet, though.

5.2.2 Revenue Management in Freight Transportation

The concept of different service propositions in transportation is very similar to the concept of different fare classes for the same flight in aviation. Barnhart *et al.* (2003) give an overview of operations research in airline revenue management. The primary objective of airline revenue management models is to determine the optimal fare mix: how many seats of each booking class should be available, given demand forecasts and limited total number of seats? Some studies on revenue management in freight transportation focus on the online policy: whether to accept or reject an incoming order. Pak and Dekker (2004) propose a method for judging sequentially arriving cargo bookings based on expected revenues. If the direct revenue of a booking exceeds the decrease in expected future revenue, the order is accepted. Bilegan *et al. (*2013) apply a similar approach on rail freight application. In their approach the decision of accepting or rejecting an arriving transport order is based on the difference in expected revenue with and without that order. These studies assume that accepting or rejecting an incoming order can be done at the operational level. Other studies acknowledge that in freight transportation orders are often agreed on in long-term contracts. Because of this, a per-order approach to revenue management is not sufficient. The traditional revenue management approach is to reserve capacity at the tactical level for a superior service, while the remainder of the capacity is offered at the operational level (Chopra and Meindl, 2014). Liu and Yang (2015) develop a two stage stochastic model for this problem: in the first stage, all long-term contracts are accommodated; in the second stage a dynamic pricing model is applied for offering the remaining slots. In all these studies, it is assumed that the planning characteristics of all orders are identical, i.e. an order of any service can be carried out with the same transportation options.

To our knowledge, no existing studies have looked into the Cargo Fare Class Mix of differentiated services with different planning characteristics. In this study we aim to determine the optimal cargo fare mix for a given service portfolio with difference in both price and lead-time. This setting introduces a new issue to the fare mix problem, as the operator must balance between higher priced service with few transportation options and lower priced services with more transport options (i.e. different modes, routes and times). Hence, a lower priced service allows more flexibility in the operational plan and is not simply inferior to a higher priced service. As transportation orders for each service type are agreed on in long-term contracts, an optimal mix between the offered services must be determined in advance, at the tactical level. Besides, all demand accepted at the tactical level must be transported; if intermodal capacity is insufficient, a high cost truck transport is needed for the excess demand. Hence, we must determine fare class limits for all services, not only for the lower priced service.

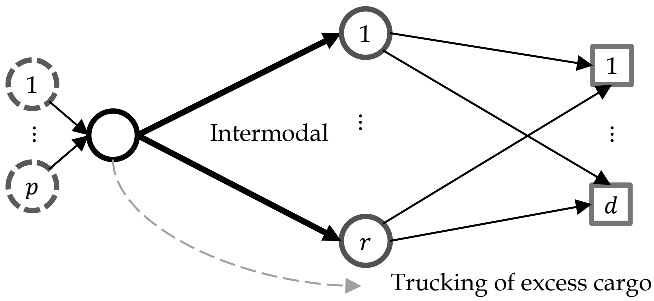
5.3 Cargo Fare Class Mix Problem

5.3.1 Practical motivation

In the CFCM problem, as we define it, the transportation provider's goal is to maximise revenue by finding the optimal balance in offered transportation services. The transportation provider runs scheduled intermodal connections with a fixed daily capacity. The transportation provider offers a range of two or more services, each service denotes a *fare class*. A fare class is characterised by a specific price and specific lead time, ranging from a high price fast service to a low price slow service. For instance, the fast service is higher priced per container, but must be transported immediately; whereas the slow service is lower priced, but has a longer delivery lead time and allows optimising the capacity utilisation, because demand varies over the days. It is assumed that using the available capacity does not invoke additional costs. This corresponds to a company operating its own trains or vessels. As a lower priced service offers more planning flexibility, it is not necessarily inferior to a higher priced product. All accepted demand must be transported, because of commitments to the customer and if the intermodal capacity is not enough, expensive trucking is used. Hence, an optimal balance requires a booking limit for *each* fare class. As discussed in the literature overview (Section 5.2), this is different from traditional cargo revenue management, in which only one (inferior) fare class is limited. Another distinct difference with existing literature is that accepting or rejecting incoming orders cannot be decided on during the operational phase, because long-term commitments are provided in advance and customers typically have a repeating demand. To represent long-term commitments in our model, we consider daily booking limits, determined on a tactical level (before the operational phase). With fixed booking limits for each service, the operator can optimally use his fixed transportation capacity to target different segments allowing revenue maximisation. We will show that it is better to allow overbooking, or in other words, the sum of the booking limits may exceed the daily intermodal capacity, as for the lower class we have the option to transport it later. The general CFCM problem must accommodate fare classes for transportation services to multiple inland destinations considering a transportation network. In this chapter, we demonstrate the benefit of booking limits for each fare class on a single intermodal corridor, with one intermodal route, e.g. a train connection between a deep-sea terminal (like Rotterdam) and an inland terminal (such as Venlo). In the next sections, we first present a general modelling framework for the CFCM problem, after which we define the specific model for such a single corridor for our study.

5.3.2 Modelling framework

The CFCM problem for inland transportation has three dimensions. The tactical planning problem considers multiple routes r and destinations d for transporting all cargo. Because the intermodal transportation problem is mostly related to one deep-sea port, we do not distinguish between multiple origins. Transportation orders arrive in multiple fare classes; the number of fare classes p is the third dimension. We use the 3 dimensions to classify the problem type of the CFCM problem as CFCM (r, d, p), as shown schematically in Fig. 5.1. Each fare class is associated with a maximum transportation time. In the tactical problem we define booking limits for each class. In the repetitive operational problem, incoming transportation requests for a fare class are accepted up to the booking limit for that fare class. It is assumed that all orders arrive one by one. Then, the operational transportation plan for all accepted orders is created, assigning each order to a route towards the destination or postponing the order to the next period. After executing the transportation plan, we continue with the next period. The goal of the operational transportation plan is to minimise costs within capacity restrictions and to transport all accepted orders within the time limits related to the fare class ordered by the customer. In this chapter, we study the CFCM problem of a single corridor, providing insights to be used as a building block for future extensions.

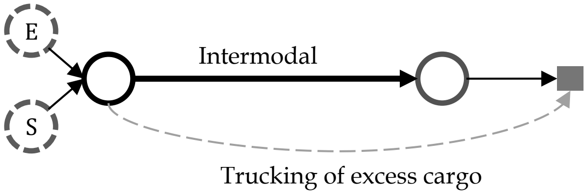


Cargo Fare Class Mix problem with r intermodal routes, d destinations and p fare classes

Fig. 5.1 CFCM (r,d,p)

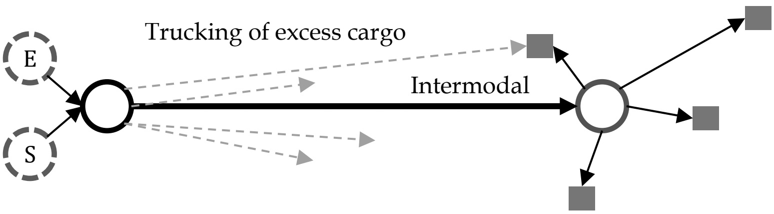
5.3.3 CFCM problem for an intermodal corridor

To show the benefits of the CFCM model with limits for each fare class, we consider a single intermodal corridor with two products in this chapter. Such a case is representative of a typical intermodal hinterland corridor between a deep-sea terminal and a hinterland terminal. Inland transportation providers such as EGS are currently considering to offer a Standard and Express service types on such a corridor but do not have insight in the optimal balance yet. First, we will focus on daily booking limits for two services for a single route, single destination case, and derive a solution for the CFCM (1,1,2) model (Fig. 5.2). Subsequently, we consider the case of two fare classes for a single route, with multiple destinations, the CFCM (1,d,2) model (Fig. 5.3). In the latter case, the costs of using a truck to transport excess demand varies for different destinations. With some realistic assumptions, we show that the CFCM (1,1,2) model can be applied to CFCM (1,d,2) as well. For this, we assume that using the intermodal connections is beneficial for all destinations considered, compared with the alternative, direct trucking. Also, we assume that the difference in distance for the various destinations is relatively small, compared to the total distance and that the amount of cargo is distributed over all destinations.



Cargo Fare Class Mix problem with 1 route, 1 destination and 2 fare classes

Fig. 5.2 CFCM (1,1,2)



Cargo Fare Class Mix problem with 1 route, d destination and 2 fare classes

Fig. 5.3 CFCM (1,d,2)

We derive an analytical model for the CFCM (1,1,2) problem with daily booking limits. This model's focus is on optimising revenue from 2 product types, Express and Standard, for a fixed capacity C on one route to one destination. In case of Express transportation, the container is transported within 1 day. For Standard transportation, the container is transported within 2 days. At the tactical level, the available demand (not restricted by booking limits) of daily transportation requests is assumed to be characterised by discrete distributions $N_{\mathrm{E}}(t)$ and $N_{\mathrm{S}}(t)$. It is assumed that the demand on consecutive days for a fare class follows identical, independent distributions. Also, we assume $N_{\mathrm{E}}(t)$ and $N_{\mathrm{S}}(t)$ are independent and having different distributions.

$$N_E(t) \sim p_E(k) = P(N_E = k), k = 0,1,2, \ldots,$$

$$N_S(t) \sim p_S(k) = P(N_S = k), k = 0,1,2, \ldots,$$

where $p_{\mathcal{F}}(k)$ denotes the probability of receiving k transportation requests for fare class $\mathcal{F}$ on a day. Transportation requests on a daily basis for a fare class are accepted until the booking limit for that fare class is reached, the remaining demand is assumed lost. For carrying out the transportation, the operator has a daily transportation capacity C that can be used for service requests of type E and/or S. Excess demand that cannot be transported in time by daily capacity C must be transported by using an (expensive) truck move. This must be avoided, so in order to prevent accepting too many requests, the operator only accepts demand up to the daily booking limits for both request types: L_{E} and L_{S}. With this, the distributions of *daily accepted demand* become:

$$D_E(t) = min(N_E(t), L_E)\,, D_S(t) = min(N_S(t), L_S) \tag{5.1}$$

$$P(D_E(t) = k) = p_E(k), k = 0,1,2, \dots, L_E - 1 \tag{5.2}$$

$$P(D_E(t) = L_E) = 1 - \sum_{k=0}^{L_E-1} p_E(k)$$

And, likewise,

$$P(D_S(t) = k) = p_S(k), k = 0,1,2, \dots, L_S - 1 \tag{5.3}$$

$$P(D_S(t) = L_S) = 1 - \sum_{k=0}^{L_S-1} p_S(k)$$

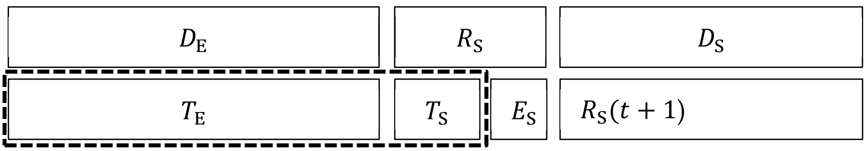
In the remainder, the indicator (t) is omitted from the notation for simplicity, unless specifically required for clarity. It is assumed that the accepted demand of type E is given priority, as, by agreement, the orders of type S can be postponed to the next day. It makes no sense to accept more Express orders than the capacity limit, because the amount of orders exceeding C cannot be transported with the available capacity, i.e. $L_{\mathrm{E}} \leq C$. Hence, every day, all accepted demand of type E is transported, denoted by T_{E}. The remaining capacity is used for transporting accepted demand of type S; the transported amount of type S is denoted by T_{S}. On any day, the stack of orders to be transported consists of three types: today's accepted demand of type E (D_{E}), the remainder of yesterday's demand of type S (R_{S}) and today's demand of type S (D_{S}). The demand D_{S} of today that is not transported, is considered on the next day, denoted as $R_{\mathrm{S}}(t+1)$. If the postponed demand $R_{\mathrm{S}}(t+1)$ cannot be transported the day after, it is considered as excess demand (E_{S}). Three situations can occur:

1. the available capacity is sufficient for transporting D_E and part of R_{S} (see Fig. 5.4a), the remainder of R_{S} is in excess of capacity C and must be transported alternatively (E_{S});
2. the available capacity is sufficient for transporting D_E, R_{S} and part of D_{S} (see Fig. 5.4b);
3. the available capacity is sufficient for transporting all demand (see Fig. 5.4c).

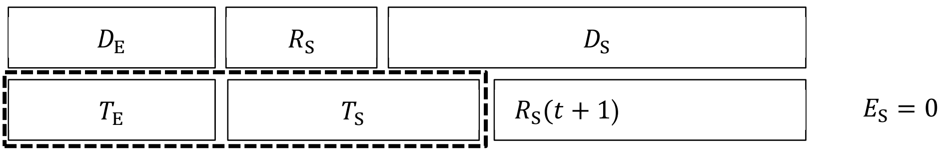
The revenue maximising problem is to select booking limits that maximise the total revenue J from the accepted demand, with fares per accepted request f_E and f_S respectively, while considering a penalty of size p for all excess demand. This penalty can be considered as the costs for an emergency delivery outside of the system's capacity C, e.g. by truck:

$$\max_{L_E, L_S} J = f_E \mathbb{E}(D_E) + f_S \mathbb{E}(D_S) - p\mathbb{E}(E_S). \tag{5.4}$$

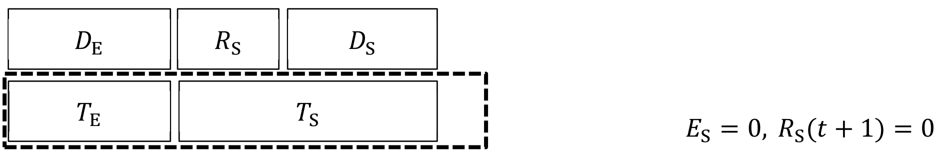
The cost term for excess demand distinguishes this model from existing problems, as transportation of the accepted Standard product is obligatory as well. The expected excess $\mathbb{E}(E_S)$ depends on the booking limits L_E, L_S and in the next section we will derive the formulation for this quantity.



a) Result situation 1: Transported, excess and remaining



b) Result situation 2: Transported and remaining



c) Result situation 3: All demand transported

Fig. 5.4 Transportation plan based on fixed capacity (3 situations)

5.4 Solution method for the CFCM problem for an intermodal corridor

For solving (5.4), we first derive a set of equations for the expected value of D_E, D_S and E_S as a function of capacity C and the booking limits L_E and L_S. These expressions are then used to find the booking limits L_E and L_S that result in maximum revenue J.
The distributions of accepted demand D_E, D_S depend according to (5.1) only on the independent demand patterns N_E and N_S (assumed to be known) and on the chosen limits L_E and L_S. Formulations for $\mathbb{E}(D_E)$ and $\mathbb{E}(D_S)$ follow from (5.1) − (5.3):

$$\mathbb{E}(D_E) = \sum_{k=0}^{L_E} kP(D_E = k) = \sum_{k=1}^{L_E - 1} kp_E(k) + L_E\left(1 - \sum_{k=0}^{L_E - 1} p_E(k)\right) \tag{5.5}$$

$$\mathbb{E}(D_S) = \sum_{k=1}^{L_S - 1} kp_S(k) + L_S\left(1 - \sum_{l=0}^{L_S - 1} p_S(k)\right). \tag{5.6}$$

An explicit formulation for the excess demand E_S is not straightforward, as it depends on D_E and R_S, of which the latter depends on the situation of the day before. In order to find an expression for E_S, we introduce a Markov Chain for the expected value of R_S in Section 5.4.1. Using this Markov Chain, the expected revenue J can be determined for given fixed booking limits. In Section 5.4.2 we introduce a formulation for the revenue maximisation problem considering variable booking limits.

5.4.1 Markov Chain for the expected excess demand

Considering given booking limits and demand patterns, the arriving transportation requests per day are known and provided by (5.1) − (5.3). The state of the transportation system depends on the number of orders that are left over from the day before, R_S. This process has the Markov property: for a given day t, the state is fully described by $R_S(t)$, the number of Standard service containers remaining from day $t - 1$, and independent from previous states. The Markov state is denoted as $R_S(t)$, or in short R_S^t. We are looking for an expression of the expected excess demand $E_S(t)$ that is not transported. Using Fig. 5.4, we can derive the following equation:

$$E_S(t) = max(R_S^t + D_E(t) - C, 0)$$

Considering the Markov state R_S^t we can formulate the probability distribution of the excess demand:

$$P(E_S = m) = \begin{cases} P(D_E \le C - R_S^t) & m = 0 \\ P(D_E = C + m - R_S^t) & m > 0. \end{cases} \tag{5.7}$$

To find the probability of excess demand, we take the sum over all $m > 0$:

$$P(E_S > 0) = P(D_E > C - R_S^t). \tag{5.8}$$

In order to determine the Markov transition probabilities, we need to determine the probability distribution of the remaining demand for the next day, R_S^{t+1}, given the remaining demand of the current day R_S^t:

$$P(R_S^{t+1} = j | R_S^t = i). \tag{5.9}$$

We will denote this as $p_{R_S}(i,j)$. We distinguish between the situation with excess demand ($E_S > 0$) and without excess demand ($E_S = 0$). The transition probabilities are then provided by

$$p_{R_S}(i,j) = P(R_S^{t+1} = j, E_S > 0 | R_S^t = i) + P(R_S^{t+1} = j, E_S = 0 | R_S^t = i). \tag{5.10}$$

For the case in which excess demand occurs ($E_S > 0$), all new Standard demand cannot be transported (see Fig. 5.4a). Hence, R_S^{t+1} will be equal to the realised Standard demand of today:

$$p_{R_S}(i,j) = P(D_S = j) \qquad E_S > 0 \tag{5.11}$$

Combining this with the probability of excess demand occurring (5.8), we obtain:

$$P(R_S^{t+1} = j, E_S > 0 | R_S^t = i) = P(D_S = j)\, P(D_E > C - i) \tag{5.12}$$

For the case in which no excess demand occurs ($E_S = 0$), we distinguish between transporting all demand (Fig. 5.4c, $R_S^{t+1} = 0$) or leaving some demand for the next day (Fig. 5.4b, $R_S^{t+1} > 0$):

$$p_{R_S}(i,j) = \begin{cases} P(D_E + D_S + R_S^t \le C) & j = 0 \\ P(D_E + D_S + R_S^t - C = j) & j > 0 \end{cases} \qquad E_S = 0 \tag{5.13}$$

We consider the following. As no excess demand occurs ($E_S = 0$), all of R_S^t is transported. This leaves a number of slots S for transporting D_S. If $S \ge D_S$, all demand is transported ($R_S^{t+1} = 0$), otherwise we have:

$$S = D_S - R_S^{t+1} \tag{5.14}$$

with probability distribution:

$$P(S = s) = P(D_E + R_S^t = C - s), \tag{5.15}$$

where $0 \le s \le C - R_S^t$. For all cases in which (5.15) is nonzero, we have $D_E = C - R_S^t - s \le C - R_S^t$. From (5.7), it follows that in these cases no excess demand occurs ($E_S = 0$).

Using the expressions (5.14) − (5.15) we can rewrite (5.13) as:

$$P(R_S^{t+1} = j, E_S = 0 | R_S^t = i) = \begin{cases} \sum_{s=0}^{C-i} P(D_E + i = C - s) P(D_S \le s) & j = 0 \\ \sum_{s=0}^{C-i} P(D_E + i = C - s) P(D_S = s + j) & j > 0 \end{cases} \tag{5.16}$$

Substituting equations (5.12) and (5.16) in (5.10), we get the general transition probabilities:

$$p_S(i,j) = \begin{cases} P(D_S = 0) P(D_E > C - i) + \sum_{s=0}^{C-i} P(D_E + i = C - s) P(D_S \le s) & j = 0 \\ P(D_S = j) P(D_E > C - i) + \sum_{s=0}^{C-i} P(D_E + i = C - s) P(D_S = s + j) & j > 0 \end{cases} \tag{5.17}$$

We denote the steady-state distribution of the Markov state R_S as $\pi(j) = P(R_S^\infty = j)$, i.e. $\pi(j)$ denotes on a day in the long run the probability of postponing j transportation orders to the next day. To find the distribution of $\pi(j)$, we need to find a solution to the Markov equilibrium equations, as in Kelly (1975):

$$\pi_j = \sum_i \pi_i \, p_S(i,j), \tag{5.18}$$

$$\sum_i \pi_i = 1, \tag{5.19}$$

with $p_S(i,j)$ as in (5.17). For given booking limits, this can be solved by finding a feasible solution to the set of linear equations (5.18) − (5.19).

Using the steady state expression π_j for the distribution of R_S in the expression for the distribution of E_S from (5.7), we can find the expected value of the excess demand $\mathbb{E}(E_S)$:

$$P(E_S = m) = \begin{cases} \sum_{q=0}^{L_S} P(D_E \le C - q) \pi_q & m = 0 \\ \sum_{q=0}^{L_S} P(D_E = C + m - q) \pi_q & m > 0 \end{cases}$$

$$\begin{aligned}\mathbb{E}(E_S) = \sum_{m=0}^{L_S} mP(E_S = m) = \sum_{m=1}^{L_S} mP(E_S = m)\\ = \sum_{m=1}^{L_S} m \sum_{q=0}^{L_S} P(D_E = C + m - q)\pi_q\end{aligned} \tag{5.20}$$

Now, the expected revenue J for fixed booking limits L_E and L_S can be determined using the expressions for the expected demand (5.5) $-$ (5.6) and expected excess demand (5.20) in equation (5.4). A method to find the optimal booking limits of the CFCM (1,1,2) problem is provided in the next section.

5.4.2 CFCM (1,1,2) model

In Section 5.4.1 we derived the expression to find the expected revenue for given booking limits. In this section, we repeat all assumptions and aggregate all expressions to formulate the CFCM (1,1,2) model. The CFCM (1,1,2) model aims to maximise the expected revenue J of two different transportation services that must be transported on a single corridor with fixed capacity C to a single destination. Accepted orders for the Express service must be transported on day 1, accepted orders for the Standard service must be transported on day 1 or 2. The demand for both products is provided as $p_E(k) = P(N_E = k)$ and $p_S(l) = P(N_S = l)$, with revenue per order f_E and f_S, respectively. Accepting an order, but transporting it by truck instead of intermodally, is penalised with penalty p. This can be considered the cost of using a truck for transportation. The main decision variables are the limits L_E and L_S. Orders are automatically accepted until these limits, and rejected after that. The model is based on a Markov Chain described in the previous section. The Markov equilibrium is denoted by dependent variable π_q, denoting the probability that q Standard orders on a day are postponed to the next day. The model is defined by maximising objective (5.4), with the expressions for the expected demand (5.5) $-$ (5.6) and expected excess demand (5.20), subject to the Markov equilibrium equations (5.19) $-$ (5.21). The model is valid for any empirical or theoretical distributions of the (discrete) demands N_E, N_S in a transportation corridor with a fixed daily capacity C.

5.4.3 CFCM (1,d,2) model and solution method

The derived equations for the CFCM (1,1,2) model largely hold for the CFCM (1,d,2) problem as well: the transportation provider offers an Express and a Standard service towards all destinations. The only difference is that the excess penalty (the cost of transporting by truck) differs for each destination. Assuming that transportation requests are handled in the order of arrival and that the delayed

Standard product are not prioritised based on the excess penalty, the probability distribution for the excess penalty of an excess container is constant. We can therefore use the following to represent the average excess penalty p_a:

$$p_a = \sum_d \lambda_d p_d, \tag{5.21}$$

where p_d denotes the penalty costs for an excess order towards destination d and λ_d denotes the fraction of demand destined to destination d. The CFCM(1,d,2) model is provided as Model 5.1.

If orders are not necessarily handled in order of arrival, it may be beneficial to send the cheapest options on truck. In that case, (5.21) will be an upper bound of the penalty costs. Because of our earlier assumption that the difference in distance for all destinations is relatively small, it is expected that Model 5.1 will still provide a tight approximation of the optimum. In the next section we apply a sensitivity analysis to address the impact of this assumption: we compare the results with the case of using the maximum trucking costs as excess penalty. The CFCM (1,d,2) model is non-linear in variables π_q and L_S because the probabilities of the actual demand D_E and D_S are multiplied by the Markov state probabilities π_q. These probabilities both depend on the decision variables L_E and L_S. Also, the variables L_E and L_S are integer. Generally, J as a function of the decision variables L_E and L_S is non convex. Therefore, it is difficult to find the optimal solution for the CFCM (1,d,2) model directly.

However, for fixed values for L_E and L_S, the model reduces to finding a solution to the set of linear equations (5.18) – (5.19). Hence, determining the expected revenue J for fixed booking limits is easy with the model. The optimal booking limits can be found by enumerating all possible combinations (L_E, L_S). Assuming $p > f_E$, we can conclude that $L_E \leq C$, as any accepted Express booking more than the capacity results in the penalty, which is larger than the revenue for that booking. Similarly, assuming $p > f_S$, we can conclude that $L_S \leq 2C$ as Standard bookings must be transported within 2 days with 2 times the daily capacity. Hence, enumeration requires $2C^2$ times solving the LP problem of Model 5.1 with fixed (L_E, L_S). Regular problem sizes of the CFCM (1,d,2) problem are often limited in practice, as many intermodal corridors have a daily capacity $C \leq 100$ container slots. In the next section, the model is demonstrated in a case study.

Model 5.1 CFCM $(1, d, 2)$ model

$$\max_{L_E, L_S} J = f_E \mathbb{E}(D_E) + f_S \mathbb{E}(D_S) - p_a \mathbb{E}(E_S)$$

Where

$$\mathbb{E}(D_E) = \sum_{k=1}^{L_E-1} k p_E(k) + L_E \left(1 - \sum_{k=0}^{L_E-1} p_E(k)\right)$$

$$\mathbb{E}(D_S) = \sum_{l=1}^{L_S-1} k p_S(l) + L_S \left(1 - \sum_{l=0}^{L_S-1} p_S(l)\right)$$

$$\mathbb{E}(E_S) = \sum_{m=1}^{L_S} m \sum_{q=0}^{L_S} P(D_E = C + m - q)\pi_q$$

subject to:

$$\pi_0 = \sum_{i=0}^{L_S} \pi_i \left[P(D_S = 0) P(D_E > C - i) + \sum_{s=0}^{C-i} P(D_E + i = C - s) P(D_S \leq s) \right]$$

$$\pi_j = \sum_{i=0}^{L_S} \pi_i \left[P(D_S = j) P(D_E > C - i) + \sum_{s=0}^{C-i} P(D_E + i = C - s) P(D_S = s + j) \right], (j > 0)$$

$$\sum_{i=0}^{L_S} \pi_i = 1$$

$$L_E, L_S \in \mathbb{N}$$

$$\pi_q \geq 0$$

5.5 Case Study of the CFCM problem in an intermodal corridor

The importance of the CFCM concept can be seen in the following example. Consider a corridor with daily capacity equal to 1. Suppose that every day exactly 1 request Standard arrives (with revenue 1), on average every 3 days one request for Express (with revenue 1.25), and the excess penalty is 2. In the classical revenue management approach, Standard will be limited to 1 and the Express will always be accepted. This will automatically result in incurring the penalty for every time

an Express order is accepted. The additional revenue from the Express order does not outweigh the penalty. The resulting average revenue is 0.75 per day. In the CFCM approach, two limits are considered, and Express will not be accepted, leading to a better resulting revenue of exactly 1 per day. The CFCM method outperforms the typical revenue management approach by one third. It will be clear that the benefit of the CFCM approach compared with the traditional alternative can be arbitrary large for cases where penalty p goes to infinity, for a given difference in revenue between the fare classes, $f_E - f_S$.
To demonstrate the CFCM (1,d,2) model in a practical setting we carry out three sets of experiments based on the EGS network. EGS is an intermodal network operator based in Rotterdam, offering intermodal connections between the deep-sea terminals in Rotterdam and around 20 inland locations (European Gateway Services, n.d.). Currently offering transportation services in a traditional way, EGS is now considering to offer a differentiated portfolio with Standard and Express service, as studied in this chapter. In the first experiment set, we show the value of an optimal fare class mix compared to traditional methods (Section 5.5.1). With the second set we show the value of the outcome of the CFCM (1,d,2) model in a large set of parameter settings, to support the selection of suitable corridors for the introduction of a differentiated service portfolio in the EGS network (Section 5.5.2). Thirdly, we study the effect of two critical aspects in our model: the penalty value and the lead time for the Standard product (Section 5.5.3). Although the penalty value is critical for determining the cost impact of an excess demand, we show that the optimal fare class limits are not sensitive to the estimated penalty value. Also, a simulation study into the effect of longer lead times is included. Our model is developed for a two-fare class portfolio, in which the secondary (Standard) product has twice the lead time of the primary (Express) product.

In all experiments, the cost and demand parameters are based on realistic numbers from the practice of the EGS network. Note that the CFCM (1,d,2) model can be used for any pair of discrete demand distributions. In these experiments, Poisson distributions are assumed for the demand, with average demand chosen such that it is equal or above the available capacity, such that the model has to find a trade-off between Express and Standard.

5.5.1 Optimal Cargo Fare Class Mix compared to traditional offerings

Firstly, we study the value of offering two services with a booking limit for each service, by comparing the CFCM (1,d,2) optimum with traditional alternatives. For this, we consider a small test case with capacity $C = 20$ and Poisson distributed demands with average 15 for both Express and Standard. For these we determine optimal booking limits using the CFCM (1,d,2) model. As comparison, we consider alternative approaches that a transportation provider could take:

1. offering Express and Standard, with limits based on the CFCM $(1,d,2)$ model.
2. offering both products, but putting *no limit on Express* (i.e. accepting Express up to capacity C). This is considered the classical approach according to Littlewood (1972/2005) of only limiting the 'inferior' product.
3. offering *Express service only*, ignoring Standard service demand. We assume that the Express service is not considered as a substitute for the Standard demand so the demand is lost.
4. offering *Standard service only*, ignoring Express demand. We assume that the Standard service is not considered as a substitute for the Express demand so the demand is lost.
5. offering *Standard service as substitution for Express demand*, assuming the Standard service can be a substitute for Express demand: so all customers with Express demand now book a Standard service and allow a delayed transport.
6. offering both, but putting *no limit on Standard* (i.e. accepting Standard up to capacity $2C$).

An overview of the settings for these experiments is provided in Table 5.1. Alternative 3-5 are used in practice in intermodal transportation and are added for comparison: each transportation provider offers a single service type. According to EGS experts, the Express service is not a realistic substitute for Standard demand, as Standard customers are especially interested in the lower tariff. In the alternatives 2 and 6, both fare classes are offered with a limit on only one of the fare classes. Alternative 2 is the typical approach in existing models for revenue management in logistics.

For each of the experiments, Table 5.2 lists the optimal booking limits, the expected revenue, the expected capacity utilisation and the expected excess demand. For experiments in which no limit on Express is determined, we take the maximum capacity C, and similarly, if no limit for Standard is determined, we take the maximum capacity $2C$ (as it can be postponed maximally one day). Also, the computation time T is reported. The expected capacity utilisastion η is computed using:

$$\eta = \frac{\mathbb{E}(D_E) + \mathbb{E}(D_S) - \mathbb{E}(E_S)}{C}.$$

The results show that the proposed method of offering two product types (experiment 1, 2 and 6) can significantly improve the expected revenue, compared to only selling one product type (experiment 3-5). Also, the results show that the average utilisation of the available capacity is significantly higher in the case of combining both products than in case of only considering one of both products (compare experiments 3-5 with all others). If Express and Standard are combined, generally, the sum of optimal booking limits exceeds the system capacity. In

experiment 3, in which only Express is sold, the optimal booking limit $L_E = C$, whereas in experiment 4, in which only Standard is sold, the optimal booking limit $L_S > C$. These results are as expected, because the additionally accepted demand can be transported on the next day.
The classical revenue management alternative based on Littlewood (not limiting Express) results in an expected revenue closest to the CFCM approach. Still, using optimal booking limits for both Express and Standard services yields in a revenue increase: experiment 1 shows an increase in expected revenue of 2.9% over experiment 2. Note that the industry standard profit margin is around 5%, indicating that this increase in revenue corresponds to increasing profit by 58%. On top of that, a comparison between the CFCM $(1, d, 2)$ approach and the alternative of determining only one limit, cannot be made on expected revenue alone. In practice, customers of both Standard and Express services need long term commitments. Also customers of a slower Standard service require a steady flow of cargo, e.g. containers towards a warehouse. Without a limit on the Express service for the same capacity, the Standard customers are more often faced with capacity shortage. As shown in Table 5.2, without a limit on Express, the expected excess is higher, which must be delivered in an alternative way (an excess of 1.09 in experiment 2 compared to only 0.13 in experiment 1).

Table 5.1 Experiment setting of comparisons to alternatives of the CFCM $(1, d, 2)$ model

Case	*Capacity* C	*Demand Express*	*Demand Standard*	*Fare* $(f_E; f_S)$	*Penalty* p_a
CFCM $(1, d, 2)$	20	Poisson(15)	Poisson(15)	110; 95	175
No limit on Express	20	Poisson(15)	Poisson(15)	110; 95	175
Express service only	20	Poisson(15)	0	110; 95	175
Standard service only	20	0	Poisson(15)	110; 95	175
Standard w/ substitution	20	0	Poisson(30)	110; 95	175
No limit on Standard	20	Poisson(15)	Poisson(15)	110; 95	175

Table 5.2 Results of comparisons to alternatives of the CFCM $(1, d, 2)$ model

Case	*Optimal booking limits* $L_E; L_S$	*Expected revenue* J	*Capacity utilisation* η *[%]*	*Expected excess* $\mathbb{E}(E_S)$	*Comp. time* T *[s]*
CFCM $(1, d, 2)$	14; 7	2063	98.9	0.13	5.3
No limit on Express	(20) ; 6	2005	98.5	1.09	0.3
Express service only	20; -	1627	73.9	0	4.7
Standard service only	- ; 40	1425	75.0	0	4.8
Standard w/ substitution	- ; 20	1895	99.8	0	4.7
No limit on Standard	5; (40)	1908	98.1	0.38	0.4

5.5.2 Corridor comparison for European Gateway Services

Secondly, to illustrate how the proposed model supports European Gateway Services in selecting suitable corridors to introduce the differentiated portfolio, we study instances with different demand and cost parameters. For these, we compare the results of 3 policies, corresponding to experiments 1,2 and 5 in the previous section: i.e. a situation in which all demand is fulfilled with the Standard service (close to the current situation and referred to as the traditional approach), and two variants in which two fare classes are considered, i.e. the CFCM (1,d,2) problem, and Littlewood's version with *No limit on express*. The company has insight that demand for both Standard and Express services exist, but does not know the demand distributions for Express and Standard for various price levels. Therefore, we aim to show the impact of using either Littlewood or CFCM for a range of demand scenarios in comparison with the traditional situation. Table 5.3 lists all combinations of tested parameters. We use normalised prices, with Standard service set to 1 and we consider Express services priced from 1.05 to 1.2 (i.e. between 5% and 20% mark-up for Express services). In each setting we consider a range of demand patterns, with total demand N varying between 90%-140% of capacity and Express demand N_E varying between 0%-100% of the capacity. All combinations of parameters results in 315 experiments per capacity level; for $C = 25$, we considered a finer grained range of values for Express demand: $N_E \in \{1, 2, \dots, 25\}$, which results in 1,377 experiments.

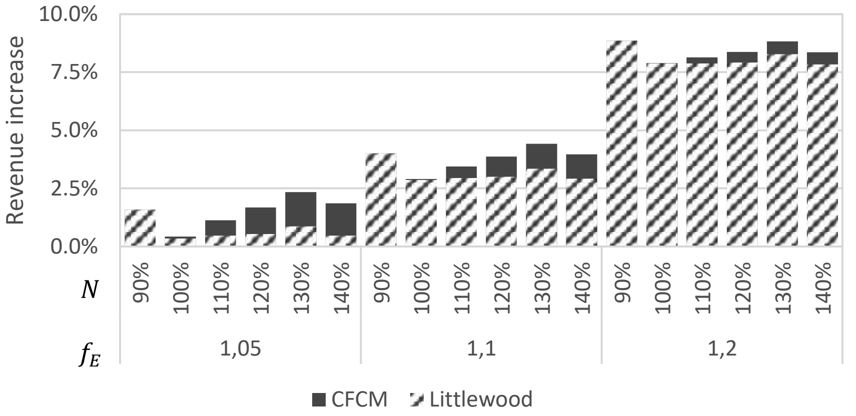
Table 5.3 Experiment setting of corridor comparison with CFCM $(1, d, 2)$ model

Parameter	*Values*
Capacity C	25, 50, 100
Average total demand N	$[90\%, 100\%, \dots, 140\%]\ C$
Average Express demand N_{E}	$[0, 20\%, \dots, 100\%]\ C$*
Standard fare f_{S}	1
Express fare f_{E}	1.05, 1.1, 1.2
Excess trucking cost p_a	1.5, 1.75, 2

* For $C = 25$, $N_E \in \{1, 2, \dots, 25\}$

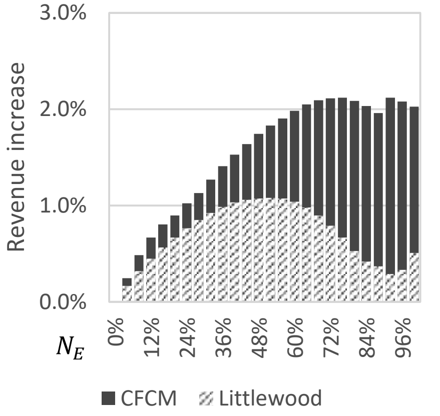
For $C \in \{25, 50, 100\}$ the results show the same trends. In all experiments, the CFCM policy results in higher expected revenue than a Littlewood policy. Both policies with two fare classes generally outperform the traditional approach, except for some cases: The Littlewood policy underperforms the traditional policy if Express demand is high, while the mark-up is low. The CFCM policy underperforms the traditional policy in very rare cases with a low mark-up and in which all demand is considerd to be Express. In such cases, the reduction in flexibility (because all demand has to be transported in one day) is not sufficiently compensated by the additional revenue of Express orders. In practice, it is not realistic that (almost) all

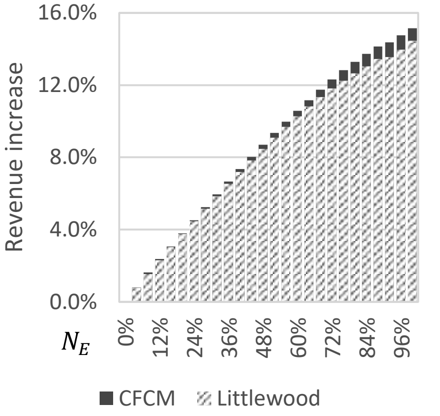
demand which is traditonally treated with a Standard policy, would shift to Express service in a two fare class policy.
In Fig. 5.5-5.7 the revenue increase of the two-fare class policies over the traditional policy is depicted. The striped bars give the expected revenue using a policy according to Littlewood. The solid part of the bar indicated the additional revenue if a CFCM policy is used instead. Fig. 5.5 shows that the benefit of using a two fare class policy increases with the height of the Express mark-up. The CFCM model especially improves expected revenue compared to using Littlewood for lower markups and a higher level of total demand. The data in Fig. 5.5 is an average over all ratios of Express and Standard demand. Fig. 5.6 shows the impact of the amount of Express cargo (as percentage of the daily capacity). For a low value of the Express markup, Littlewood is most beneficial for intermediate amounts of Express cargo. For a high markup, the benefit of Littlewood is increasing with the level of Express cargo. On top of Littlewood's benefit, the CFCM model provides an improvement that increases with higher fractions of Express cargo. From Fig. 5.6, we can distinguish three effects: firstly, the revenue increases with selling more Express (at a higher fare). Secondly, as the Littlewood policy cannot reduce the amount of Express orders coming in, an increase of Express demand results in a reduction in revenue because of reduced flexibility. The CFCM policy reverses this effect. Lastly, for high numbers of Express cargo, the utilisation risk is reduced, which results in an increased revenue, even for the Littlewood policy for a low Express markup. Fig. 5.7 shows that the benefit of using Littlewood reduces for increasing costs of excess trucking. This decline is for a large amount compensated by using CFCM.



$(C = 25, p = 1.5)$

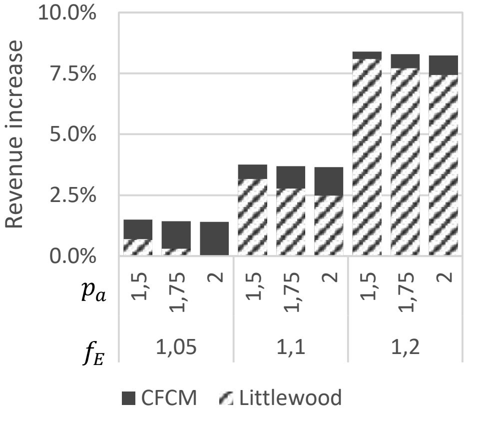
Fig. 5.5 Revenue increase over trad. approach per Express mark-up and demand level





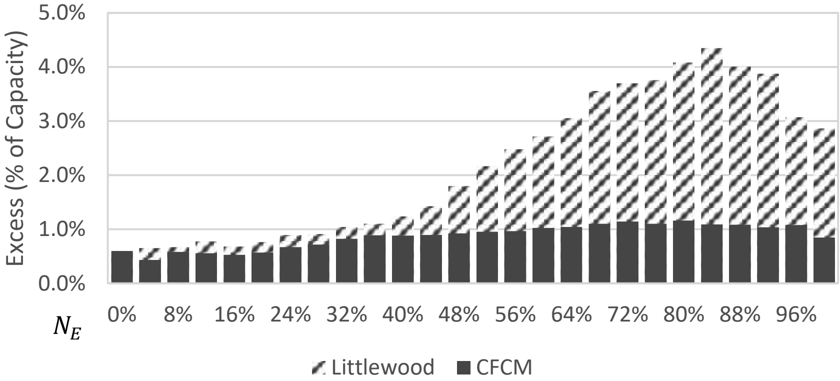
Low mark-up ($C = 25, p = 1.5, f_E = 1.05$) High markup ($C = 25, p = 1.5, f_E = 1.2$)

Fig. 5.6 Revenue increase over trad. approach for various fractions of Express demand



($C = 25$)

Fig. 5.7 Revenue increase for several levels of excess trucking costs and Express mark-up



$(C = 25, N \geq 25)$

Fig. 5.8 Average excess cargo for various fractions of Express demand

The results of this case study show that a two-fare class policy is very beneficial compared to the traditional approach. For a corridor in which a high mark-up can be charged, a Littlewood model suffices. However, especially in cases in which the potential mark-up is not so high, but a significant interest in Express service exits, the CFCM model adds additional benefit. These insights help EGS in selecting the most promising corridor to implement the new service portfolio of Express and Standard services.

Furthermore, the results show that for several of the corridors, the Littlewood policy results in a higher excess demand, especially for higher levels of Express demand (Fig. 5.8). This indicates a reduced reliability for the customer. Finally, the results show an increased utilisation rate of the corridor capacity for the CFCM approach, compared to the traditional approach. The purpose for EGS with introducing a differentiated portfolio is to increase both utilisation of inland trains and vessels, and to increase reliability of container transports arriving on time. Based on the results, we advise to focus on corridors in which significant interest in Express service exists and set the Express mark-up to a level in which a substantial level of Express demand is attracted.

5.5.3 Sensitivity analysis for the research setting

We analyse the sensitivity of our results for two critical aspects of our model: the penalty parameter p_a and the leadtime of the Standard product. First, we describe the impact of the penalty value. In the previous sections, we assumed a average value p_a to denote the cost of excess trucking to all destinations d. We perform a sensitivity analysis based on experiment 1 of Section 5.1, to find the impact of this assumption: would the optimal limits change for different values of p and how much would the expected revenue change? Under the CFCM policy, we found that varying the excess penalty $p \in [0.8p_a, 1.5p_a]$ does not affect the resulting limits ($L_E = 14, L_S = 7$), and does not affect the expected amount of excess cargo (0.13). In practice, the costs of excess trucking to destination around an inland location will vary much less than the studied range for p. Using the Littlewood policy (no limit on excess), the optimal limit for the Standard product is affected slightly by the penalty: for $\frac{p}{p_a} < 1.05$ the optimal limit was found to be $L_S = 6$, for larger values of p the optimal limit resulted in $L_S = 5$. Fig. 5.9 shows the expected revenue for several levels of p, i.e. several levels of trucking costs, or trucking distance. It can be seen that the expected revenue of the CFCM$(1, d, 2)$ model is much less sensitive for the level of the excess penalty, than the classical approach. Furthermore, the CFCM$(1, d, 2)$ model outperforms the classical approach by 1-5% over the tested range.

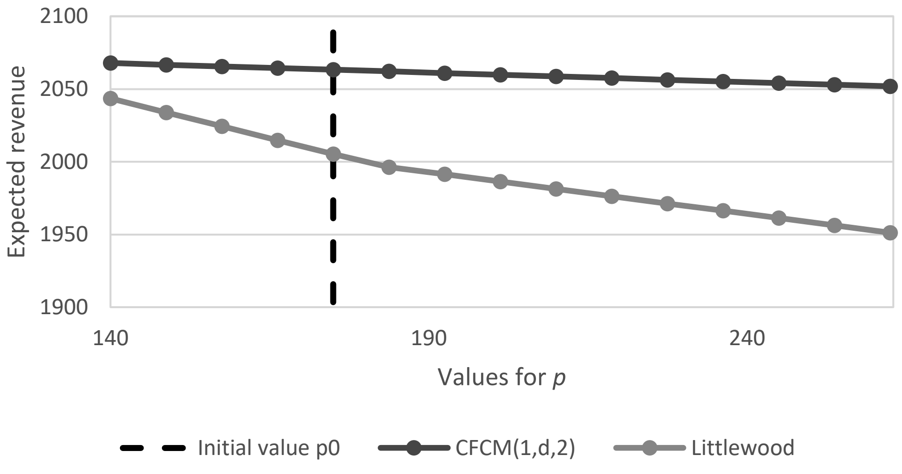


Fig. 5.9 Sensitivity analysis of expected revenue for penalty value p

Finally, we consider the effect of a longer lead time for the Standard demand. Suppose we use the optimised limits from our proposed model. Given these limits, we consider the impact if the Standard demand could be delayed longer. In such a case, the risk of excess cargo is reduced. Therefore, the expected revenue for such a case is at least as high as in the regular case, and potentially higher, due to a reduction of excess trucking costs. The maximum reduction is equal to the expected excess trucking costs:

$$p\mathbb{E}(E_S)$$

This corresponds to a situation in which no time limit for excess cargo exists, provided that the long term average of demand is below the capacity:

$$\mathbb{E}(D_E) + \mathbb{E}(D_S) \leq C$$

This holds in general in the CFCM model, as the optimal limits are selected such that no steady amount of excess cargo arises.
For a finite time limit for delivering Standard $t_s > 2$, the expected amount of excess cargo may be reduced compared to the case analysed in the previous sections (for $t_s = 2$). We will use simulation to show that the additional cost saving of increasing the lead time from 2 to 3 days is negligible under practical circumstances. For this, we will make an analysis in two steps. First, for fare class limits optimised under the assumption of $t_s = 2$, we will simulate the resulting excess cargo under a policy of $t_s = 2$ and $t_s = 3$. Provided the longer lead time for Standard, the optimal fare class limits may be higher. Therefore, secondly, we use simulation to show that increasing the fare class limits (for the policy with $t_s = 3$) has a negligible effect on the expected revenue.
For experiment 1 in Table 5.1, we generate 10 series of random demand for 1000 days. We use the optimal booking limits as obtained with the CFCM policy (based on 2 day delivery for Standard). In this setting, we consider the effect of using a 2 days lead time in comparison with a 3 days lead time, assuming all clients accept this longer leadtime. Using the same random feed of demand data, we also consider increased fare class limits for both products: we simulate the 10 series using all combinations of fare class limits $\{L_E, L_E+1, \dots L_E+5\}$ and $\{L_S, L_S+1, \dots L_S+5\}$. In Table 5.4, the results are reported: the average revenue from the simulation for a 2 day policy, the percentage cost savings in case of a 3-day policy with equal limits and the percentage cost savings with higher limits. Since the cost savings by using higher limits are so small (smaller than the random effect), the highest cost savings occurred for different limits in the ten demand series. Therefore, in order to report the maximum cost savings possible for a 3 day policy with higher limits, we took for each of the 10 demand series the maximum possible cost savings out of the results for all combinations of increased limits.

Table 5.4 Results of simulation studies for 2 and 3 day lead time for Standard products

Mean and standard deviation provided, based on 10 runs of 1000 days

Case	*Average revenue (2 day policy)*	*Cost saving (3 day policy)*	*Cost saving (3 day policy, higher limits)*
C=20; $\mu_E = 15$; $\mu_S = 15$	2063±6	2075±2	2075±2
		(+0.6%)	(+0.6%)

The average revenue obtained by the simulations validates the results of the analytical model. Also, an additional revenue increase of 0.6% can be obtained by a policy of 3 days delivery for Standard, provided customers are willing to accept that. However, for the studied corridor the optimal limits are not affected, and the optimal limits resulting from the CFCM$(1, d, 2)$ model can be used for this case as well.

5.6 Conclusions

In this chapter, we have proposed the Cargo Fare Class Mix (CFCM) problem. This problem arises from current practice in intermodal networks for container transportation, which start offering a range of transportation services with different leadtimes. The CFCM problem differs from the existing Fare Class Mix problem, as accepted demand can be planned on different transportation routes or modes. Because of the difference in planning characteristics between the service types, the CFCM problem also differs from classical revenue management in freight, such as Littlewood. In the CFCM setting, a lower priced product is not necessarily inferior than a higher priced product. The key insight is that finding the optimal balance between offered services provides an opportunity to increase revenue. We developed a solution method for the CFCM problem for a single corridor. In answer to research question 5, “What is the value of planning flexibility for synchromodal networks?”, we conclude that the revenue increase is significant for various settings. In a case study, we found that signficant revenue potential can be gained by setting limits for all fare classes, compared to classical approaches of limiting only the lower priced fare class. Introducing a two-fare class service portfolio can result in a significant increase in expected revenue, both by using a Littlewood policy or a CFCM policy. In order to answer research question 6, “How can the optimal fare class mix for a synchromodal corridor be found?”, we conclude that our proposed method gives optimal fare class mix results for a synchromodal corridor. The benefit of CFCM over Littlewood’s revenue management is largest for high Express demands at low mark-up prices for Express service. In such cases, CFCM prevents the increase of excess trucking that would be required in a Littlewood policy. Generalising, the insights are applicable to all applications in which multiple fare classes are offered that not only differ in price, but also in service characteristics. Therefore, we expect similar results for applications in parcel delivery, typically balancing Express or Standard delivery, and webshop inventory management, potentially reducing inventory if not all customers require immediate delivery.

We have proposed a framework to indicate the variant of the problem that is studied. The problem for inland transportation has several dimensions: the considered number of routes r, the considered number of destinations d and the considered number of transportation service types p. We denote the problem variant as CFCM (r,d,p). We have provided an analytical formulation and solution method for the CFCM $(1, d, 2)$ problem. We showed that both utilisation rates and reliability are increased by introducing a 2 fare class portfolio of which the secondary product has leadtime of twice the primary product. We showed in some case studies that considering multiple fare classes with booking limits for each fare class can significantly increase expected revenue compared to only offering one service type or compared to limiting only one of the offered fare classes. These case studies exemplify how our model supported European Gateway Services in selecting a suitable corridor to start offering differentiated fare classes. On these corridors utilisation is increased and opportunity costs reduced. The results showed that in some cases the optimal fare class mix consists of limits that exceed available capacity. We showed that the model's outcomes are insensitive to the penalty value for excess cargo. Finally, we considered the case of leadtimes for the secondary product of more than twice the primary product. Using simulations, we showed for the EGS corridors that the expected revenue increases slightly, however, the optimal fare class limits are not affected.

In the next chapter, we will use the currently proposed model for the CFCM $(1, d, 2)$ problem and extend it for more general variants of the CFCM (r,d,p) problem. To develop a model for multiple routes, we aim to decompose a multi-route network into multiple corridors, each modelled as CFCM $(1, d, 2)$. Considering the corridors in order of increasing costs, the excess of the previous corridor can be accommodated in the present corridor provided capacity is available.

6 Cargo Fare Class Mix problem in Synchromodal Container Transportation

Chapter 5 introduced the Cargo Fare Class Mix (CFCM) problem, which aims to find the optimal fare class mix for a given cargo transportation network based on known client demands. It is based on the fare class mix problem for aviation passengers with two major differences, as a consequence from transporting cargo instead of passengers. Firstly, the CFCM's premise is that long-term commitments to customers must be provided, such that a customer has a guaranteed daily capacity. Secondly, cargo may be rescheduled or rerouted, as long as the customer's delivery due date is met. Therefore, the optimisation problem is to select fare class limits at a tactical level up to which transportation is guaranteed on a daily basis at the operational level. Any guaranteed demand exceeding the available network capacity during operation, must be transported by truck at increased expenses for the network operator. In this chapter, we propose a faster method than the previously proposed solution method for a single corridor network and we provide proof of the optimality of the result. Using this, we extend the problem to an intermodal network of multiple corridors, in order to answer research question 7: "To what extent is it relevant to consider the synchromodal network structure when optimising the fare class mix?". After the problem description in Section 6.1, Section 6.2 provides an overview of literature on revenue management in freight transportation, as well as on synchromodal networks. In Section 6.3, three extensions of the CFCM problem are proposed: an improved optimal solution method for single corridor CFCM problems, an optimal solution for 2-corridor CFCM problems and a lower and upper bound for multiple corridor CFCM networks. Section 6.4 will provide a case study to compare the results of these three methods to an intermodal network based on the EGS case. Finally, Section 6.5 will provide an overview of the chapter's conclusions.

Keywords *: Intermodal planning, synchromodal planning, container transportation, revenue management, fare class sizes.*

6.1 Introduction

In Chapter 1 (Van Riessen *et al.*, 2015-c) we described our observations on two sides of synchromodality: transportation network planning and product design of transportation services. One side involves finding the best possible solution to a transportation problem; however, without flexibility – i.e. multiple options per order – no possibility for optimisation exists. Therefore, the other side involves focusing on the right amount of flexibility in the order pool. This combination is relevant for any application in which the customer has a lot of influence on the degrees of freedom for the transportation plan, e.g. inland container transportation, online retail, express parcel delivery and ride sharing applications. This chapter will focus on the application of inland container transportation, including a case study for the synchromodal network of European Gateway Services (EGS).
By addressing transportation planning and product offering simultaneously, our research aims to create a bridge between the operations management of optimising transportation planning and the revenue management of optimising the service portfolio. In practice, in traditional intermodal networks customers usually have strict requirements regarding the route, mode and time of a transport, which restrict the transportation planning problem. These types of restrictions are generally ignored in literature. In Section 1.3.1, an overview of the literature on the topic of synchromodal transportation is provided. However, multiple studies have shown that customers have interest in transportation services that provide more flexibility to the transporter, as long as they receive the right incentives (Verwij, 2011, Tavasszy *et al.*, 2015, Dong *et al.*, 2017, Khakdaman, *et al.* 2017). In Chapter 5 (Van Riessen *et al.*, 2017), we presented the Cargo Fare Class Mix in a case study of a single corridor. We considered offering two transportation services on a single transportation corridor: Express delivery (1 day, only a single option available for the transporter) and Standard (2 days, multiple options available to the transporter). The goal was to maximise revenue for the transporter by finding the optimal balance between the two products, with the higher priced Express service yielding a higher revenue but fewer planning options and the lower priced Standard service providing more planning flexibility. This balance can be achieved by setting fixed daily limits for each fare class, up to which demand is accepted. All accepted demand must be transported by the intermodal operator. In this chapter we present a generalisation of the Cargo Fare Class Mix model for a network of multiple corridors. The driver for this research is not solely to increase profit, but mainly to increase asset utilisation (resulting in a more sustainable transportation network, more efficient use of asset and infrastructure and a reduction in operational costs). In the traditional capacity allocation problem (e.g. Littlewood 1972/2005), only the inferior product is limited, to guarantee enough capacity for the higher priced product. We show that by including the network planning problem in the portfolio design, our models give different results than in a traditional revenue management setting: The cost savings resulting from an efficient transportation plan are the main

reason that the Standard product is not inferior to the Express product when considering profit maximisation.

6.1.1 Problem description

We consider an intermodal hinterland transportation network consisting of a set of intermodal corridors between a single deep-sea terminal and multiple inland terminals. From the inland terminals, d destinations can be accessed by truck. This is considered last-mile trucking, or haulage. Without loss of generality, in the remainder of this chapter we consider import transportation in this network, i.e. transport from the deep-sea terminal towards the inland destinations. For export transportation (towards the deep-sea terminal) a similar set of services is offered, resulting in a similar problem not addressed here. Fig. 6.1 gives a schematic overview of the type of network considered. Transport over the network is operated by a synchromodal network orchestrator, responsible for all transports within the network. The network orchestrator offers two transportation service levels between the deep-sea terminals and each destination: Standard and Express. The Express product guarantees delivery within one time period, the Standard product guarantees delivery within two periods. For the Express service level, a higher price is charged than for the Standard service. The customer pays the price for the requested service level, regardless of how the transport is carried out (i.e. which modality). We assume that transport requests for both services arrive on a daily basis, according to known, independent distributions. Also, we assume that all travel times are within one period.

Typically, long-term commitments must be provided to customers to guarantee daily transportation up to a certain number of containers per day. Determining these limits occurs on the tactical level. Then, on the operational level transport requests are accepted or rejected by the network operator as they arrive (by phone or email), based on the predetermined limit, before the operational transportation plan is constructed. Hence, at the time of accepting or rejecting a booking, it is not yet known whether actual capacity at the time of loading will suffice. All accepted transportation requests are referred to as accepted demand. Subsequently, a transportation plan is created to transport all accepted demand within the required time limits.

If the network orchestrator has insufficient intermodal capacity to fulfil all demand, the alternative is to use transport by truck from the deep-sea terminal directly to the final destination. This direct trucking comes at a cost that exceeds the incurred revenue, and must thus be avoided. To minimise the necessity of direct trucking and to maximise expected revenue, a maximum booking limit must be determined for each service level (i.e. for each fare class). All transportation requests are accepted up to that daily limit.

In practice, the cargo fare class mix problem for inland transportation has many dimensions. The operational planning problem considers multiple routes r and multiple destinations d for transporting all cargo. This must be done within the time limits agreed with the customer for the product; the number of fare classes p is the third dimension. We use these dimensions to classify the problem type of the CFCM problem as CFCM(r, d, p). This problem was introduced in Chapter 5 (Van Riessen *et al*. (2017) as the *Cargo Fare Class Mix* (CFCM) problem, in which we studied a simplified version of this problem, considering only one corridor. This was denoted as the CFCM-$(1, d, 2)$ class of problems. This chapter addresses the generalised class of CFCM-$(r, d, 2)$ problems.

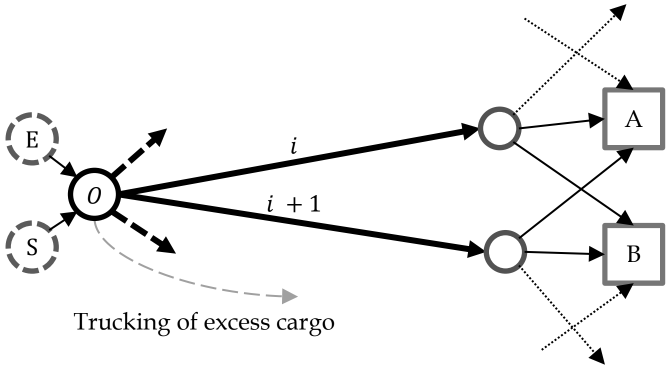


Fig. 6.1 Schematic overview of the CFCM $(r, r, 2)$ problem

6.2 Literature overview

First, we provide an overview of some relevant works on revenue management in freight transportation in general. Subsequently, we focus on the developments in synchromodal network planning, and the associated pricing and revenue management policies.

6.2.1 Revenue Management in Freight Transportation

In general, revenue management is concerned with demand-management decisions. Revenue management decisions can be of three basic types: (1) structural decisions, on selling format and/or segmentation mechanism; (2) price decisions, on the pricing policy over all segments, including discounting; and (3) quantity decisions, on accept or reject decisions, and on how to allocate capacity per segment, product or channel (Talluri and Van Ryzin, 2004). Typically, price information of competitors is public information, providing constraints for the second decision, while quantity information is not. On top of that, we learned from our experience with EGS that the shipping industry dislikes price volatility generally. Therefore, for the CFCM problem we assume constant prices for each product and we consider long-term commitments, ignoring the time factor. As a result, the quantity decision

is our main interest here: how to distribute our capacity over the product types and, hence, how to accept and reject incoming requests.
Talluri and Van Ryzin (2004) describe Littlewood's model for freight services differentiated by quality: Littlewood's model assumes 2 distinct market segments (no substitution), with sequentially arriving demand, i.e. the demand for the inferior product (class 2) arrives before the demand for the superior product (class 1). The optimal result is to handle the incoming demand one by one according to a simple rule. For each incoming demand for class 2 and a remaining capacity x, accept it if the price for class 2 (p_2) exceeds the expected revenue for that slot for class 1:

$$p_2 \geq p_1 P(D_1 \geq x).$$

This approach can be extended to n product classes by a dynamic programming approach. It is generally accepted that the effect of group bookings (instead of one-by-one) can be ignored as long as group bookings can be split or if a sufficient number of small groups is available.
Several works have studied the joint optimisation of pricing and production decisions in a manufacturing setting, e.g. in Bajwa *et al.* (2016). See Tang (2010) for an overview of studies into the interaction between marketing and operations. Armstrong and Meissner (2010) provide an overview of revenue management in railway transportation, but found little literature on the topic. Most studies consider optimal network flow, although some studied different segments based on service quality. For example, Kwon, *et al.* (1998) consider rail car scheduling, taking into account the priority of specific rail cars. More recent studies typically assume implicitly geographic segmentation, based on transportation corridor or destination, including Ypsilantis (2016, pp. 47-82), who considers an intermodal network and Crevier *et al.* (2012), who consider pricing per request in a railway network. More research on network logistics and demand management in an intermodal setting is considered in the next section on *Synchromodal hinterland transportation*.
The issue of multiple products in a flow network has also been addressed in queuing theory, e.g. Mazzine *et al.* (2005) who studied a two-class priority queue for Bernoullian arrival processes. However, several aspects of the CFCM problem make it very hard to be modelled as a queuing network. For instance, the finite capacities of intermodal services must be considered as finite queues with *blocking*. Exact solutions for blocking networks with more than two nodes can only be obtained by numerical solutions of the underlying Markov chain (Bolch *et al.,* 2006).

6.2.2 Synchromodal hinterland transportation

In Section 1.2.1 we provided an overview of recent literature related to synchromodal hinterland transportation. An overview was provided in Table 1.1. In this chapter, the interaction between the service offering (including pricing) and the transportation planning is of particular interest for our topic. Some studies have considered the pricing and properties of transportation services, usually in combination with logistics planning. For instance, Li *et al.* (2015) designed a pricing scheme based on average costs, rather than actual costs per itinerary, thus allowing a reduction of the standard price due to network efficiencies. Dullaert and Zamparini (2013) study the impact of lead time variability in freight transport. Crevier *et al.* (2012) compared a pricing strategy for specific itineraries, with a strategy of pricing transportation requests. Bilegan *et al.* (2013) introduced a revenue management strategy of accepting or rejecting bookings on a railway corridor. Similarly, Wang *et al.* (2016) consider accept-reject decisions for a barge transportation network, including some customers with long-term commitments. Finally, in Chapter 5 (Van Riessen *et al.*, 2017) we introduced the framework of the CFCM problem and provided solutions for an optimal fare class mix on a single corridor. These studies all show that substantial revenue gains can be achieved by a pricing policy that is optimised considering the logistics planning for different geographical areas (destinations and/or corridors). However, as far as we know, none have considered the effect of multiple products with varying lead times in an intermodal network setting. In Chapter 5 we used a revenue management approach aimed at market segmentation by transport time horizon. In this chapter, we extend our earlier work on the CFCM problem to include geographic market segmentation as well. We assume that market information on demand and prices is already known, based on which we aim to find optimal booking limits for synchromodal products. As indicated in Table 1.1, this focus on product conditions differentiates our work from earlier synchromodal research that considers product characteristics. Although our work is specifically focused on a multi-corridor network with multiple modes, we do not specifically consider the impact of differences in mode. Instead, our work focuses on selecting the best route and time of transportation from the perspective of the transportation network operator.

6.3 Methodology for solving the CFCM problem in intermodal networks

Our research builds on our work in Chapter 5 (Van Riessen *et al.*, 2017) addressing a single corridor Cargo Fare Class Mix problem; a summary of the relevant results is provided in Section 6.3.1. Fig. 6.2 provides a schematic overview of the methodology used in this chapter. In Section 6.3.1, we extend the solution method from Chapter 5 with a more efficient solution method and optimality proofs are given. In Section 6.3.2, an analytical result for a two-corridor network is derived, i.e. two different routes to two inland terminals, representing a barge or rail connection. In Section 6.3.3 an approach for an intermodal corridor with r corridors is proposed, by iteratively using the single corridor optimisation and a network rerouting heuristic. In order to quantify the optimality gap of the proposed heuristic, we show that we get close to the two-corridor optimum with our proposed approximation method. As in Talluri and Van Ryzin (Ch 3.3, 2005), the large dimensionality of this network capacity control problem requires approximation methods for larger networks.

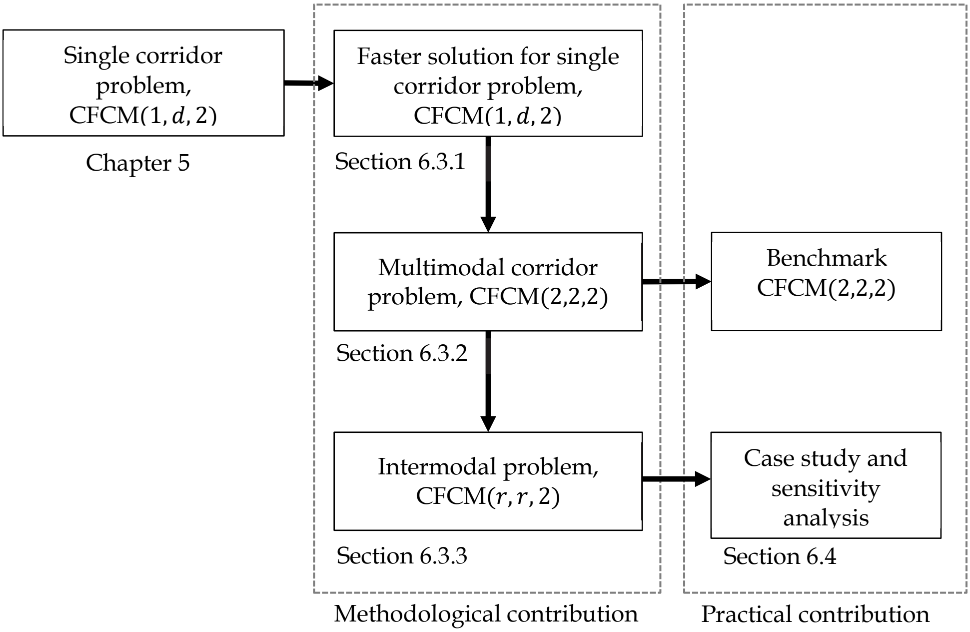


Fig. 6.2 Structure of the methodology and contribution

6.3.1 Improved solution method for single corridor CFCM$(\mathbf{1}, \boldsymbol{d}, \mathbf{2})$

In Chapter 5 (Van Riessen, *et al.*, 2017), we introduced an analytical solution to the CFCM $(1, d, 2)$ problem. For the sake of completeness, the main aspects of the earlier proposed approach are compactly presented here.
In the revenue management objective of the CFCM $(1, d, 2)$ model, we focus on optimising revenue for a fixed capacity C on one route to one destination. On this corridor, two products are offered: Express and Standard, at a fare f_{E} and f_{S}, respectively, with the available demand in the market denoted by the random variables D_{E} and D_{S}. Express must be transported within one period, while the demand for Standard transportation can be postponed one period. In contrast with Chapter 5, we need to consider transportation costs for consistency with the multi-corridor models later in this chapter. Transportation has a cost of c per unit. As the transportation company provides long-term commitments, we need to find optimal booking limits $L_{\mathrm{E}}, L_{\mathrm{S}}$ for each class at the tactical level. At the operational level, all incoming demand arrives first, before the operational transportation plan is

constructed. Incoming demand is accepted up to the limit for that class. Hence, at the time of accepting or rejecting a booking, it is not yet known whether actual capacity at the time of loading will suffice. All accepted transportation requests are referred to as accepted demand, or transportation volume, denoted by random variables T_{E} and T_{S}, respectively. Let $\cdot\,(t)$ denote the value of a random variable at a given time period t.

$$T_E(t) \;= min(D_E(t), L_E)\,, T_S(t) = min(D_S(t), L_S)$$

Any Standard not transported intermodally within two periods was considered as excess in Chapter 5, and neede to be transported by sending a truck directly to the destination at a (very high) cost exceeding the potential revenue. This is now relabeled as overflow O, for consistency with the models later in this chapter. The additional cost of this truck transport on top of the regular transportation costs c is denoted by p. We assume that all travel times are within one period, hence selecting the day of departure within the guaranteed delivery period is sufficient: for Express within 1 period or for Standard within 2 periods. Any slots not used are denoted as surplus (or slack) slots S. Consider the network in Fig. 6.3, with one origin 0, two products $\mathcal{F} \in \{\text{E}, \text{S}\}$, an intermodal corridor i and destinations $j \in \{\text{A}, \text{B}, \dots, d\}$.

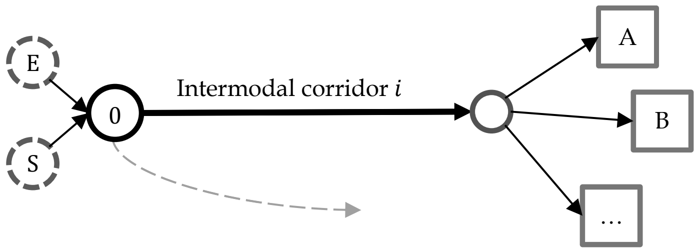


Fig. 6.3 Network of a CFCM $(1, d, 2)$ −problem (schematic)

In order to find the optimal booking limits L_{E} and L_{S}, we need to solve

$$\max_{L_E, L_S} J = (f_E - c)\mathbb{E}T_E + (f_S - c)\mathbb{E}T_S - (p - c)\mathbb{E}O + \mathbb{E}[\psi(L_E, L_S)], \tag{6.1}$$

subject to the condition that all accepted demand must be transported in time, either by an intermodal connection or by a truck transport for excess cargo not fitting on available intermodal capacity. With $\psi(L_{\text{E}}, L_{\text{S}})$, we denote the potential value of slack slots. In subsequent sections, we will use this for estimating the value of slack slots for rerouting. For a single corridor this can be ignored, so in the remainder of this section, we will consider $\psi = 0$. In Van Riessen *et al.* (2017), the optimal solution was found by enumerating the value of (6.1) for all feasible values of $L_{\text{E},i}$ and $L_{\text{S},i}$ for a corridor i. We will use the subscript i in the remainder to denote a single corridor, since we will reuse the formulation for situations with multiple corridors later. Each iteration was solved using a Markov Chain for the amount of Standard demand postponed to the next period, denoted by R_i, with transition probabilities $p_i(v,w)$ denoting $P(R_i(t+1)=w|R_i(t)=v)$ for corridor i:

$$p_i(v,w) = \begin{cases} P(T_{S,i}=0)P(T_{E,i}>C-v) + \sum_{z=0}^{C-v} P(T_{E,i}+v=C-z)P(T_{S,i}\le z) & w=0 \\ P(T_{S,i}=w)P(T_{E,i}>C-v) + \sum_{z=0}^{C-v} P(T_{E,i}+v=C-z)P(T_{S,i}=z+w) & w>0 \end{cases} \tag{6.2}$$

We denote the steady-state distribution of the Markov state of corridor i (R_i) as $\pi_i(w) = P(R_i^\infty = w)$, i.e. $\pi_i(w)$ denotes for corridor i on a day in the long run the probability of postponing w transportation orders to the next day. To find the distribution of π_i, we need to find a solution to the Markov equilibrium equations, as in Kelly (1975):

$$\pi_i(w) = \sum_i \pi_i(v)\, p_i(v,w), \tag{6.3}$$

$$\sum_w \pi_i(w) = 1. \tag{6.4}$$

The probability distributions of overflow cargo and slack slots are provided by:

$$\mathbb{P}(O_i=y) = \begin{cases} \sum_{q=0}^{C_i} \pi_i(q)\mathbb{P}(T_{E,i}\le C_i-q) & y=0 \\ \sum_{q=0}^{C_i} \pi_i(q)\mathbb{P}(T_{E,i}=C_i+y-q) & y>0 \end{cases} \tag{6.5}$$

$$\mathbb{P}(S_i=z) = \begin{cases} \sum_{q=0}^{C_i} \pi_i(q) \sum_{e=0}^{C_i} \mathbb{P}(T_{S,i}\ge C_i-q-e)\mathbb{P}(T_{E,i}=e) & z=0 \\ \sum_{q=0}^{C_i} \pi_i(q) \sum_{e=0}^{C_i-q} \mathbb{P}(T_{S,i}=C_i-z-q-e)\mathbb{P}(T_{E,i}=e) & z>0 \end{cases} \tag{6.6}$$

The derivation of (6.5) − (6.6) can be found in Appendix 6.A. With the distribution of π_i, we obtain the following expression for the expected value of the overflow, by summing over all potential overflow values (denoted by m):

$$\mathbb{E}(O_i) = \sum_{m=1}^{L_{S,i}} m \sum_{q=0}^{L_{S,i}} P\big(T_{E,i} = C_i + m - q\big)\pi_i(q) \tag{6.7}$$

Furthermore, we have

$$\mathbb{E}\big(T_{E,i}\big) = \sum_{k=1}^{L_{E,i}-1} k p_{E,i}(k) + L_{E,i}\left(1 - \sum_{k=0}^{L_{E,i}-1} p_{E,i}(k)\right) \tag{6.8}$$

and, similarly,

$$\mathbb{E}\big(T_{S,i}\big) = \sum_{l=1}^{L_{S,i}-1} l p_{S,i}(l) + L_{S,i}\left(1 - \sum_{l=0}^{L_{S,i}-1} p_{S,i}(l)\right). \tag{6.9}$$

Given certain limits for the Express and Standard demand, the expected profit, based on the distribution of Overflow and Slack slots, can be determined. In the enumeration approach of Van Riessen *et al.* (2017), (6.2) to (6.9) need to be computed for every iteration consecutively to obtain the results for (6.1). Here, we provide a much faster optimal algorithm. We propose an algorithm that searches optimal solutions by increasing the limits step-by-step. The selection of the limit that is best increased is based on an estimate of the additional profit. As the solution space is not convex, one such search is not sufficient to find a maximum. In order to efficiently search the solution space, we use several rules to structurally eliminate potential combinations of limits.

The proposed procedure to find the optimal limits $L_{\mathrm{E},i}, L_{\mathrm{S},i}$ is given in Algorithm 6.1. The algorithm starts by excluding combinations of limits that will never be the optimal solution. Firstly, if the sum of both limits is less than the daily capacity, there will always be slack slots. It is without risk of a penalty to increase the limits up to at least the capacity. Therefore, there will always be an optimal solution that satisfies $L_{\mathrm{E},i} + L_{\mathrm{S},i} \geq C_i$. Secondly, if the expectation of the average accepted demand for a certain combination of limits is higher than the capacity, then in the long-term this will result in structural excess. Since the cost of excess is higher than any expected revenues, this can never be optimal. Therefore, in the optimal solution it will always hold that $\mathbb{E}_{L_{\mathrm{E},i}}\big(T_{\mathrm{E},i}\big) + \mathbb{E}_{L_{\mathrm{S},i}}\big(T_{\mathrm{S},i}\big) \leq C_i$. Thirdly, if increasing a limit no longer results in additional demand, we do not explore further. I.e., for a sufficiently small number ϵ, we exclude combinations of limits for which either Express or Standard satisfies $\mathbb{E}_{L_{\mathcal{F},i}+1}\big(T_{\mathcal{F},i}\big) - \mathbb{E}_{L_{\mathcal{F},i}}\big(T_{\mathcal{F},i}\big) < \epsilon$. The remaining combinations of limits must be explored to find the optimum. We use three additional results to search the remaining combinations efficiently. Firstly, we can reduce the search with the following result: the expected profit has a single maximum for one variable limit, if the other limit is fixed (Proof 6.1, Appendix 6.B). Then, we can exclude more potential combinations using the following:

$$if\ J_{L_{E,i},L_{S,i}} \geq J_{L_{E,i}-1,L_S}\ and\ J_{L_{E,i},L_{S,i}} \geq J_{L_{E,i},L_S-1}\ then\ J_{L_{E,i},L_{S,i}} \geq J_{L_{E,i}-x,L_{S,i}-y}, \quad \forall x, y \geq 0$$

i.e., if the expected profit for two given limits is larger than the profits obtained when one of the limits is reduced by 1, then this profit exceeds all scenarios with limits lower than or equal to the given limits (Proof 6.2, Appendix 6.B). Likewise, this also holds for increasing limits (Proof 6.3, Appendix 6.B):

$$if\ J_{L_{E,i},L_{S,i}} \geq J_{L_{E,i}+1,L_S}\ and\ J_{L_{E,i},L_{S,i}} \geq J_{L_{E,i},L_S+1}\ then\ J_{L_{E,i},L_{S,i}} \geq J_{L_{E,i}+x,L_{S,i}+y}. \quad \forall x, y \geq 0$$

With these results, if a local optimum is found, then the lower corner and upper corner of the search space can be excluded. We use these results in Algorithm 6.1. We apply Algorithm 6.1 and for step 3a. we use a greedy search algorithm, by iteratively increasing limits. Let $L_{\mathcal{F},i}^{+1}$ denote increasing the limit $L_{\mathcal{F},i}$ with 1 ($\mathcal{F} \in \{\mathrm{E}, S\}$), then an estimate for the expected change in profit is given by:

$$\Delta J = (f_{\mathcal{F}} - c_i)\mathbb{P}\big(T_{\mathcal{F},i} = L_{\mathcal{F},i}^{+1}\big) - \widehat{\Delta O}_i,$$

in which $\widehat{\Delta O}_i$ is an estimator of the expected change in overflow cost of the demand. For the estimator $\widehat{\Delta O}_i$ we use the distribution of slack slots of the current solution. In case we consider incrementing an Express limit (L_{E}^{+1}), we consider that if no slack slots are available for L_{E}, the additional demand accepted due to increment could not be transported. Therefore, in these cases, the result is an overflow unit:

$$\widehat{\Delta O}_i = p\ \mathbb{P}(S_i = 0)\ \mathbb{P}\big(T_{E,i} = L_{E,i}^{+1}\big)$$

For Standard, this is the case if no slack slots are available twice in a row:

$$\widehat{\Delta O}_i = p\ \mathbb{P}(S_i = 0)\mathbb{P}(S_i^{t+1} = 0 | S_i = 0)\ \mathbb{P}\big(T_{S,i} = L_{S,i}^{+1}\big) \approx p\ \mathbb{P}(S_i = 0)^2\mathbb{P}\big(T_{S,i} = L_{S,i}^{+1}\big),$$

in which S_i^{t+1} denotes the number of slack slots in the next period. Other estimators for the expected change in overflow cost can be used in Algorithm 6.1 as well. Note that the quality of this estimator influences the efficiency of the search, but not the optimality of the result, since we explore or exclude all combinations. At each point in which the estimate ΔJ does not show an improvement, we verify whether an actual local optimum is found by evaluating all neighbouring limit combinations. If no improvement in expected profit can be found by increasing one of both limits, we use the results from Proof 6.1 – 6.3 to exclude more combinations. We iterate until all combinations have been searched or excluded. The previously proposed solution method (Van Riessen *et al.*, 2017) required enumerating all $2C_i^2$ combinations of limits, for each of which a solution to Markov Chain (6.3) − (6.4) must be found. In this new approach, with every iteration we can exclude combinations in which one of the limits is the same as the maximum found (Proof 6.1). Therefore, with our newly proposed approach we have to do maximally C_i searches. Using Proofs 6.2 and 6.3, more combinations are excluded, therefore reducing the search time per iteration and likely reducing the total number of searches even further.

Algorithm 6.1 Optimal solutions for the CFCM$(1, d, 2)$ problem

1 Create a list of all combinations of potential limits $L_{\mathrm{E}} \in \{0,1, \dots, C_i\}$ and $L_{\mathrm{S},i} \in \{0,1, \dots, 2C_i\}$

2 Remove from that list all combinations that satisfy one or more of the following:

$$L_{E,i} + L_{S,i} < C_i$$

$$\mathbb{E}_{L_{E,i}}(T_{E,i}) + \mathbb{E}_{L_{S,i}}(T_{S,i}) > C_i$$

$$\mathbb{E}_{L_{\mathcal{F},i}+1}(T_{\mathcal{F},i}) - \mathbb{E}_{L_{\mathcal{F},i}}(T_{\mathcal{F},i}) < \epsilon,$$

3 Now, considering all remaining combinations of limits, use the following steps for finding $\max_{L_{\mathcal{F},i}} J_i$ iteratively. It is based on Proof 6.1-6.3 in Appendix 6.B.

a. In the list of all remaining combinations of limits, find a local optimum of the expected profit $J_i(L_{\mathrm{E},i}, L_{\mathrm{S},i})$ based on (6.2) − (6.9) and store the value.

b. For the current values $L_{\mathrm{E},i}$ and $L_{\mathrm{S},i}$, apply results from Proof 6.1-6.3:
Remove all combinations that satisfy $L_{\mathrm{E},i} + x, L_{\mathrm{S},i} + y \quad \forall x, y \geq 0$
Remove all combinations that satisfy $L_{\mathrm{E},i} - x, L_{\mathrm{S},i} - y \quad \forall x, y \geq 0$

c. Restart from step a., until no more combinations of limits remain.

4 Select the limit combination that results in the highest expected profit.

6.3.2 Optimal results for the two-corridor problem CFCM$(2, 2, 2)$

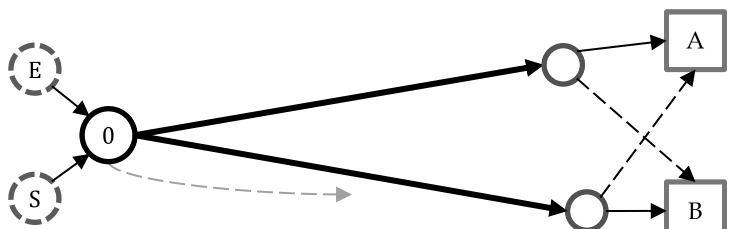


Fig. 6.4 Network of a CFCM (2,2,2) −problem (schematic)

In this section, an optimal approach for the CFCM(2,2,2) problem is proposed, i.e. with one origin 0, connected by two corridors, $i \in \{1,2\}$ with capacities C_i to 2 destinations $d \in \{\mathrm{A}, \mathrm{B}\}$ (Fig. 6.4). We assume that all regular demand for destination A is typically routed over corridor 1, and, similarly, destination B over corridor 2. The distribution of transportation requests (or independent demand) on corridor i is denoted as D_i with transportation costs $c_{i,d}$ for transporting over corridor i to destination d. The network operator offers two transportation services $\mathcal{F} \in \{\mathrm{E}, \mathrm{S}\}$, denoting Express delivery for delivery within one period and Standard delivery for delivery of cargo within two periods, respectively. The associated fares $f_{\mathcal{F},i}$ denote the price of service $\mathcal{F}$ for the destination belonging to corridor i. For both services $\mathcal{F}$, we need to find the optimal booking limits on each corridor i, denoted as $L_{\mathcal{F},i}$. Incoming transportation requests are accepted up to the booking limit. $T_{\mathcal{F},i}$ denotes the accepted demand, i.e. the transport volume per period for corridor i on service $\mathcal{F}$,

$$T_{\mathcal{F},i}(t) = max\left(D_i(t), L_{\mathcal{F},i}\right).$$

We assume that the cargo is allocated in order of highest expected profit. Therefore, all Express demand is given priority, and based on our assumption that $T_{\mathrm{E},i}(t) \leq C_i$, Express demand is only transported on its preferred corridor. Subsequently, the second priority is the Standard demand remaining from the previous period, $R_i(t)$. Any slots not in use by $T_{\mathrm{E},i}(t)$ are used for transporting this cargo. If the slots on the standard corridor are insufficient for $R_i(t)$, we consider the remaining demand as overflow, denoted by $O_i(t)$. If slots remain after allocating $R_i(t)$, the third priority is the new Standard demand for this period, $T_{\mathrm{S},i}(t)$. Then, the last slots are considered slack or surplus slots, denoted by $S_i(t)$. These slots are available for overflow cargo from other corridors. Finally, let $E_i(t)$ denote the amount of excess cargo, for all cargo of $R_i(t)$, which could not be transported on corridor i, nor on surplus slots of other corridors. This cargo could not be transported in time by any intermodal corridor and must be delivered by truck. For corridor i, the order of priority is summarised in Table 6.1. In the case of two corridors, the only alternative for corridor 1 is corridor 2, and vice versa. The potential planning situations are depicted schematically in Fig. 6.5.

Table 6.1 List of priority in allocating cargo to corridor i

Priority	*Cargo*	
1	$T_{\mathrm{E},i}(t)$	
2	$R_i(t)$	
3	$T_{\mathrm{S},i}(t)$	
4	$O_j(t)$	$j \neq i$

In order to find optimal fare class limits for the CFCM(2,2,2) problem, we formulate an analytical model based on a Markov Chain. Our goal is to find limits $L_{\mathrm{E},i}, L_{\mathrm{S},i}$ that result in the maximum expected profit:

$$\max_{L_{E,i},L_{S,i}} J = \sum_{\mathcal{F},i}\left[\left(f_{\mathcal{F},i} - c_{i,d}\right)\mathbb{E}\left(T_{\mathcal{F},i}\right) - p\mathbb{E}(E_i)\right], \tag{6.10}$$

subject to the condition that all accepted demand must be transported in time, either by an intermodal connection or by a truck transport of excess cargo not fitting on available intermodal capacity. To maximise (6.1), we need to determine $\mathbb{E}\left(T_{\mathcal{F},i}\right)$, and $\mathbb{E}(E_i)$. We use R_i^t to denote the remainder of Standard demand from the day before, and R_i^{t+1} to denote the remainder of current day's Standard demand that must be transported the next day. The cargo routing rules give us the following relations (see Fig. 6.5) for the CFCM(2,2,2) problem:

$$R_1^{t+1} = min\left(T_{S,1}, max\left(T_{E,1} + T_{S,1} + R_1 - C_1, 0\right)\right) \tag{6.11}$$

$$O_1 = max\left(R_1 + T_{E,1} - C_1, 0\right) \tag{6.12}$$

$$E_1 = max\left(R_1 + T_{E,1} - C_1 - S_2, 0\right) = max(O_1 - S_2, 0) \tag{6.13}$$

$$S_2 = max\left(C_2 - T_{E,2} - T_{S,2} - R_2, 0\right) \tag{6.14}$$

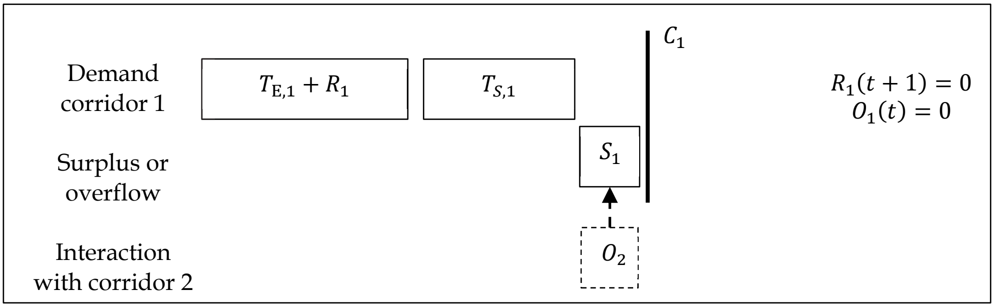
From (6.11) – (6.14), we see that R_1^t, O_1 only depend on corridor 1, and S_2 only depends on corridor 2. We consider two corridors in this section. Generalising, R_i^t, O_i and S_i do not depend on corridors other than i. We can describe the state of a single corridor by (R_i). Only E_i depends on other corridors. $R_i(t+1)$ only depends on corridor i, by demand T_i and remaining demand $R_i(t)$.

Therefore, we can re-use the corridor-specific equations (6.2) – (6.9) for the CFCM$(1, d, 2)$ problem from Section 6.3.1. Note that these expressions do not depend on the other corridor, because of the assumed order of cargo allocation (Table 6.1). If Overflow from other corridors would be allocated before $T_{S,i}$, R_1^{t+1} would become dependent on other corridors, resulting in a much more complex Markov Chain. This is not considered in our study.

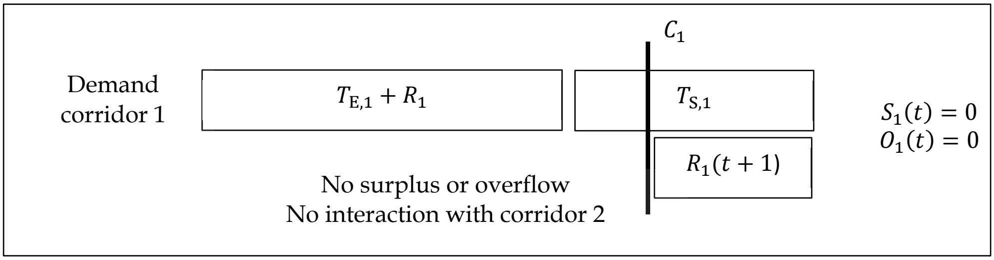
Assuming the demand distributions on both corridors are independent, and using (6.5) – (6.6), we can derive the probability that overflow cargo can be transported on slack slots on the alternative corridor. For corridor 1, the expression is as follows:

$$\mathbb{P}(E_1 = k) = \begin{cases} \sum_{y=0}^{2C_1} \mathbb{P}(O_1 = y)\mathbb{P}(S_2 \geq y) & k = 0 \\ \sum_{y=k}^{2C_1} \mathbb{P}(O_1 = y)\mathbb{P}(S_2 = y - k) & k > 0 \end{cases}$$

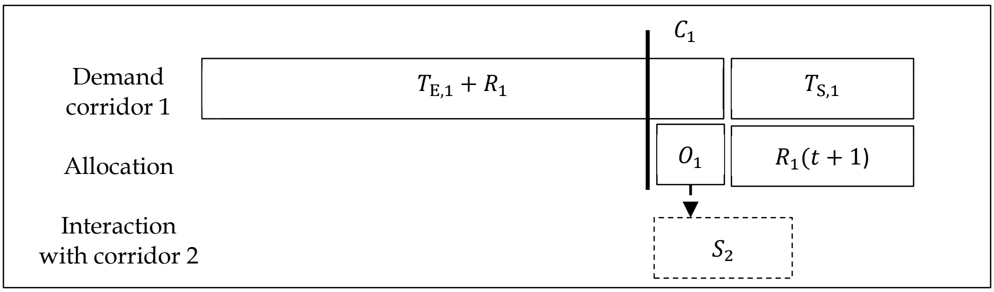
To find the optimal limits $L_{\mathcal{F},i}$ for a CFCM(2,2,2) problem, we apply the procedure as shown in Algorithm 6.2, similar to Algorithm 6.1. In this case we cannot use the 3 rules of excluding limit combinations, since Overflow cargo could be rerouted.
In the next section, we will use (6.5), (6.6), (6.15) in an approximation scheme for lower and upper bounds in a generalised intermodal network with multiple corridors.



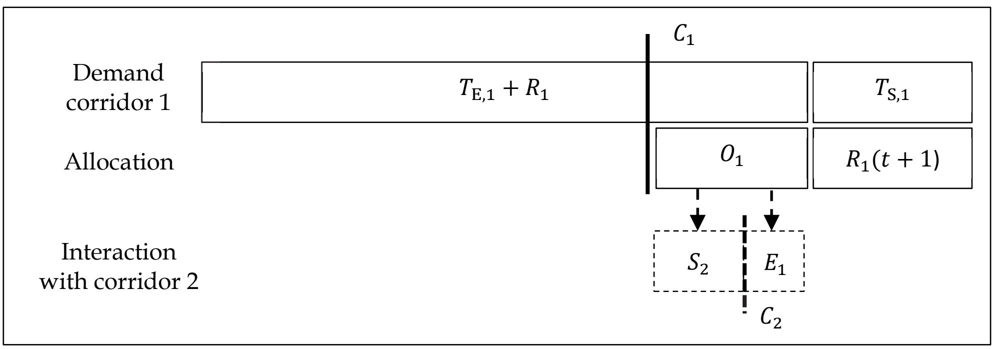
a) Surplus slots are (partially) used by overflow cargo of corridor 2



b) No surplus, no overflow



c) Overflow cargo is accommodated on surplus slots of corridor 2



d) Excess overflow cargo is transported by truck

Fig. 6.5 Transportation plan: options for corridor 1 and interactions with corridor 2

Algorithm 6.2 Optimal limits for the CFCM(2,2,2) problem

1 For both corridors, create a list of all combinations of potential limits, $L_{\mathrm{E},i}$ and $L_{\mathrm{S},i}$ $(i = 1,2)$.

2 Compute the solution for each combination of limits (as in step 3 of Algorithm 6.1):

a. Determine $\mathbb{P}(O_i = y)$ and $\mathbb{P}(S_i = z)$, using (6.5) − (6.6).

b. For each limit, determine the expected additional profit for $L_{\mathcal{F}}^{+1}$:

$$\Delta J = (f_{\mathcal{F}} - c_i)\mathbb{P}(T_{\mathcal{F}} = L_{\mathcal{F}}^{+1}) - \widehat{\Delta O}$$

in which $\widehat{\Delta O}$ is an estimator for the penalty increase by $L_{\mathcal{F}}^{+1}$

c. Select the limit for which an increase results in maximum expected profit and increment with 1. Solve the Markov Chain with (6.2) − (6.4) for the new limits.

3 Create a list of all combinations of limits for both corridors: $L_{\mathcal{F},i}$ $(\mathcal{F} \in \{\mathrm{E},\mathrm{S}\}, i \in \{1,2\})$.

4 Remove from that list all combinations that result in suboptimal solutions:

a. The sum of all limits is less than daily capacity

$$\sum_{\mathcal{F},i} L_{\mathcal{F},i} \leq C_1 + C_2$$

b. The expectation of the average accepted demand for a certain set of limits is higher than the capacity

$$\sum_{\mathcal{F},i} \mathbb{E}_{L_{\mathcal{F},i}}(T_{\mathcal{F},i}) > C_1 + C_2$$

c. The expected additional demand when incrementing a limit becomes negligible

$$\mathbb{E}_{L_{\mathcal{F},i}+1}(T_{\mathcal{F},i}) - \mathbb{E}_{L_{\mathcal{F},i}}(T_{\mathcal{F},i}) < \epsilon,$$

where ϵ is an arbitrary small number.

5 For all remaining combinations of limits, enumerate the expected profit (6.10), based on the obtained Markov solutions in step 2 and (6.15).

6 Select the limit that results in the highest profit.

6.3.3 Intermodal problem, CFCM$(\boldsymbol{r}, \boldsymbol{r}, \mathbf{2})$

To study the value of rerouting in a synchromodal network, we consider a network of intermodal connections, denoted as the CFCM$(r, r, 2)$ problem: multiple corridors connect from a deep-sea port to the inland. The deep-sea port and its inland corridors form a one-level tree structure, as depicted in Fig. 6.1. We also assume independent demand per corridor, directed to precisely one destination per corridor (i.e., we do not distinguish between multiple warehouses around an inland terminal). In this section, we propose methods for finding a lower and upper bound for this version of the CFCM problem. By doing so, an estimate is provided of the benefit of rerouting in a synchromodal network in comparison to optimising all corridors separately.

From the previous section, we know that the overflow O_i of a corridor does not depend on other corridors, and neither does the amount of slack slots S_i. The excess demand E_i does depend on alternative corridors. We assume that the effective amount of excess cargo can be reduced using the expected surplus slots on alternative corridors. Also, we assume that if any excess trucking occurs, it is not important which container will be transported by excess trucking. Therefore, to find the network optimum, we can re-use the iterations of the single-corridor optimisation to get distributions of O_i and S_i. However, we need to find the number of rerouted containers to determine how much of the overflow remains as excess E_i. In Section 6.3.3.1, we propose a method for finding the lower bound for the optimal CFCM in such a network. This method is based on a sub-problem of the original problem, in which a corridor can be the alternative to at most one other corridor. In Section 6.3.3.2, we propose a method for finding an upper bound, by ignoring potential penalties.

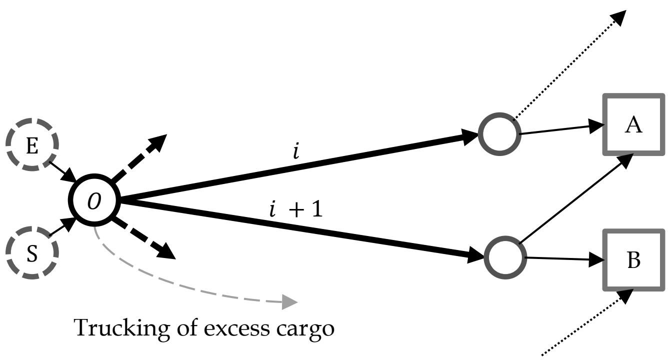


Fig. 6.6 Schematic overview of CFCM $(r, r, 2)$ problem with single alternatives

6.3.3.1 Lower bound for optimal network solution, based on single alternative corridors

By considering all corridors individually, using the result from Section 6.3.1, a lower bound for the network solution is obtained that uses no rerouting at all. Here we propose a better lower bound assuming that each corridor is the alternative for at most one other corridor. We assume that the unique alternatives have been determined, based on lowest rerouting costs. See Fig. 6.6 for a schematic overview of corridors with single alternatives. With this approach, we only have to consider two 'neighbouring' corridors, in order to assess the impact of changing a limit.

For finding the optimal limits that result in the highest expected profit J, our approach is as follows. In the first phase, we consider all corridors separately, and determine optimal limits using the approach from Section 6.3.1. We keep the result for all iterations. In the second phase, we consider the rerouting possibilities between corridors. Considering the rerouting possibilities, it is likely that the optimal limits are different. Firstly, it is likely that it is optimal to have higher total limits than the optimal single-corridor limits, since overflow can likely be rerouted. We consider this as the *reduced overflow cost eff*ect. Second, there may be a positive effect of decreasing a limit in one corridor, for the benefit of accepting more cargo on another corridor. We consider this as the *slack slot value effect*. Note that changing a limit on a corridor i influences two other corridors: on the one hand, by increasing a limit on corridor i, the expected overflow $\mathbb{E}O_i$ may be increased, which could increase the expected excess $\mathbb{E}E_i$ as well. Depending on the price, cost and penalty parameters, there is a trade-off between increasing a limit on corridor i and reducing limits on the *alternative* corridor a. Let the cost of transporting cargo from corridor i via the alternative corridor a be denoted by $c_{a,i}$. On the other hand, the same effect may exist with the corridor for which i is the alternative, the *bequeathing* corridor. Let this bequeathing corridor be denoted by b, and let $\mathbb{E}(E_b)$ denote the expected excess from that corridor. A trade-off exists between increasing a limit on corridor i and reducing limits on the bequeathing corridor b.

For a single corridor, the profit is denoted by:

$$\begin{aligned} J_i\left(L_{E,i}, L_{S,i}\right) = \left(f_{E,i} - c_i\right)\mathbb{E}\left(T_{E,i}\right) + \left(f_{S,i} - c_i\right)\mathbb{E}\left(T_{S,i}\right) + c_i\mathbb{E}(O_i) \\ - c_{a,i}\mathbb{E}(O_i - E_i) - p\mathbb{E}(E_i) + \left(p - c_{a,b}\right)\mathbb{E}(O_b - E_b) \end{aligned} \tag{6.16}$$

These two effects, the reduced overflow cost effect and the slack slot value effect, can be made quantifiable by replacing the penalty value with a virtual penalty $p_{i,v}$, and introducing a slack slot value $s_{i,v}$. The virtual penalty is the average rerouting costs per overflow unit, while the slack slot value is the average cost saving per slack slot. They are provided by the following equations:

$$p_{i,v} = \begin{cases} \dfrac{c_{a,i}[\mathbb{E}(O_i) - \mathbb{E}(E_i)] - p\mathbb{E}(E_i)}{\mathbb{E}(O_i)} & if\ \mathbb{E}(O_i) > 0 \\ 0 & otherwise \end{cases} \tag{6.17}$$

$$s_{i,v} = \begin{cases} \dfrac{\left(p - c_{a,b}\right)[\mathbb{E}(O_b) - \mathbb{E}(E_b)]}{\mathbb{E}(S_i)} & if\ \mathbb{E}(S_i) > 0 \\ 0 & otherwise \end{cases} \tag{6.18}$$

Note that $c_{a,b}$ here denotes the costs of rerouting cargo from corridor b via its alternative, which is our current corridor i. Rewriting, we can use (6.17) − (6.18) to rewrite (6.16) to a virtual corridor profit $J_{i,v}$:

$$J_{i,v}\left(L_{E,i}, L_{S,i}\right) = \left(f_{E,i} - c_i\right)\mathbb{E}\left(T_{E,i}\right) + \left(f_{S,i} - c_i\right)\mathbb{E}\left(T_{S,i}\right) - \left(p_{i,v} - c_i\right)\mathbb{E}(O_i) + s_{i,v}\mathbb{E}(O_b - E_b) \tag{6.19}$$

Two key insights are important for our approach. Firstly, equation (6.19) has the same structure as the maximisation goal for a single corridor as in (6.1), with penalty p set to $p_{i,v}$ and slack slot value ψ set to $s_{i,v}\mathbb{E}(O_b - E_b)$. In this way, we can use $p_{i,v}$ and $s_{i,v}$ to include the benefits of network rerouting in the single-corridor formulation and reuse Algorithm 6.1 per corridor for finding a solution fast. Secondly, the solution of the Markov Chains (step 3-iv.) in Algorithm 6.1 does not depend on the value of $p_{i,v}$ and $s_{i,v}$, but only on the limits $L_{\mathrm{E},i}, L_{\mathrm{S},i}$. Therefore, all previously solved Markov Chains for specific limits can be reused for later computations for different values of $p_{i,v}$ and $s_{i,v}$.

Using these insights, we propose a double iterative solution algorithm: a network-wide iterative procedure aims to iteratively find optimal limits, until no more improvement to the network revenue can be found. Each iteration considers every corridor separately, and per corridor an iterative procedure is used to estimate the values for $p_{i,v}$ and $s_{i,v}$, given the slack slot distribution of the alternative corridor a and the overflow of the bequeathing corridor b. This approach is given as Algorithm 6.3. It works for any multi-corridor CFCM$(r, r, 2)$ network, in which a corridor has at most one bequeathing corridor. An extension in which a corridor is the alternative for multiple corridors is not fundamentally excluded by our assumptions, but would require rewriting (6.16) − (6.19) and Algorithm 6.3 for a case with multiple bequeathing corridors. Although such an extension would potentially increase the value of network rerouting, the increase would not be significant for real-world problems, as we will show in Section 6.4. Since such an extension would substantially complicate the notation of the analysis, we have not included it in this chapter.

Algorithm 6.3 Network solution for the CFCM$(r, r, 2)$ problem

1 For each corridor i, apply Algorithm 6.1, to find corridor-optimal values for $L_{E,i}, L_{S,i}$. For each corridor, save all solved Markov Chains for later use.

2 Determine the total network revenue J by rerouting any overflow demand, if possible. If this is the first iteration, or if the newest J exceeds the previous one, continue. Else go to 5.

3 For each corridor i, find the revenue maximising limits, provided the state of the other corridors.

- a. Determine the virtual corridor value $J_{i,v}$ with (6.19), considering the rerouting between corridor b, i and a. If this is the first iteration, or if the newest $J_{i,v}$ exceeds the previous one continue. Else go to e.
- b. Determine the virtual penalty $p_{i,v}$, and slack slot value $s_{i,v}$ using $(6.17) - (6.18)$.
- c. Find optimal limits given these values for $p_{i,v}$ and $s_{i,v}$, using Algorithm 6.1. Re-use previously solved Markov Chains for specific values $L_{E,i}, L_{S,i}$ whenever possible. Save all newly solved Markov Chains.
- d. Restart at a., until converged.
- e. Continue for corridor $i + 1$. If this was the last corridor, go to 4.

4 Restart at 2, until converged.

5 Finish by determining the lower bound for the total expected profit for the limits found:

$$J^{LB} = \sum_i J_i(L_{E,i}, L_{S,i}).$$

6.3.3.2 Upper bound for network solution, based on minimum alternative corridor cost

An upper bound is found if we consider the case in which all overflow can be rerouted over the cheapest alternative. I.e., we replace the penalty of each corridor by the rerouting cost of its alternative corridor:

$$J_i^{UB}(L_{E,i}, L_{S,i}) = (f_{E,i} - c_i)\mathbb{E}(T_{E,i}) + (f_{S,i} - c_i)\mathbb{E}(T_{S,i}) - (c_{a,i} - c_i)\mathbb{E}(O_i), \qquad j \neq i$$

in which $c_{a,i}$ denotes the cost of the cheapest alternative route:

$$c_{a,i} = \min_j c_{j,i}$$

In this upper bound, only demand-routing options that are unprofitable are excluded. For cases in which the profit outweighs the rerouting costs, i.e. $(f_{S,i} - c_i) > (c_{a,i} - c_i)$, this is not a very tight bound. However, if rerouting is expensive compared to the profit per container, i.e. $(f_{S,i} - c_i) < (c_{a,i} - c_i)$ or even $(f_{E,i} - c_i) < (c_{a,i} - c_i)$, this bound is expected to be rather tight. Effectively, this is reducing the network problem to multiple single corridor problems with a penalty of $c_{a,i}$. For completeness, this procedure is provided as Algorithm 6.4.

Algorithm 6.4 Algorithm for an upper bound for the CFCM$(r, r, 2)$ problem

1 For each corridor separately:
   a. Find cost of the cheapest alternative that can be used in case of overflow, i.e. the cost of rerouting over another corridor, or the costs of excess trucking.
   b. Set the cost of excess trucking to this value.
   c. Apply Algorithm 6.1 to get an upper bound of the profit on that corridor.

2 Take the sum of the profits of all corridors to obtain the network upper bound:

$$J^{UB} = \sum_i J_i^{UB}(L_{E,i}, L_{S,i}).$$

6.4 Case Study of the CFCM problem in the EGS network

In this section, the procedure proposed for the CFCM$(r, r, 2)$ problem is applied to two cases. The cases represent two different parts of the synchromodal transportation network of EGS. Case 1 considers the transportation of containers from the port of Rotterdam to two destinations in the industrial Ruhr area: Venlo and Duisburg. Case 2 represents transportation to Central Europe, i.e. five corridors from Rotterdam to inland terminals in Southern Germany and France. Table 6.2 provides a general overview of the two corridors and the main differences. Case 1 represents a two-corridor network structure with high volume and relatively short distances. Therefore, the costs for trucking excess demand and the additional costs for rerouting are tolerable. On the other hand, Case 2 represents a five-corridor network with much lower throughput to a more distant and more widely dispersed area (see Fig. 6.7). Therefore, both excess trucking and rerouting come at substantial additional costs. In the remainder of this section we consider all parameters, such as capacity and prices, based on forty-foot containers, or forty-foot equivalent units (FEU). We consider the import flow, i.e. from the deep-sea port towards the inland terminal. We make a comparison between these two cases, and how the effect of a network approach for the fare class limits differs between these cases.

Table 6.2 Two case studies with the CFCM$(r, r, 2)$ model

	Case 1	*Case 2*
Locations	Duisburg, Venlo	Nuremberg, Munich, Stuttgart, Strasbourg, Aschaffenburg
Distance [km]	209-239	520-870
Corridor import per day [FEU]	50-150	5-15

Deep-sea port: (A) ECT Rotterdam
Case 1: (B) Venlo, (C) Duisburg,
Case 2: (D) Aschaffenburg, (E) Strasbourg, (F) Stuttgart, (G) Nuremberg and (H) Munich.

Fig. 6.7 Case study locations EGS network

6.4.1 Network solution high demand target area: Rotterdam - Ruhr area

EGS operates two high-volume corridors between the port of Rotterdam and the Ruhr area, Venlo, and Duisburg. Both rail and barge services operate on the corridors, but we ignore transportation time and do not distinguish between the modes. The average distance from the port of Rotterdam is 219 km. The distance between both locations is 53 km. In order to apply Algorithm 6.3, we make the following assumptions. We consider all parameters, such as capacity and prices, based on forty-foot containers, or forty-foot equivalent units (FEU). We consider the import flow, i.e. from the deep-sea terminal towards the inland terminal. For the capacity, we take the average available slots per day on each corridor. The transportation cost per FEU is based on the average slot costs of all rail and barge slots. For demand and prices, we will use input from EGS's internal research into the market for synchromodal products. We assume Poisson distributed demand.
The transportation cost matrix is determined as follows: if a container is transported on the regular corridor, i.e. towards a final destination towards the end of that

corridor, we use the average slot costs. If an alternative route is selected, this will incur different slot costs for the corridor transport, and on top of that the local delivery is more expensive as the container must be rerouted to its original destination area. Therefore, for an alternative route, we use the slot costs on the alternative route, and in addition the extra costs for local truck delivery. The cost matrix for Case 1 is provided in Table 6.3. For confidentiality reasons, we cannot disclose the detailed information on pricing and costs. Instead, we provide the information normalised to the lowest costs. For the same reason, demand is normalised to the highest demand.

Table 6.3 Parameters case 1 - high demand target area

	Destination		
	Venlo	*Duisburg*	*Alternative*
Costs [normalised]			
Rotterdam-Venlo	1.00	1.12	(+12%)
Rotterdam-Duisburg	1.21	1.10	(+10%)
Excess trucking	2.05	2.05	
	(+105%)	(+83%)	
Pricing			
Express	1.33	1.52	
Standard	1.16	1.32	
Network volumes [normalised]			
Capacity per corridor	1.00	0.34	
Demand	1.00	0.34	
% Express demand	30%	30%	

Table 6.4 Results for case 1 – high demand target area

Case	*Optimal booking limits* $L_E; L_S$	*Expected revenue* J	*Capacity utilisation* η *[%]*	*Expected excess* $\mathbb{E}(E_S)$	*Comp. time* T *[s]*
Corridor optimum (CO)	107;152	45.31	99%	0.1%	159
CO with rerouting (RR)	107;152	45.33	99%	0.1%	159
Network lower bound (LB)	102;152	45.33	99%	0.1%	262
Network upper bound (UB)	114;216	45.79	99%	0.6%	297

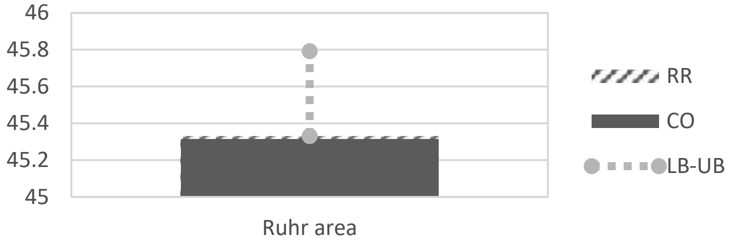


Fig. 6.8 Daily profit in case 1 – high demand target area

The results are provided in Table 6.4 and the expected profits are visualised in Fig. 6.8. By applying Algorithm 6.1 to both corridors separately, the optimal limits for these corridors are found. Together, these corridors give an expected daily profit of 45.33. Applying Algorithm 6.3 to this case does not provide a higher expected profit and gives the same solution as individually optimising the corridors. This is also a lower bound for the network optimum. Algorithm 6.4 gives an upper bound for the network optimum of 45.79, which is 1% over the lower bound.

6.4.2 Network solution dispersed long-distance area: Rotterdam – Central Europe

In the second case, we consider container transportation between Rotterdam and five inland terminals in Central Europe, Nuremberg, Munich, Aschaffenburg, Stuttgart and Strasbourg. The average distance of these location from the port of Rotterdam is 635 km. No barge transport is considered, but for each of the five locations we consider the rail connection. The distance between the five inland locations ranges from 169-676 km. For this case, we consider a horizon for Express of 3 days, and for Standard twice that, 6 days. Therefore, in order to apply Algorithm 6.3, we make the following assumptions. For the capacity, we take the average available slots on 3 days on each corridor. The transportation cost per FEU is based on the average slot costs of all rail slots. For demand and prices, we will use input from EGS's internal research into the market for synchromodal products. We assume Poisson distributed demand. The transportation cost matrix is determined as in the previous case, and is provided in Table 6.5. The results are tabularised in Table 6.6, and the profits are shown in Fig. 6.9. By applying Algorithm 6.1 to each corridor individually, we get a total expected profit of 7.54. Subsequently, we apply Algorithm 6.3, to consider the benefits of the network. After step 2 of Algorithm 6.3, we have the expected profit considering network rerouting, based on the limits of the individual corridor optima. This gives a slight increase, to an expected profit of 7.58. By finishing Algorithm 6.3, we obtained an improved network solution, 7.60, which is a lower bound for the network optimum. The upper bound for the network optimum is obtained by Algorithm 6.4, and equals 7.73.

Table 6.5 Parameter setting case 2 – Dispersed demand in long-distance area

The direct route is double underlined, the alternative route is single underlined						
Destination	*Nurem-berg*	*Munich*	*Stutt-gart*	*Stras-bourg*	*Aschaffen-burg*	*Alter-native*
Costs [normalised]						
Rtm - Nuremberg	1.00	1.22	1.31	1.51	1.24	(+22%)
Rtm - Munich	1.24	1.00	1.31	1.59	1.53	(+31%)
Rtm - Stuttgart	1.34	1.34	1.02	1.19	1.27	(+17%)
Rtm - Strasbourg	1.68	1.79	1.31	1.04	1.49	(+43%)
Rtm - Aschaffenburg	1.33	1.62	1.33	1.48	1.01	(+32%)
Excess trucking	2.50 (+150%)	2.50 (+150%)	2.50 (+146%)	2.50 (+140%)	2.50 (+149%)	
Pricing						
Express (+15%)	1.27	1.27	1.42	1.17	1.25	
Standard	1.10	1.10	1.23	1.02	1.09	
Network volumes [normalised]						
Capacity per corridor	1.00	0.30	0.20	0.20	0.20	
Demand	1.00	0.30	0.20*	0.20*	0.20*	
% Express demand	30%	30%	30%	30%	30%	

*projected data for new corridors, no sufficient data available yet.

Table 6.6 Results for case 2 – Dispersed destinations in a long-distance area

Case	*Optimal booking limits* $L_E; L_S$	*Expected revenue* J	*Capacity utilisation* η *[%]*	*Expected excess* $\mathbb{E}(E_S)$	*Comp. time* T *[s]*
Corridor optimum (CO)	42;49	7.54	82%	0.1%	3
CO with rerouting (RR)	42;49	7.58	82%	0.0%	3
Network lower bound (LB)	44;50	7.60	82%	0.0%	12
Network upper bound (UB)	54;71	7.73	84%	1.0%	13

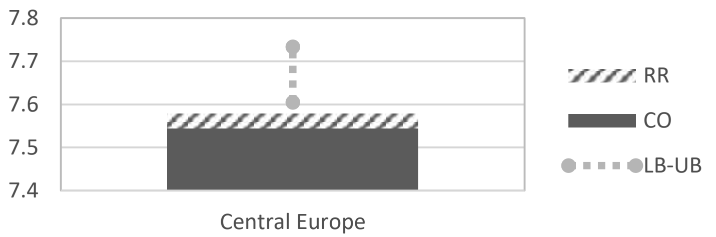


Fig. 6.9 Profit in case 2 – Dispersed destinations in a long-distance area

6.4.3 Sensitivity analysis

The results of the studied cases show that the benefit of a network solution depends on the settings of the network. To obtain more insight in relevant aspects of the problem that influence the network effect, we performed a sensitivity analysis in a stylised setting with two corridors. We consider a couple of corridors, one ofwhich has a moderate profit margin and one a substantial profit margin (see Table 6.7). In the table, three parameters are denoted by (x, y, z); for each experiment, one of these parameters is changed to one of the alternative values indicated in the table; changing one parameter at a time. With parameter x, we study the sensitivity to excess trucking costs (the costs of excess trucking changes for both corridors simultaneously). Parameter y is used for changing only corridor 1: the demand on this corridor is varied in a wide range to see its effect on the network profitability and effectiveness of our proposed method. Finally, parameter z is used to study the sensitivity to the ratio between Express and Standard demand. All other settings are denoted in Table 6.7, the standard settings for (x, y, z) are denoted between brackets. Fig. 6.10 shows the resulting profits for the Standard case of Table 6.7.

Table 6.7 Standard experiment setting sensitivity analysis

	Standard setting		*Sensitivity analysis*
	Corridor 1	Corridor 2	
Costs			
Direct route	1.00	1.00	
Alternative route	1.15	1.15	
Excess trucking	x (4)	x (4)	$x = [2, \ldots, 6]$
Pricing			
Express	1.25	1.55	
Standard	1.10	1.30	
Network			
Capacity (C)	30	30	
Demand (% of C)	y (70%)	100%	$y = [20, 30, \ldots, 150]\%$
% Express demand	z (30%)	z (30%)	$z = [10, 20, \ldots, 80]\%$

More details are provided in Table 6.8. By applying Algorithm 6.1 to both corridors individually, the optimums per corridor are found. The sum of this gives the corridor optimum (CO) of 12.79. In the corridor optimum, rerouting (RR) provides little additional profit (12.87, +0.6%). Applying Algorithm 6.2 gives the network optimum (NO) of 13.04 (+1.3%, compared to RR). Algorithm 6.2 provides the global optimum, but the computation time is only feasible for a simple benchmark case such as this one. Applying Algorithm 6.3 – which is more scalable to larger problems – results in a lower bound, in this case close to the optimum: 12.97. Still, this is only +0.8% over the result based on corridor optimums with rerouting (RR). An upper bound can be found with Algorithm 6.4, resulting in 13.17. For this setting, the benefit of a network solution is negligible. The question is, does that hold for all situations?

Table 6.8 Results of Algorithm 6.1-6.4 for CFCM(2,2,2) problem

Case	*Optimal booking limits* $L_E; L_S$	*Expected revenue* J	*Capacity utilisation* η *[%]*	*Expected excess* $\mathbb{E}(E_S)$	*Comp. time* T *[s]*
Corridor optimum (CO)	33;57	12.79	81%	0.0%	1
CO with rerouting (RR)	33;57	12.87	81%	0.0%	1
Network lower bound (LB)	35;58	12.97	82%	0.0%	3
Network upper bound (UB)	45;78	13.17	82%	0.9%	3
Network optimum (NO)	48;47	13.04	82%	0.0%	1738

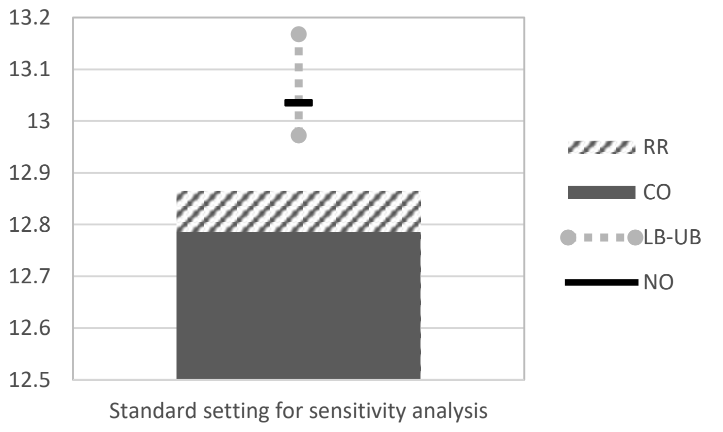
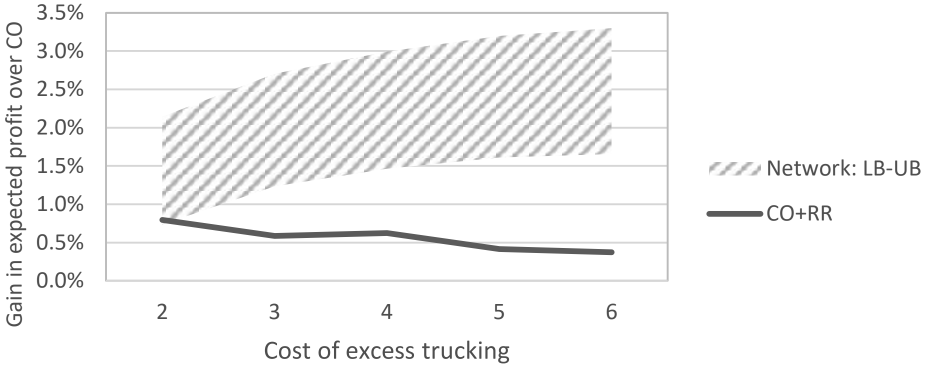
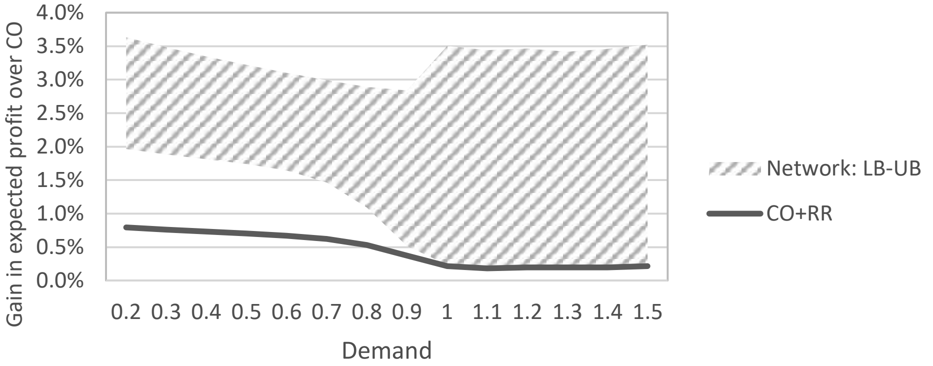


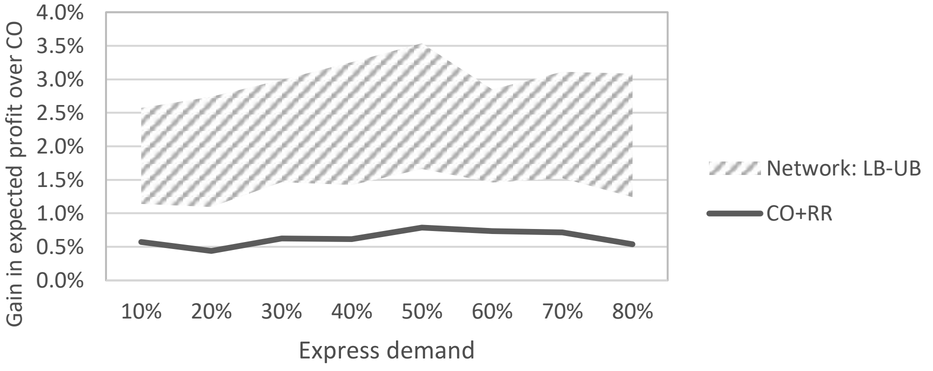
Fig. 6.10 Profit for standard setting (basis for sensitivity analysis)



a) Benefit of rerouting and network solutions for different costs of excess trucking



b) Benefit of rerouting and network solutions for different levels of demand



c) Benefit of rerouting and network solutions for different levels of Express demand

Fig. 6.11 Results sensitivity analysis

With a low cost of excess trucking, the benefit of rerouting diminishes, whereas in a situation with very high excess trucking costs the potential benefit of a network solution increases. This effect can be seen in Fig. 6.11a: the network gain is largest for higher values of excess trucking costs. Fig. 6.11b shows the effect of demand volume in comparison with capacity. For corridor 1, demand is varied between 20% and 150% of its capacity, while demand on the second corridor is kept constant. The effects on our methods for the lower and upper bound are different. If demand is low, the lower bound results in a higher profit than if only considering rerouting based on the single corridor optimum. It shows that our lower bound method is beneficial to exploit available capacity. However, if demand is high, our lower bound method equals the corridor solution with rerouting. On the other hand, the upper bound increases if demand is high, since our proposed upper bound method ignores capacity constraints on the alternative corridor.
Finally, Fig. 6.11c shows the effect of Express demand. From the figure, we can see that from low to high fractions of Express, rerouting and network solutions provide similar benefits.

6.5 Conclusions

With the introduction of the Cargo Fare Class Mix problem, we aimed to create a bridge between the operations management of optimising transportation planning and the revenue management of optimising the service portfolio in synchromodal container networks. The previously introduced method was only suitable for smaller single corridor problems, which needed to be extended for answering research question 7: "To what extent is it relevant to consider the synchromodal network structure when optimising the fare class mix?"
In this chapter we have improved our earlier method, making it much faster and suitable for larger corridors. Secondly, we proposed an approach for finding limits in the CFCM$(r, r, 2)$ problem. This approach is suitable for use in practice, as we demonstrated in a case study of two parts of the EGS network. We also showed how sensitive the problem is in various settings:

- For higher excess trucking cost levels, the network approach is beneficial. If the costs of excess trucking are low relative to the intermodal transportation costs, the proposed network method provides little improvement.
- For demand levels that are low on one corridor, the improvement by considering the network approach is significant. If demand on this corridor is high compared to the available capacity, the benefit of our lower bound method for a network solution is limited, but the upper bound is high.
- The fraction of Express demand is not very important: For all Express fractions, network rerouting becomes relevant, making the network approach significant.

The above shows that an intermodal operator has multiple options to adjust demand to available capacity. Our approach aims at balancing the available Express and Standard demand in an optimal way, leveraging the flexibility in the network. Alternatively, the operator can focus on flexibility within the corridor, e.g. by concentrating on large parts of demand that can be postponed such as the Standard fare class. In the case study, we demonstrated that different settings exist within the network of EGS: a network solution adds some benefit for the Central Europe area, whereas for the Ruhr area it does not.

The results from this study are based on specific assumptions concerning the demand distribution: We assume independent distributions for both service types, ignoring the possibilities of substitution. We assume independent demand distributions per corridor, ignoring potential seasonal or market effects that influence multiple corridors simultaneously. Also, our method is aimed at cases in which a corridor is the alternative for at most one corridor. In practice, our approach is not fundamentally limited to this situation: Algorithm 6.3 can be applied to a more complex rerouting algorithm as well. However, this would not add major benefit to the class of transport problems considered in this paper but would substantially complicate the notation of the analysis. It would be interesting in future research, however, to study the impact of more advanced rerouting in more complex networks. In Chapter 7, an overview is provided of all results and overall conclusions from this dissertation, as well as further directions for future research.

Appendix 6.A Probability distributions of surplus and overflow

This appendix provides the derivation of the steady state distributions of the number of overflow containers O_i and the number of surplus (or slack) slots S_i on corridor i. First we consider slack slots. When the available cargo exceeds the capacity, the number of slack slots is zero. Otherwise, the number of slack slots equals the difference between available cargo and the capacity:

$$\mathbb{P}(S_i = z) = \begin{cases} \mathbb{P}\left(T_{E,i} + T_{S,i} + R_i \geq C_i\right) & z = 0 \\ \mathbb{P}\left(T_{E,i} + T_{S,i} + R_i = C_i - z\right) & z > 0 \end{cases} \tag{6.20}$$

The distribution of R_i is provided by $\pi_i(j) = P(R_i = j)$ as obtained by solving the Markov Chain for CFCM$(1, d, 2)$ (see Section 6.3.1). We can then rewrite (6.20) as:

$$\mathbb{P}(S_i = z) = \begin{cases} \displaystyle\sum_{q=0}^{C_i} \pi_i(q) \sum_{e=0}^{C_i} \mathbb{P}\left(T_{S,i} \geq C_i - q - e\right)\mathbb{P}\left(T_{E,i} = e\right) & z = 0 \\ \displaystyle\sum_{q=0}^{C_i - z} \pi_i(q) \sum_{e=0}^{C_i - q - z} \mathbb{P}\left(T_{S,i} = C_i - z - q - e\right)\mathbb{P}\left(T_{E,i} = e\right) & z > 0 \end{cases} \tag{6.21}$$

And by summing over z we obtain:

$$\mathbb{P}(S_i > 0) = \sum_{q=0}^{C_i} \pi_i(q) \sum_{e=0}^{C_i-q} \mathbb{P}\big(T_{S,i} < C_i - q - e\big)\mathbb{P}\big(T_{E,i} = e\big) \tag{6.22}$$

We observe that $\mathrm{S}_i \leq C_i - R_i$, and therefore $\pi_i(q) = 0, q > C_i - z$. The expected value from (6.21) is provided by:

$$\mathbb{E}(S_i) = \sum_{z=1}^{C_i} z\mathbb{P}(S_i = z) = \sum_{z=1}^{C_i} z \sum_{q=0}^{C_i-z} \pi_i(q) \sum_{e=0}^{C_i-q-z} \mathbb{P}\big(T_{S,i} = C_i - z - q - e\big)\mathbb{P}\big(T_{E,i} = e\big) \tag{6.23}$$

Secondly, we consider the distribution of the amount of overflow cargo for corridor i. When the available cargo is less than the capacity on that corridor, the number of overflow slots is zero. Otherwise, the number of overflow slots equals the difference between available cargo and the capacity:

$$\mathbb{P}(O_i = z) = \begin{cases} \mathbb{P}\big(R_i + T_{E,i} \leq C_i\big) & z = 0 \\ \mathbb{P}\big(R_i + T_{E,i} = C_i + z\big) & z > 0 \end{cases} \tag{6.24}$$

The distribution of R_i is provided by $\pi_i(j) = P(R_i \ = j)$ as obtained by solving the Markov Chain for CFCM$(1, d, 2)$ (see Section 6.3.1). We can then rewrite (6.24) as:

$$\mathbb{P}(O_i = z) = \begin{cases} \displaystyle\sum_{q=0}^{C_i} \pi_i(q)\mathbb{P}\big(T_{E,i} \leq C_i - q\big) & z = 0 \\ \displaystyle\sum_{q=0}^{C_i} \pi_i(q)\mathbb{P}\big(T_{E,i} = C_i + z - q\big) & z > 0 \end{cases} \tag{6.25}$$

By summing over z, we obtain:

$$\mathbb{P}(O_i > 0) = \sum_{q=0} \pi_i(q)\mathbb{P}\big(T_{E,i} > C_i - q\big) \tag{6.26}$$

The expected value from (A6) is obtained by:

$$\mathbb{E}(O_i) = \sum_{z=i}^{C_i} z \sum_{q=z}^{C_i} \pi_i(q)\mathbb{P}\big(T_{E,i} = C_i + z - q\big) \tag{6.27}$$

Appendix 6.B Optimality proofs

Proof 1: the expected profit has a single maximum for one variable limit, if the other limit is fixed.

In the remainder, we assume that L_E is fixed and L_S is varied, but the proof also holds the other way around. Let $\mathbb{P}_{S^{+1}}$ denote the probability of incurring one additional overflow slot, if a unit of product S is added. I.e.:

$$\mathbb{E}[\Delta T_S]\mathbb{P}_{S^{+1}} = \mathbb{E}[O|L_S + 1] - \mathbb{E}[O|L_S],$$

where $\mathbb{E}[\Delta T_S]$ denotes the expected additional Standard demand if the limit is increased by 1:

$$\mathbb{E}[\Delta T_S] = \mathbb{E}[T_S|L_S + 1] - \mathbb{E}[T_S|L_S].$$

Let $J(L_S)$ be the profit for limit L_S. Let Ω be the set of possible scenarios, and p_ω the probability that scenario ω occurs. It holds that:

$$J(L_S) = \sum_{\omega,t} p_\omega\big((f_S - c)T_S(t,\omega) - pO(t,\omega)\big) = (f_S - c)\ \mathbb{E}[T_S] - p\mathbb{E}[O].$$

We now consider $J(L_S + 1) - J(L_S)$:

$$\begin{aligned} J(L_S + 1) - J(L_S) &= (f_S - c)(\mathbb{E}[T_S|L_S + 1] - \mathbb{E}[T_S|L_S]) - p\mathbb{E}[O|L_S + 1] - \mathbb{E}[O|L_S]) \\ &= \mathbb{E}[\Delta T_S](f_S - c - p\mathbb{P}_{S^{+1}}). \end{aligned}$$

Clearly, $\mathbb{E}\left[\Delta T_{S,d}\right] \geq 0$ for all values of L_S. Hence, $J(L_S)$ is increasing with increasing L_S if $f_S - c - p\mathbb{P}_{S^{+1}} \geq 0$ and $J(L_S)$ is decreasing with increasing L_S if $f_S - c - p\mathbb{P}_{S^{+1}} \leq 0$.
The probability that an extra unit of demand will lead to a penalty increases when the limit increases, so $f_S - c - p\mathbb{P}_{S^{+1}}$ is a decreasing function. This means that $J(L_S)$ is first increasing and later decreasing, with a unique maximum at the point where $f_S - c - p\mathbb{P}_{S^{+1}}$ changes sign.

Proof 2: If the expected profit for two given limits is larger than the profits obtained when one of the limits is reduced by 1, then this profit exceeds all scenarios with limits lower than or equal to the given limits

We consider a single corridor with a single destination. Let J_{L_E,L_S} denote the expected profit in a scenario for a given L_E and L_S. We show the following:

$$if\ J_{L_E,L_S} \geq J_{L_E-1,L_S}\ and\ J_{L_E,L_S} \geq J_{L_E,L_S-1}\ then\ J_{L_E,L_S} \geq J_{L_E-x,L_S-y} \qquad \forall x,y \geq 0$$

The expected profit for a single corridor is given by:

$$J_{L_E,L_S} = (f_E - c)\ \mathbb{E}[T_E] - (f_S - c)\ \mathbb{E}[T_S] - p\mathbb{E}[E].$$

And, as in proof 1:

$$J_{L_E,L_S} - J_{L_E-1,L_S} = \mathbb{E}[\Delta T_E](f_E - c - p\mathbb{P}_{E^{+1}}) \geq 0.$$

$$J_{L_E,L_S} - J_{L_E,L_S-1} = \mathbb{E}[\Delta T_S](f_S - c - p\mathbb{P}_{S^{+1}}) \geq 0.$$

Subsequently, we consider

$$J_{L_E,L_S-1} - J_{L_E-1,L_S-1} = \mathbb{E}[\Delta T_E{}'](f_E - c - p\mathbb{P}'_{E^{+1}}).$$

Since the expected demand for one product is independent of the other products demand, we have $\mathbb{E}[\Delta T_{\mathrm{E}}] = \mathbb{E}[\Delta T_{\mathrm{E}}{}'] \geq 0$. Also, since total demand is lower, $\mathbb{P}'_{\mathrm{E}^{+1}} \leq \mathbb{P}_{\mathrm{E}^{+1}}$. Therefore, we have:

$$(f_E - c - p\mathbb{P}'_{E^{+1}}) \geq (f_E - c - p\mathbb{P}_{E^{+1}}) \geq 0$$

Consequently, $J_{L_{\mathrm{E}},L_{\mathrm{S}}-1} - J_{L_{\mathrm{E}}-1,L_{\mathrm{S}}-1} \geq 0$ and $J_{L_{\mathrm{E}}-1,L_{\mathrm{S}}-1} \leq J_{L_{\mathrm{E}},L_{\mathrm{S}}-1} \leq J_{L_{\mathrm{E}},L_{\mathrm{S}}}$. By recursion, this extends to the desired proof.

Proof 3: If the expected profit for two given limits is larger than the profits obtained when one of the limits is increased by 1, then this profit exceeds all scenarios with limits higher than or equal to the given limits

$$if\ J_{L_E,L_S} \geq J_{L_E+1,L_S}\ and\ J_{L_E,L_S} \geq J_{L_E,L_S+1}\ then\ J_{L_E,L_S} \geq J_{L_E+x,L_S+y} \qquad \forall x,y \geq 0$$

In a similar fashion as in proof 2, we obtain:

$$J_{L_E+1,L_S} - J_{L_E,L_S} = \mathbb{E}[\Delta T_E](f_E - c - p\mathbb{P}_{E^{+1}}) \leq 0.$$

$$J_{L_E,L_S+1} - J_{L_E,L_S} = \mathbb{E}[\Delta T_S](f_S - c - p\mathbb{P}_{S^{+1}}) \leq 0.$$

$$J_{L_E+1,L_S+1} - J_{L_E,L_S+1} = \mathbb{E}[\Delta T_E{}'](f_E - c - p\mathbb{P}'_{E^{+1}})$$

Again, $\mathbb{E}[\Delta T_{\mathrm{E}}] = \mathbb{E}[\Delta T_{\mathrm{E}}{}'] \geq 0$. Because demand is higher, $\mathbb{P}'_{\mathrm{E}^{+1}} \geq \mathbb{P}_{\mathrm{E}^{+1}}$. Therefore, we have now:

$$0 \geq (f_E - c - p\mathbb{P}_{E^{+1}}) \geq (f_E - c - p\mathbb{P}'_{E^{+1}})$$

From this follows that $J_{L_{\mathrm{E}}+1,L_{\mathrm{S}}+1} - J_{L_{\mathrm{E}},L_{\mathrm{S}}+1} \leq 0$ and $J_{L_{\mathrm{E}}+1,L_{\mathrm{S}}+1} \leq J_{L_{\mathrm{E}},L_{\mathrm{S}}+1} \leq J_{L_{\mathrm{E}},L_{\mathrm{S}}}$. By recursion, this extends to the desired proof.

Appendix 6.C Extensions and alternatives

As in Van Riessen, *et al.* (2017), we have used the aggregated demand for all destinations around the inland terminal to model each corridor. In reality, specific agreements per destination (or customer) in the destinations region can be made. Modelling limits per destination would result in a very large problem. Enumeration would be of order $O(|C_i|^{2d})$, that is selecting a limit $L_{\mathrm{S},d} \in \{0, \dots, 2C_i\}$ and $L_{\mathrm{E},d} \in \{0, \dots, 2C_i\}$ for each destination d. Although, the approach as in proofs 1-3 would reduce the problem size, it would still be a very large problem to solve to optimality. Here we provide two alternative modeling approaches, which we did not explore in further detail, but suggest as future research topics.

Two level stochastic modeling for CFCM (r,d,2)
Alternatively, this could be modelled as a stochastic programming problem with a sufficient number of scenarios. In a two level approach, the upper level problem must select general limits, which serve as input for the lower level problems, in which for each scenario individually the optimal transportation plan is created. Such an approach will also allow more flexible allocation strategies when creating the operational transportation plan, thereby alleviating one critical assumption in our analysis: the strict order of allocating cargo. Under our assumption, subsequently Express, all remaining Standard, the new Standard demand and lastly Overflow of bequeathing corridors is allocated. As long as the penalty p is equal for all types, and the direct costs on corridor i are lower than rerouting its bequeathing corridor ($c_i < c_{i-1,a}$), starting with Express and yesterday's Standard is always right, as it will directly induce a penalty otherwise. However, in a two-level stochastic approach, there is a possibility to on the operational level to decide to postpone some of today's standard demand, in favour of transporting overflow.

Alternative problem formulation for CFCM (r,d,2) based on customer selection
Here, we provide an outline for further research, based on a different CFCM decision problem: provided exogenous demand distributions per product and per customer, the problem is to decide whether to provide a long-term commitment to the customer or do not serve the customer at all. Since the number of possibilities for selecting TEU limits per customer and per product scales fast, this alternative approach will reduce the number of options per customer substantially: serve the customer, or not at all. This provides two potential improvements for the solution algorithm:

- The number of options becomes of order $O(2^d)$, which is significantly smaller than the order of a problem with limits per customer $O(|C_i|^{2d})$, especially for realistic numbers of customers per corridor, e.g. $d \leq 15$.
- Secondly, provided the exogenous demand of a customer, its contributing value is a combination of the expected profit of a customer, and the potential penalties included by that customer. For estimating the induced penalties, a measure must incorporate the fact that a customer with a small variation has little risk on triggering a penalty, while a customer with a long tail distribution may cause excess.

Note that accepting a customer with fully deterministic demand would reduce the problem to a new CFCM problem in which the capacity is reduced by the customer's demand.

7 Conclusion and implications

In Chapter 1, the main research question was introduced as follows: "How can synchromodal networks operate optimally?" To find the answer to that question, 7 sub research questions on three topics needed answering. The answers to those questions are provided in Chapter 2 – 6. A summary of the main results is provided Section 7.1, concluded by the answer to the main research question. Furthermore, this chapter highlights potential areas for future research on the topic (Section 7.2) and provides an epilogue on the implications of our research in practice (Section 7.3).

7.1 Summary of the main results and conclusion

Two separate trends in the container transportation practice in North-West Europe have motivated the research for this dissertation. On the one hand, competition in hinterland transportation and the societal need for a modal shift towards sustainable modes require more integrated network optimisation of container transports. On the other hand, hinterland users increasingly require a cost-effective, but flexible and reliable delivery service. The concept of synchromodality was developed as an answer to these developments, in which efficient planning is combined with a business model based on customer-oriented transportation services. Our research contributes by bringing together optimal transport planning in intermodal networks and the design of an optimal fare class mix of customer-oriented services. We have developed five models for practical problems in synchromodal networks. All models are developed with the perspective of a centralised operator in an intermodal container network, with scheduled services between a deep-sea terminal and multiple inland ports. These scheduled services can be trains or barges, but not necessarily both have to be available. Also, it is assumed that trucking capacity is available as an (expensive) overflow mode. All five models have been applied to case studies based on the intermodal container network of European Gateway Services (EGS), a subsidiary of Hutchison Ports ECT Rotterdam (ECT).

In Chapter 2, a new mathematical model is proposed to determine the optimal service schedule between the given network terminals. The model introduces two new features to the intermodal network-planning problem. Firstly, overdue deliveries are penalised instead of prohibited. Secondly, the model combines self-operated and subcontracted slots. The model considers self-operated or subcontracted barge and rail services as well as transport by truck. In a case study of the EGS network, the benefit of using container transportation with intermediate transfers is studied. The results indicate that the proposed model provides results for the service network design in modern intermodal container transport networks that are much more cost-efficient than alternative models without overdue flexibility, or without the combination of self-operated and subcontracted transport. In a case study of the EGS network, our results show that the costs of using only self-operated or subcontracted services would be 65% or 49% higher, respectively. Another result of the case study is that 22% of the costs are made to deliver on time, which was show to be very sensitive for the overdue delivery penalty. Also, the results suggest that an integrated operation of transport services and inland terminals improves network connectivity and, potentially, overall costs, by leveraging available terminal capacity.

The operational network planning problem is to allocate containers to available inland transportation services. For adequate planning it is important to adapt to occurring disturbances. In Chapter 3, a new mathematical model is proposed: the Linear Container Allocation model with Time-restrictions. This model is used for determining the influence of three main types of transit disturbances on network performance: early service departure, late service departure, and cancellation of inland services. The influence of a disturbance is measured in two ways. The *impact* measures the additional cost incurred by an updated planning in case of a disturbance. The *relevance* measures the cost difference between a fully updated and a locally updated plan. With the results of the analysis, key service properties of disturbed services that result in a high impact or high relevance can be determined. Based on this, the network operator can select focus areas to prevent disturbances with high impact and to improve the planning updates in case of disturbances with high relevance. The proposed method is used in a case study to assess the impact and relevance of transit disturbances on inland services of the European Gateway Services network. Based on the results, it is concluded that the network operator must focus on preventing early departures, as these have the highest impact. A high impact indicates a disturbance with large additional costs that cannot be reduced with a full update of the transportation plan. For instance, the unavoidable cost of an out-of-schedule departure are 7.5 times higher than the gain of using a full update instead of a local update. On top of that, full updates may incur high costs for rescheduling large amounts of containers. Therefore, generally, local updates may suffice. As an exception, the planning department of the network operator must give additional attention to cancellations of committed barge services. These showed the highest impact (up to 4 times the average costs of a service), and relatively high relevance. Although the relevance is generally low, for these cases

8% of the disturbance costs could be saved by applying more elaborate planning updates, or even a full update.

In Chapter 4 we proposed real-time decision rules for suitable allocations of containers to inland services by analysing the solution structure of a centralised optimisation method used offline on historic data. The decision tree can be used in a decision support system (DSS) for instantaneously allocating incoming orders to suitable services, without the need for continuous planning updates. The main contributions are threefold: firstly, a structured method for creating decision trees from optimal solutions is proposed. Secondly, an innovative method is used for obtaining multiple equivalent optimal solutions to prevent overfitting of the decision tree. And finally, a structured analysis of three error types is presented for assessing the quality of an obtained tree. In practice, such a DSS is beneficial, as it is easy to implement in the current practice of container transportation for three reasons: the method allows to instantly assign incoming container orders and directly answer customer requests; the method does not need advanced automation and the representation in a decision tree is comprehensible for human planning operators in practice. In case studies, the proposed DSS reduced total transportation costs significantly, compared to alternative methods (Greedy and First-Come-First-Serve): by 3% and 9% on average, respectively. The proposed method assumes that incoming orders are assigned directly, instead of planning in batches.

Solely applying the planning optimisation methods as proposed in Chapters 2-4, as well as other methods proposed in literature, yield limited results in practice, as the transportation product structure limits the flexibility to optimise network logistics. Synchromodality aims to overcome this by a new product structure based on differentiation in price and lead time. In this setting, each product is considered as a fare class with a related service level, allowing to target different customer segments and to use revenue management for maximising revenue. However, higher priced fare classes come with tighter planning restrictions and must be carefully balanced with lower priced fare classes to match available capacity and optimise network utilisation. In Chapter 5 we proposed the Cargo Fare Class Mix (CFCM) problem. It aims to find the optimal fare class mix for a given cargo transportation network based on known client demands. It is based on the fare class mix problem for aviation passengers with two major differences, as a result from dealing with cargo. Firstly, the CFCM's premise is that long-term commitments to customers must be provided, such that a customer has a guaranteed daily capacity. Secondly, cargo may be rescheduled or rerouted, as long as the customer's delivery due date is met. Therefore, the revenue maximising problem is to select optimal daily fare class limits at a tactical level up to which transportation is guaranteed at the operational level. Any guaranteed demand that does not fit on the available network capacity during operation, must be transported by truck at increased expenses for the network operator. We developed a solution method for an intermodal corridor (Chapter 5) for finding the optimal cargo fare class mix. For our case study, we showed that including the more flexible Standard product increased expected revenue with +27%, compared to a situation with only Express customers. Sensitivity analysis showed that the model is applicable to a range of settings. Using a limit on each fare class increases revenue and reliability, thereby outperforming existing fare class mix policies, such as Littlewood, especially in cases with high Express demand at a low mark-up compared to Standard service.

In Chapter 6, we proposed a faster method for the CFCM problem of single corridor networks and we provided proofs for the optimality of the result. Using this, we extended the problem to an intermodal network of multiple corridors. Finally, in several realistic case studies, we compared the value of optimising an intermodal network per corridor, or at a network level. In our case studies, we showed that generally, the benefit of considering fare class limits at the network level is limited: less than 0.2% profit increase for the base case. However, for cases with demand levels close to the capacity, with high fractions of Express demand and intermediate costs for excess trucking, the network approach is slightly more beneficial.

Summarising, our research has addressed the planning problems in synchromodal networks from two sides, firstly to optimise transportation plans for minimum costs and secondly, to optimise the fare class mix of a transportation portfolio for maximum revenue. Almost all results show a substantial room for improvement in a synchromodal setting in comparison with a traditional approach. In order to answer the main research question,

How can synchromodal networks operate optimally?

we address the important general insights:

- Perspective is crucial in synchromodal transportation. Especially in the service network design, both the type of modeling and the results depend strongly on the cost structure of the intermodal network, e.g. whether inland terminals and services are self-operated or not. For integrated networks, substantial cost savings can be attained if an integrated network plan is made, in comparison to optimising each corridor separately.
- From an optimisation perspective, when updating the transportation plan in case of a disturbance, some but limited benefit can be attained by rescheduling the entire plan. In practice, this would incur additional costs and risks, for communicating about all rescheduled containers. Therefore, synchromodal transportation operators should focus on creating good initial plans. For dealing with disturbances, it is more important to have alternatives per container available than to be able to update the entire plan.
- Both for new incoming orders, as for re-planning in case of disturbances, support for real-time planning is valuable. Although limited academic

models are directly aimed at decision support systems, our work shows that it is possible to use academic models aimed at offline application and translate the solution structure in decision trees for real-time decision support. Optimality for such real-time support is not proven, but real-time decision support potentially improves decision making in practice considerably.

- A focus on optimal planning operations is too narrow for synchromodal transportation. For better utilisations, higher revenue, and higher on-time performance, it is crucial to achieve a good fare class mix. Methods from other industries can be used as inspiration, such as the fare class mix problem from aviation, but two main differences must be considered: cargo can be rerouted and long-term commitments must be adhered to. The benefit from the flexibility that arises from offering different services is likely of more value than the potential revenue increase.
- For tactical and operational planning optimisation in synchromodal networks, it is beneficial to consider the geographic network structure for finding optimal transportation plans, i.e. to create an integral plan for a network of multiple corridors. In contrast, typically it is not necessary to consider the geographic network structure when optimising an optimal fare class mix, i.e. it generally suffices to optimise the cargo fare class mix per corridor separately.

These general insights lead to the following recommendation regarding the main question. To optimally operate a synchromodal network, an operator must focus on an integrated transportation planning approach. In contrast, marketing and sales can be organised with a local focus per inland area. A thorough understanding of demand structure per inland area is crucial. Finally, both for optimal transportation plans and for the portfolio structure, quantitative planning methods as proposed in this dissertation provide an opportunity for substantial improvement compared to relying on human insight and planning expertise for creating transportation plans or the portfolio structure.

In the next section, we will address directions for future research from an academic perspective. Subsequently, in Section 7.3, we include some of the implications and results in practice, considering the source of our case studies, ECT's subsidiary EGS.

7.2 Future research

In this dissertation, we have considered the optimisation of planning methods and the portfolio for a synchromodal network. First we provide general directions for further research on planning and portfolio's in such synchromodalnetworks.

- Although Chapter 5 and 6 include the effects of planning on the optimal portfolio design to some extent, future research could increase our understanding of the entire synchromodal system with a holistic approach into studying the mutual effects of optimising planning optimisation and portfolio design.

- For wider application of the development of synchromodal transportation, it is important that the general implications of these works will be assessed by comparing the Rotterdam case to other hinterland transportation regions with intermodal networks around the world.
- From our experience with EGS we know that the industry has only recently started considering the product portfolio in conjunction with the operational network management. Further integration of several aspects, such as network scheduling, dynamic updates, capacity sourcing and transportation product definitions requires continuous research on the topic.

Additionally, we will highlight future research opportunities for specific topics studied in this dissertation.

Service network design. Considering the service network design of synchromodal networks (Chapter 2), we recognise two directions for further research. Network development in a cooperative synchromodal transportation setting is more complex than the intermodal network design problem. Each addition of a new node or connection may influence the loads on existing ones. However, the sub-contractors of individual connections will aim for stable flows for economic operation. How can the network be expanded in a stable way, without jeopardising the operations of individual sub-contractors? To our knowledge, the problem of stable development of synchromodal network over time has not been studied, yet. Secondly, our proposed service network design model in Chapter 2 does not consider the influence of service frequencies. Future research to extend the proposed model should focus on the influence of the selected service frequencies on the path durations.

Operational planning in intermodal networks. Considering the operational network level, the operational planning of fleet deployment may improve the overall network performance. With a synchromodal transportation plan, the flexibility in transportation routes may be used in conjunction with the operational fleet deployment problem. This creates new and more complex optimisation challenges. The LCAT model from Chapter 3 could be extended to incorporate two situations that occur regularly in practice. Firstly, sometimes a committed service is skipped if demand is low. Secondly, services often make multiple consecutive stops on a route. These routes can easily be implemented in the path selection. However, depending on the actual demand, some stops may be skipped to reduce transit time and cost, which impacts available paths for some containers.

Real-time intermodal planning. Based on our results of generating decision trees for real-time intermodal planning (Chapter 4), we suggest that new applications of the proposed method must be studied. The decision tree method may be of value in many environments that require real-time decision making. The method is especially promising in situations that lack automated and standardised information exchange, such as planning in a hospital environment or for rail applications. The proposed four step method is suitable for applications in these topics, but future research must show its value in those cases. Alternatively, future research may improve the proposed method by iteratively improving the decision tree using online updating or introducing a guided decision tree learning process. For the case of intermodal transportation planning, the method must be extended to and tested for real-life networks.

Cargo fare class mix. Our results in Chapter 5 suggest additional benefit if customers are accepting longer leadtimes for the secondary product. Other extensions of the portfolio may be worth considering for future research as well, based on further detailing customer demand. With more insight in customer preferences, a product range with more flexibility regarding leadtime, or different flexibility along other dimensions could be developed. For instance, what would be the optimal balance between a product type that must travel over a fixed route, in combination with a product for which the operator may decide on routing? This requires more insight in customer demand preferences. Furthermore, future research is required to develop models for the CFCM problem that consider multiple customers per corridor. In such a situation, the intermodal operator may want to create an optimal portfolio of selected customers that match his available capacity as good as possible. Appendix 6.C outlines some possible approaches for these extensions.

In conclusion, although many studies have already been performed on the topic of synchromodal transportation recently, a wide array of extensions and new topics for further research arise. Because of the close connection with developments in practice, we expect that the attention for research on the concept of synchromodal transportation will continue to grow further in the near future.

7.3 Epilogue: Implications and results in practice

At the start of our research, in 2012, the EGS network comprised 7 inland terminals (Fig. 1.1). At the moment of publication of this dissertation, the number of inland terminals in the network has increased to 21 (European Gateway Services, n.d.). During these years, our research was continuously related to the developments in practice. Our aim was not to provide methodological applications for direct implementation in practice. We cooperated with practitioners on the development of the concept of synchromodal transportation. Since the cooperation was of high importance to the research for this dissertation, we want to highlight how our academic research contributed to practice, and also what topics need further attention.

Since the concept of synchromodality was new at the start of our research, managers required insight into what aspects were the most vital to address. Therefore, the aim of our contribution was to create insight on a managerial level into the operational challenges in synchromodal networks. Our models are based on operations in practice, but are not aimed to automate the operational level: firstly, our generalised models lack details that influence practical planning decisions; and secondly, apart from algorithm development, planning automation requires a strong focus on processes and software development beyond the scope of this research. We provide some examples of how some of our results were vital on a managerial level.

- An optimal service network design (Chapter 2) is not directly achievable in practice: on the one hand, a network operator can never start with a blank sheet and on the other hand, he is for a large part limited by the available options in practice, both for new locations, as for new services. Nevertheless, insights from Chapter 2 (and 3) contributed to EGS's ambition to offer services to multiple locations in a region. Such a cluster of locations provides options for more efficient network design, as well as resilience for disturbances.
- Optimal planning on an operational level is hard to achieve in practice as well. Again, a transportation planner never starts with a blank sheet, but is always managing a running program of planned transports. In essence, this was the motivation behind our research into local and full updates (Chapter 3). Secondly, the transportation planner often has (very) little time to implement a new solution in the transportation plan; especially if customers make requests by email or phone and expect fast responses. This motivated our work for Chapter 4, to develop decision support for real-time planning.
- Partially based on our results on centralised planning (Chapter 3), EGS decided in 2014 to cooperate with a software company for the development of a Synchromodal Trip Optimiser for a software-aided real-time planning approach. The development was finished in 2016 and at the moment of publication of this dissertation it is implemented in 50% of the network. Although the key feature of this software is an automated optimiser, with both full and local update capacities, its main contribution for EGS is to facilitate software for a centralised planning approach, including electronic communication to customers and suppliers. However, currently, two critical issues remain.
- One critical issue with EGS's planning automation is that in intermodal operations, the standardisation level of information exchanges is too low. As a result, information is often incomplete, implicit (e.g. soft knowledge from planners), or incorrect. This limits the validity of an automatically

generated plan. This issue is addressed by EGS with a focus on digital (automated) information exchange. Until sufficient digital information exchange is achieved, our approach in Chapter 4 for white box decision support may support the intermodal planning problem. For implementation in practice, it needs to be extended to cover larger network structures.

- The second critical issue is that a large share of transportation bookings allow little flexibility for planning: a typical booking from an EGS customer fixes mode, route and timing of transportation. This issue was already foreseen, and provided the main motivation for our research on the Cargo Fare Class Mix problem (Chapter 5 and 6). Master theses carried out both inside EGS as independently, showed strong evidence of a market demand for lead-time based transportation services that do not require specifying mode or route. The company has been working on such a synchromodal portfolio, and initial pilots are promising.
- To further promote the idea of synchromodal booking and planning, EGS was one of the developers of a serious game aimed at planners and customers, *SynchroMania*. Our work on the topic in general, and more specifically in Chapter 3, was used as a basis for the game. Practitioners considered it a useful tool to get insight in the value of planning flexibility in synchromodal transportation. It is used by educational institutes as a class room tool to teach about intermodal container logistics. The game shows that the balance between optimal real-time network planning and network flexibility is vital. More flexibility increases the problem complexity, but potentially allows better solutions (Buiel *et al.,* 2015).

At the time of publication of this dissertation such a synchromodal portfolio is not widely adopted in practice yet, although it is tested in a pilot phase. It is an open question beyond the scope of this dissertation what the main reason is for the slow implementation progress. Is that the lack of understanding by practitioners of the potential of differentiated transportation services, the 'delay' due to practical implementations, or is it a truly fundamental problem in hinterland logistics? The result of our research in Chapter 5 and 6 shows that large potential revenue is available if a synchromodal portfolio succeeds, and that it is most likely sufficient to optimise per individual corridor only. We strongly urge practitioners in intermodal transportation to continue their effort for achieving the required mind shift and overcoming practical barriers. Only by such a continued effort, intermodal transportation can provide a truly integrated transportation solution and become synchromodal transportation.

Samenvatting (Nederlands)

Het onderzoek voor dit proefschrift is gemotiveerd door twee afzonderlijke trends in de praktijk van het containervervoer in Noordwest-Europa. Aan de ene kant wordt een meer geïntegreerde netwerkoptimalisatie van containervervoer vereist door zowel concurrentie in het achterlandvervoer als de maatschappelijke behoefte aan een modal shift naar duurzame modaliteiten. Aan de andere kant eisen achterlandpartijen een kosteneffectieve, maar flexibele en betrouwbare leveringsdienst. Het concept synchromodaliteit is ontwikkeld als antwoord op deze ontwikkelingen, waarbij efficiënte planning gecombineerd wordt met een business model gebaseerd op klantgerichte vervoersdiensten. Ons onderzoek draagt bij aan het combineren van optimale transportplanning in intermodale netwerken en het ontwerpen van een optimale tariefklasse mix van klantgerichte diensten. We hebben vijf modellen ontwikkeld voor praktische problemen in synchromodale netwerken. Alle modellen zijn ontwikkeld met het oog op een gecentraliseerde exploitant van een intermodaal containernetwerk met lijndiensten tussen terminals in een zeehaven en meerdere achterlandterminals. Deze geplande diensten kunnen treinen of barges zijn, maar niet noodzakelijkerwijs zijn beide beschikbaar naar alle bestemmingen. Ook wordt ervan uitgegaan dat de vrachtwagencapaciteit beschikbaar is als (dure) overloopmodaliteit. Alle vijf modellen zijn toegepast in casestudies op basis van het intermodale containernetwerk van European Gateway Services (EGS), een dochteronderneming van Hutchison Ports ECT Rotterdam (ECT).

In hoofdstuk 2 wordt een nieuw wiskundig model voorgesteld om het optimale dienstschema tussen de gegeven netwerkterminals te bepalen. Het model introduceert twee nieuwe eigenschappen voor het intermodale netwerk-planningprobleem. In de eerste plaats worden te late leveringen gestraft in plaats van verboden. Ten tweede combineert het model slots op eigen diensten (*committed*) met ingekochte slots bij derden (*subcontracted*). Het model beschouwt committed of subcontracted barge- en spoordiensten evenals vervoer per vrachtwagen. In een casestudie van het EGS-netwerk wordt het voordeel bestudeerd van de mogelijkheid van twee opeenvolgende transporten van een container met een tussenliggende overslag. Uit de resultaten blijkt dat het voorgestelde model resulteert in een veel kostenefficiënter dienstschema voor moderne intermodale

containervervoernetwerken dan alternatieve modellen zonder de mogelijkheid van late leveringen, of zonder de combinatie van committed en subcontracted slots. Uit onze resultaten van een casestudie van het EGS-netwerk blijkt dat de kosten van het gebruik van alleen committed of alleen subcontracted diensten respectievelijk 65% of 49% hoger zouden zijn. Een ander resultaat van de casestudie is dat 22% van de kosten wordt gemaakt voor op tijd leveren, wat zeer gevoelig blijkt voor de hoogte van de late-leveringsboete. Ook suggereren de resultaten dat een geïntegreerde exploitatie van vervoersdiensten en achterlandterminals het aantal netwerkverbindingen en mogelijk de algemene kosten verbetert.

Op operationeel niveau bestaat het netwerkplanningsprobleem uit het verdelen van containers over beschikbare intermodale transportdiensten. Voor adequate planning is het belangrijk om het plan continue aan te passen aan storingen die zich voordoen. In hoofdstuk 3 wordt een nieuw wiskundig model voorgesteld: het lineaire containerallocatiemodel met tijdsbeperkingen (LCAT). Dit model wordt gebruikt voor het bepalen van de invloed van drie hoofdtypes van transportverstoringen op netwerkprestaties: vroegtijdig vertrek, laat vertrek en annulering van intermodale diensten. De invloed van een storing wordt op twee manieren gemeten. De *impact* meet de extra kosten ten gevolge van een bijgewerkte planning in geval van een verstoring. De *relevantie* meet het kostenverschil tussen een volledig geactualiseerd en een lokaal geactualiseerd plan. Met de resultaten van de analyse kunnen de belangrijkste service-eigenschappen van verstoorde diensten die een hoge impact of hoge relevantie hebben, worden bepaald. Op basis hiervan kan de netwerkoperator focusgebieden selecteren om storingen met grote impact te voorkomen en planningupdates bij storingen met een hoge relevantie te verbeteren. De voorgestelde methode wordt gebruikt in een casestudie om de impact en de relevantie van verstoringen op intermodale diensten van het EGS-netwerk te beoordelen. Op basis van de resultaten is geconcludeerd dat de netwerkoperator zich moet concentreren op het voorkomen van vroege vertrektijden, aangezien deze de grootste impact hebben. Een hoge impact geeft een storing aan met grote extra kosten die niet kunnen worden verminderd met een volledige update van het transportplan. Bijvoorbeeld, de onvermijdelijke kosten van een vroeg of laat vertrek zijn gemiddeld 7,5 keer hoger dan de besparing die te behalen is bij het gebruik van een volledige update in plaats van een lokale update. Bovendien kunnen volledige updates hoge kosten meebrengen voor het herplannen van grote hoeveelheden containers. Daarom kunnen lokale updates meestal voldoende zijn. Als uitzondering dient de planningsafdeling van de netwerkoperator extra aandacht te besteden aan annuleringen van binnenvaartdiensten. Deze hebben de hoogste impact (tot 15.000), waarvan zelfs een relatief lage kostenreductie van 8% (de relevantie) een substantiële besparing oplevert bij meer uitgebreide planning updates of zelfs een volledige update.

In hoofdstuk 4 worden real-time beslissingsregels voorgesteld voor geschikte toewijzingen van containers voor intermodale diensten. De beslisregels worden verkregen op basis van de analyse van de oplossingsstructuur van historische gegevens, offline gecreëerd met een gecentraliseerde optimalisatiemethode. De zo verkregen beslisboom kan worden gebruikt in een beslissingsondersteuningssysteem (DSS) voor het onmiddellijk toewijzen van inkomende bestellingen naar geschikte diensten, zonder dat er behoefte is aan continue automatische planning updates. De belangrijkste bijdragen van dit werk zijn drievoudig: ten eerste wordt een gestructureerde methode voor het maken van beslisbomen uit optimale oplossingen voorgesteld. Ten tweede wordt een innovatieve methode gebruikt voor het verkrijgen van meerdere equivalente optimale oplossingen om overfitting van de beslisboom de voorkomen. En ten slotte wordt een gestructureerde analyse van drie fouttypes voorgesteld om de kwaliteit van een verkregen boom te beoordelen. In de praktijk is een dergelijke DSS nuttig, omdat het om drie redenen eenvoudig te implementeren is in de huidige praktijk van containervervoer: de methode maakt het mogelijk om direct inkomende containerbestellingen toe te wijzen en klantenverzoeken direct te beantwoorden; de methode heeft geen geavanceerde automatisering nodig, en de representatie in een beslisboom is in de praktijk begrijpelijk voor menselijke planners. Bij casestudies heeft de voorgestelde DSS de totale transportkosten aanzienlijk verminderd, in vergelijking met alternatieve methoden (Greedy en First-Come-First-Serve): respectievelijk 3% en 9%. De voorgestelde methode gaat ervan uit dat de binnenkomende orders rechtstreeks worden toegewezen, in plaats van een plan dat periodiek wordt opgesteld.

Het toepassen van de planningsoptimalisatiemethoden zoals voorgesteld in de hoofdstukken 2-4, alsmede andere methodes die in de literatuur worden voorgesteld, levert beperkte resultaten in de praktijk, aangezien de structuur van de transportproducten de flexibiliteit beperkt om netwerklogistiek te optimaliseren. Synchromodaliteit streeft ernaar om dit te overwinnen door een nieuwe productstructuur op basis van differentiatie in prijs en looptijd. Hierin wordt elk product beschouwd als een tariefklasse met een gerelateerd serviceniveau, zodat verschillende klantsegmenten kunnen worden bediend en revenue management kan worden gebruikt om de inkomsten te maximaliseren. Echter, hogere tariefklassen zijn voorzien van striktere planningsbeperkingen en moeten zorgvuldig worden afgewisseld met lagere tariefklassen om aan te sluiten op de beschikbare capaciteit en de bezettingsgraad in het netwerk te optimaliseren. In hoofdstuk 5 stellen we het Cargo Fare Class Mix (CFCM) probleem voor. Hierin wordt gestreefd naar het vinden van de optimale tariefklassemix voor een bepaald vrachtvervoersnetwerk op basis van bekende klanteisen. Het is gebaseerd op het tariefmixprobleem voor luchtvaartpassagiers met twee grote verschillen, als gevolg van het omgaan met vracht. Ten eerste is het uitgangspunt van het CFCM dat langlopende verplichtingen aan klanten moeten worden vervuld, zodat een klant een gegarandeerde dagelijkse capaciteit heeft. In de tweede plaats kan de lading worden hergepland of hergerouteerd, zolang aan de afleverdatum van de klant wordt voldaan. Daarom is er een revenue management probleem op een tactisch niveau om de optimale tariefklasselimieten te bepalen. Op operationeel niveau moet dagelijks transport tot aan die limiet worden gewaarborgd. Eventuele gegarandeerde vraag die niet past in de beschikbare netwerkcapaciteit tijdens de operationele fase, moet per vrachtwagen worden vervoerd tegen (hoge) kosten voor de netwerkoperator. We hebben een oplossingsmethode ontwikkeld voor een intermodale corridor (hoofdstuk 5) voor het vinden van de optimale tariefklassemix. In onze casestudie bleek dat het toevoegen van het flexibelere Standaardproduct de verwachte omzet met +27% verhoogde, in vergelijking met een situatie met alleen Express klanten. Gevoeligheidsanalyses hebben aangetoond dat het model van toepassing is op een reeks probleemvarianten. Het gebruik van een limiet op elke tariefklasse vergroot de omzet en betrouwbaarheid, ten opzichte van bestaande tariefmixaanpakken, zoals Littlewood. Dat is voornamelijk zo in gevallen met een hoge Express-vraag die tegen een kleine meerprijs wordt verkocht in vergelijking met het standaardproduct.

In hoofdstuk 6 wordt een snellere methode gepresenteerd voor het oplossen van het CFCM-probleem voor individuele corridors, met bewijsvoering voor de optimaliteit van het resultaat. Op basis hiervan hebben we het probleem uitgebreid naar een intermodaal netwerk van meerdere corridors. Ten slotte vergeleken we in verschillende realistische casestudies de waarde van het optimaliseren van een intermodaal netwerk per corridor of op netwerkniveau. In onze casestudies hebben we aangetoond dat in het algemeen het voordeel van het overwegen op het netwerkniveau beperkt is: minder dan 0,2% winststijging voor de basis casus. De netwerkbenadering is het meest voordelig in gevallen met vraagniveaus dicht bij de capaciteit, met hoge fracties van Express-vraag en gemiddelde kosten voor de inzet van vrachtwagens.

Samenvattend, ons onderzoek heeft betrekking op twee type vraagstukken in synchromodale netwerken, ten eerste voor het vinden van de optimale transportplanning tegen minimale kosten en ten tweede het optimaliseren van de tariefklassemix van een transportportfolio voor maximale inkomsten. Bijna alle resultaten tonen een substantiële ruimte voor verbetering in een synchromodale omgeving in vergelijking met de gangbare aanpak. Om de hoofdonderzoeksvraag te kunnen beantwoorden,

Hoe kunnen synchromodale netwerken optimaal functioneren?

adresseren we de volgende belangrijke algemene inzichten:

- Perspectief is cruciaal bij synchromodaal transport. Vooral in het servicenetwerkontwerp hangt zowel het type van modellering als het resultaat sterk af van de kostenstructuur van het intermodale netwerk, bijvoorbeeld of de achterlandterminals en diensten zelf uitgevoerd worden of door onderaannemers. Met een geïntegreerd netwerkplan kunnen aanzienlijke kostenbesparingen worden bereikt in vergelijking met een plan per afzonderlijke corridor.

- Met het bijwerken van een transportplan in geval van een verstoring, kan er vanuit een optimaliseringsperspectief maar een beperkt voordeel worden bereikt door het gehele plan te herzien, ten opzichte van een lokale update. In de praktijk zou dit bovendien kosten en risico's opleveren voor het communiceren over alle hergeplande containers. Daarom moeten synchromodale transportbedrijven zich met name richten op het creëren van goede initiële plannen. Voor het omgaan met verstoringen is het belangrijker om alternatieven per container beschikbaar te hebben dan het volledige plan te kunnen updaten.
- Zowel voor nieuwe binnenkomende transportopdrachten, als bij herplanning bij storingen, is ondersteuning voor real-time planning waardevol. Hoewel beperkte academische modellen beschikbaar zijn voor dergelijke beslissingsondersteunende systemen, blijkt uit ons werk dat het mogelijk is om academische modellen bedoeld voor offline toepassing te gebruiken en de oplossingsstructuur te vertalen in beslissingsbomen voor real-time ondersteuning. Optimaliteit voor dergelijke real-time ondersteuning is niet bewezen, maar de praktijk van real-time besluitvorming kan hiermee aanzienlijk worden verbeterd.
- Een focus op enkel optimale planning is te beperkt voor synchromodaal transport. Voor hogere bezettingsgraden, hogere inkomsten en een groter aandeel tijdige levering, is het cruciaal om een goede tariefklassemix te hebben. Methoden uit andere industrieën kunnen als inspiratie worden gebruikt, zoals het tariefklassemixprobleem van de luchtvaart, maar twee verschillen moeten in overweging worden genomen: lading kan worden geherrouteerd en langetermijnverplichtingen moeten worden nageleefd. Het voordeel van de flexibiliteit die voortvloeit uit het aanbieden van verschillende diensten is waarschijnlijk van meer waarde dan de potentiële omzetstijging.
- Voor het maken van een optimaal tactisch of operationeel transportplan in synchromodale netwerken is het nuttig om rekening te houden met de geografische netwerkstructuur. Met andere woorden, er kan een kosteneffectiever transportplan gemaakt worden als meerdere corridors integraal beschouwd worden. Daarentegen is het voor het vinden van de optimale tariefklassemix meestal niet nodig om rekening te houden met de geografische netwerkstructuur. In dit geval is het voldoende om de optimale tariefklassemix per corridor te bepalen.

Deze algemene inzichten leiden tot de volgende aanbeveling met betrekking tot de hoofdvraag. Om een synchromodaal netwerk optimaal te kunnen bedienen, moet een operator zich richten op een geïntegreerde transportplanning. Daarentegen kan marketing en verkoop georganiseerd worden met een lokale focus per afzetgebied in het binnenland. Een grondig inzicht in de vraagstructuur per afzetgebied is cruciaal. Ten slotte, zowel voor optimale vervoersplannen als voor de portefeuillestructuur, bieden kwantitatieve planningsmethoden zoals voorgesteld in dit proefschrift kansen op grote verbetering ten opzichte van het maken van vervoersplannen en portefeuillestructuur op basis van menselijk inzicht en planningskennis.

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Curriculum Vitae

Bart van Riessen was born in Rotterdam on April 21, 1987. Growing up in the neighbourhood of the Rotterdam ports created a lasting connection. In 2003, for a history practicum, he chose to study the company Europe Container Terminals (ECT). In 2008 he obtained his Bachelor degree in Mechanical Engineering from Delft University of Technology (TU Delft). From 2008 to 2010 he was a fulltime team member of the Delft solar car team, first as a mechanical engineer for the Nuna5 car, later as a race strategist for this car in the World Solar Challenge (WSC) 2009 in Australia (second place) and a Technical Manager for the Suzuka Dream Cup 2010 in Japan (third place). After this he was one of the initiators behind the team's supervisory board. Until 2016 he was a member of this board, with the goal to bring the team back to winning results and to improve quality by connecting university research to the technical developments. Since, the team won the (biannual) WSC in 2013, 2015 and 2017, and the (biannual) South African Solar Challenge in 2014 and 2016.

In 2012, Bart returned his attention to the port of Rotterdam: he went to ECT for a Master's thesis internship. With the thesis, he received his Master degree in Mechanical Engineering, track Transportation Engineering and Logistics (TU Delft) and his Master degree in Econometrics, track Quantitative Logistics & Operational Research from Erasmus University Rotterdam (EUR) in 2013, both *cum laude*.

Afterwards, Bart started as a part-time business analyst at ECT, while working on his PhD research on synchromodal container transportation supervised by EUR and TU Delft, separately funded by Erasmus Smartport and co-supported by the Dept. of Maritime and Transport Technology (TU Delft). Aiming to bridge the gap between academia and industry, on behalf of ECT he participated in 4 research projects. The last part of his PhD research took place in one of these, ISOLA. From 2013-2017, he initiated and supervised 9 Master thesis interns at ECT, with students from EUR, TU Delft, Rotterdam Shipping and Transport College, Eindhoven University of Technology and University of Groningen. During the same period, at EUR he supervised student theses on Bachelor and Master level, and lectured courses on hinterland transportation and management science. He presented his scientific work in several academic conferences, such as LOGMS, IFSPA, IAME, ICCL and ODYSSEUS. With his background in academic research and industry practice in maritime hinterland transportation, he was invited as a speaker at research seminars in Groningen, Hamburg, Copenhagen, Savannah and Bergen. In 2016, he was one of the founders of 2Trees, a company for strategic logistics advice. This company aims to bring a scientific approach with optimisation and simulation techniques to small and medium enterprises. The approach is related to Chapter 4 of this dissertation.

In 2017, Bart started in a new position at ECT as a Product Manager for digital and supply chain services. In this capacity, he aims to create a state-of-the-art information platform for supply chain visibility, and he hopes to continue connecting logistics researchers to the maritime industry.

Academic portfolio

Publications

Articles in peer-reviewed journals

Van Riessen, B., Negenborn, R. R. and Dekker, R. (2017). The Cargo Fare Class Mix problem for an intermodal corridor: revenue management in synchromodal container transportation. *Flexible Services and Manufacturing Journal*, 1-25. doi: 10.1007/s10696-017-9285-7.

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Working papers

Van Riessen, B., Mulder, J., Negenborn, R. R. and Dekker, R. (2017). *The Cargo Fare Class Mix problem in synchromodal networks*. Manuscript in preparation.

Book chapters

Dekker, R. and Van Riessen, B. (2013). Rotterdam as linking pin in intercontinental container transport: trends and research in Smart Port. In B. Kuipers (Ed.), *Smart Port perspectives* (pp. 119-128). Rotterdam: Erasmus Smartport Rotterdam.

Teaching

Lecturer

- Management Science 3, Maritime Economics and Logistics, Erasmus University Rotterdam (2016 & 2017).

Guest lectures

- Container logistics and inland networks, minor Port management and Maritime Logistics, Erasmus University Rotterdam (2014-2016).
- Achterlandverbindingen, Rotterdam Mainport University (2015)
- Ports in Global Networks, Rotterdam School of Management, Erasmus University Rotterdam (2015).
- Over de Rotterdamse haven, deel 1 en 2, HOVO, Erasmus University Rotterdam (2016).

Supervisor

- Master thesis Operations Research & Quantitative Logistics, Erasmus University Rotterdam (2014 - 2016)
- Bachelor thesis Econometrics and Operational Research, Erasmus University Rotterdam (2016)
- Master thesis Maritime Economics and Logistics, Erasmus University Rotterdam (2015 & 2017)

PhD courses

- Introduction to TRAIL (TRAIL)
- Fundamental domain knowledge (GP-OML)
- Freight Transport Management (GP-OML)
- Stated Preference Data Collection & Discrete Choice Modelling (TRAIL)
- From Horse to Porsche: innovations in Transport & Logistics (TRAIL)

Conferences attended with an academic presentation

- International Conference on Operations Research (OR), Rotterdam, The Netherlands, 2013.
- International Conference on Logistics and Maritime Systems (LOGMS), Singapore, 2013.
- Erasmus Smart port poster session, Rotterdam, The Netherlands, 2013.
- TRAIL PhD congress, Delft, The Netherlands, 2013.
- TSL Workshop, Asilomar (CA), USA, 2013 (only attended, without presentation).
- Conference of the International Federation of Operational Research Societies (IFORS), Barcelona, Spain, 2014.
- International Forum on Shipping, Ports and Airports (IFSPA), Hong Kong, 2014.
- International Conference on Logistics and Maritime Systems (LOGMS), Rotterdam, The Netherlands, 2014.
- Erasmus Smart port poster session, Rotterdam, The Netherlands, 2014.
- TRAIL PhD congress, Delft, The Netherlands, 2014.
- International Association of Maritime Economists Conference (IAME), Kuala Lumpur, Malaysia, 2015.
- International Conference on Computational Logistics (ICCL), Delft, The Netherlands, 2015.
- International Conference on Logistics and Maritime Systems (LOGMS), Hong Kong, 2015.
- International workshop on Freight Transportation and Logistics (ODYSSEUS), Ajaccio, France, 2015.
- Applications of Optimization (AOO), Copenhagen, Denmark, 2016.
- International Conference on Logistics and Maritime Systems (LOGMS), Sydney, Australia, 2016.
- Port Logistics Workshop, Savannah (GA), USA, 2017.
- International Conference on Logistics and Maritime Systems (LOGMS), Bergen, Norway, 2017.

Recognitions

- Winner of the best pitch during the Mandeville Masterclass (Rotterdam, May 27, 2015).
- Winner of science battle during the Topsector Logistics conference (Rotterdam, April 1, 2015).
- Audience award for best poster during the Smart Port Poster Session (Rotterdam, October 2, 2014).
- Nomination for the Best Econometric Thesis Award 2013 (Erasmus

University Rotterdam). Final 5 nominees.

- Nomination for Erasmus Smart Port Thesis Award 2013 (Erasmus University Rotterdam, Delft University of Technology, Port of Rotterdam, Deltalinqs). Final 3 nominees.

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Symbols

(i, j, m) : corridor between i and j for mode m 25
a : designated alternative corridor 146
b : designated bequathing corridor 146
c: cargo class 25
C: set of cargo classes *or* capacity 25, 110
$c_{f,s}$: fixed cost for service s 51
c_{dm} : costs of using mode m to destination d 66
c_{dt}^{c} : cost per TEU of direct trucking container class c 46
c_F : transfer costs 29
c_{ijm} : corridor costs per TEU 29
c_p : costs per path 52
$c_{\check{s}}$: costs contributed to a service 51
$C_{\check{s}}$: set of container classes and demand patterns planned on disturbed service $\check{s}$ 49
c_T : total costs 81
c_t^c : cost for direct trucking of a container of cargo class *c* 75
c_τ : overdue delivery costs 29
d : destination 66
$d_{c,q}$: transportation volume of cargo class c and pattern q 25
d^c : demand of class c 46
D_F : accepted demand of fare class $F \in \{E, S\}$ 110
d_{ijm} : corridor length 29
d_s : disturbance of service s 49
E : Express demand 110
$E(\cdot)$: expectancy operator 80
F : set of fare classes 141
F_{d_s}: cost impact of a full update after disturbance d_s 50
f_F : fares for fare class $F \in \{E, S\}$ 111

The ERIM PhD Series

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Dissertations in the last five years

Abbink, E.J., *Crew Management in Passenger Rail Transport*, Promotors: Prof. L.G. Kroon & Prof. A.P.M. Wagelmans, EPS-2014-325-LIS, http://repub.eur.nl/pub/76927

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Alexiou, A. *Management of Emerging Technologies and the Learning Organization: Lessons from the Cloud and Serious Games Technology*, Promotors: Prof. S.J. Magala, Prof. M.C. Schippers and Dr I. Oshri, EPS-2016-404-ORG, http://repub.eur.nl/pub/93818

Almeida e Santos Nogueira, R.J. de, *Conditional Density Models Integrating Fuzzy and Probabilistic Representations of Uncertainty*, Promotors: Prof. U. Kaymak & Prof. J.M.C. Sousa, EPS-2014-310-LIS, http://repub.eur.nl/pub/51560

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This dissertation proposes an integrated approach for optimising synchromodal container transportation, motivated by two separate trends in the container transportation practice in North-West Europe. On the one hand, competition in hinterland transportation and the societal need for a modal shift towards sustainable modes require more integrated network optimisation of container transports. On the other hand, hinterland users increasingly require a cost-effective, but flexible and reliable delivery service. The concept of synchromodality was developed as an answer to these developments, combining efficient planning with a business model based on customer-oriented transportation services. This dissertation contributes by bringing together optimal transport planning in intermodal networks and the design of an optimal fare class mix of customer-oriented services. It includes 5 new models for operating such a synchromodal transportation network: service network design, disturbance analysis, real-time decision support and two variants of the cargo fare class mix design. All models are developed with the perspective of a centralised operator in an intermodal container network, with scheduled services between a deep-sea terminal and multiple inland ports. These scheduled services can be trains or barges, but not necessarily both have to be available. All 5 models have been applied to case studies based on the intermodal container network of European Gateway Services (EGS), a subsidiary of Hutchison Ports ECT Rotterdam (ECT).

About the author

Bart van Riessen obtained a Master degree in Mechanical Engineering from TU Delft and a Master degree in Econometrics from EUR. Afterwards, he started in a part-time position at ECT on hinterland developments and in a separate position at the Econometric Institute (Erasmus University Rotterdam) for his Ph.D. research, co-supervised by the Dept. of Maritime and Transport Technology (TU Delft). His aim is to bridge the gap between academic transportation research and the transportation and logistics industry.

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