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Choice-Driven Methods for Decision-Making in Intermodal Transport
Behavioral heterogeneity and supply-demand interactions

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Choice-Driven Methods for Decision-Making in Intermodal Transport

Behavioral heterogeneity and supply-demand interactions

Adrien NICOLET

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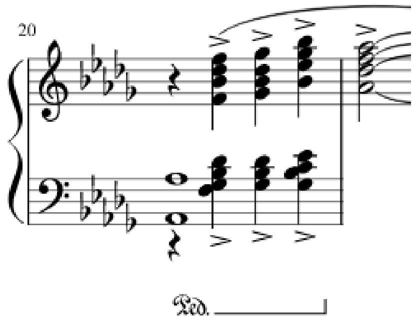

Joe Hisaishi

Preface

The 4-year journey of a PhD takes you through many challenges: intellectual of course, but also emotional ones. Although overwhelming at times, this adventure was a great opportunity to develop, make peace with, and strengthen many aspects of my personality. Now that it comes to an end, I take this opportunity to thank the persons who supported me throughout this journey.

First of all, I am deeply grateful to my Promotors, Bilge Atasoy and Rudy Negenborn, for their constant support and trust. Thank you Bilge, for all the insightful research discussions, for your availability and responsiveness, and for your outstanding supervision – both friendly and highly professional. Thank you Rudy, for your thorough guidance and openness throughout my PhD, as well as being an attentive ear to the needs of the section's PhDs.

During these 4 years, I was also involved in the NOVIMOVE research project, through which I developed professional and friendly relationships. For making our work package a very nice environment, I would like to thank Peter, Ivo, Eva, Jennifer, Felipe, Charis, Cyril, Jonas, and Edwin.

I am also grateful to my former colleagues: Yimeng, Rie, Breno, and Wenjing, for the inspiration they have given me and their guidance when I needed it.

Throughout this PhD journey, I have met and got along many friends and colleagues. It has been a unique experience to connect with so many inspiring and kindhearted persons, coming from so many different cultures. Since I cannot name everybody, I thank all the people who make the Maritime department a very pleasant and lively working environment: it is always a pleasure to grab a coffee, share a beer, or go down a ski slope together!

In particular, a very big thank you to Nikos, Nikos, Xiaohuan, Çiğdem, and Ahmed, for being such great friends throughout the ups and downs of the PhD trajectory. I am especially grateful for the adventures we shared in Chile, Greece, and Switzerland, the late-night tennis games and the invaluable support. Thank you to my office mates Ana, Raïsa, and Sankarshan, for the very nice and relaxed vibes, the board game evenings, and the Friday afternoon piano sessions. Thank you to Estelle, Alina, and Yunpeng, for

their support and guidance in the first half of my PhD. Thank you to the great persons I met during the second half of my PhD, in particular: Apostolos, Charlotte, Niek, Marco, Abhishek, Kostas, Alejandro, Sara, Andrea, and Jayvee, for the great nights out, the broken glasses, the lighthearted laughs, the deep connections, and the travels we shared together. And thank you Sana for accompanying me in the last miles of the PhD and making the stressful times sweeter.

Lastly, I have a special dedication to my lovely grandmother, who passed away just a week before the start of my PhD journey: thank you for all the happiness and comfort I have received! And a final huge thank you to my mother, my father, my sister, and my brother for being always there for me, for the great times we have when they visit me in Delft, and for the unconditional support they provided throughout my studies.

Adrien Nicolet
Delft, October 2024

Contents

Chapter 1

Introduction

The global economy is facing a range of challenges including: climate change, supply chain disruptions, and a cost-of-living crisis. As a key determinant of economic growth, the container transport system requires constant improvement to effectively tackle these challenges. In particular, it needs to be sustainable to cut down greenhouse gas emissions, adaptive to ensure resilient supply chains, and efficient to guarantee affordable products to the consumers. To achieve these objectives, measures need to be taken, as suggested in the European Green Deal (European Commission, 2023). Such measures can consist in developing technical innovations, investing in transport infrastructure, or implementing incentive policies.

In this thesis, we develop choice-driven methods capturing the behavior and interactions of the main actors in the container transport system to assist in the assessment of such improvement measures. This introductory chapter first presents the context of this research and the adopted supply-demand framework in Section 1.1. We then provide a literature overview and highlight the research challenges in Section 1.2. Our research questions are presented in Section 1.3, while Section 1.4 states the main contributions of this thesis. Finally, Section 1.5 gives the overall structure of this dissertation.

1.1 Research background

In the context of globalized container shipping, a typical transport chain is made of three parts: 1) inland transport from the origin of the cargo to the seaport of departure, 2) intercontinental transport by the sea, 3) inland transport from the seaport of arrival to the final destination of the cargo. Hinterland transport specifically refers to the initial and final parts of this transport chain. It plays a key role in container shipping as it represents the biggest share of the total costs: Notteboom & Rodrigue (2005) estimated that this share lies between 40% and 80%. Therefore, improving hinterland transport will result in substantial gains also at the global scale.

The hinterland transport system is highly sophisticated as it contains multiple inland terminals, potentially spread over several countries. Typically, multiple modes of transport are available, while being operated by various carriers that provide services to transport goods. Their customers consist of a high number of shippers, i.e. companies looking for services to transport their goods. Next to the shippers and carriers, the system comprises many other stakeholders, such as terminal operators, port authorities, infrastructure managers, or governments. All of these individual actors have their own behaviors and objectives: for example, reducing greenhouse gas emissions, maximizing profits, minimizing delays, augmenting safety, and so on. Finally, these entities maintain different relationships with each other: two companies can have a contractual relationship, whereas a government can impose rules on other actors via legislation. All these reasons make the system profoundly complex, as illustrated in Figure 1.1. Furthermore, the inherent uncertainties, such as demand fluctuations, operational disruptions, and climatic events, further complicate the system.

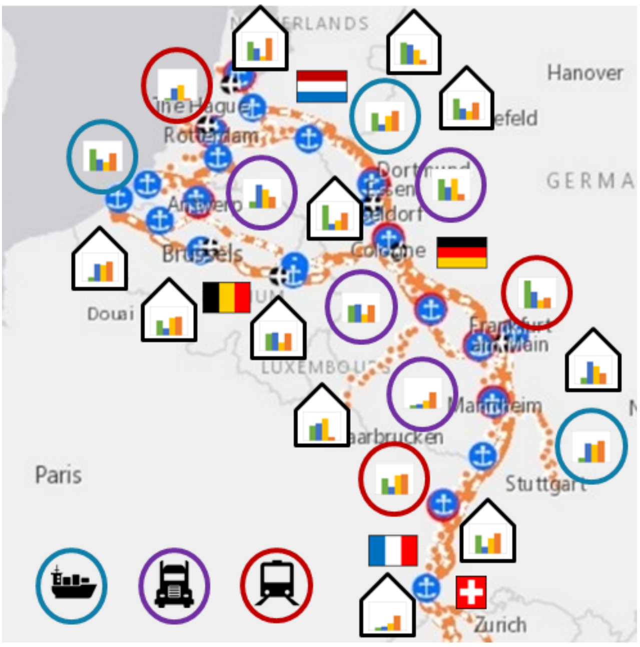

Figure 1.1: The Rhine section of the Rhine-Alpine corridor (European Commission, 2021), covering 5 countries with 3 transport modes: road, rail and inland waterway transport.

A thorough understanding of the freight transport system is essential to come up with efficient improvement measures (Combes & Leurent, 2007). In particular, freight models help addressing various questions faced by policy makers, such as: what are the effects of economic growth on the transport needs?, how will a new infrastructure influence the transport flows?, what are the CO_2 emissions per transport modes?, and so on (Tavasszy et al., 1998). The models also offer quantitative evidence and forecasting to decision-makers for the ex-ante evaluation of policies, investments, or innovations (Tavasszy, 2020). Therefore, realistic and accurate models are needed to make the best possible decision. Notably, it is crucial to account for the various behaviors and relationships of the different stakeholders. Indeed, freight transport involves more than just the physical movement of containers through the network; it is shaped by the decisions and interactions of agents within the system. As highlighted by Meersman & Van de Voorde (2019), the reactions of stakeholders to structural changes have been neglected in past models, which led to poor estimations of a policy's consequences. Therefore, behavioral elements add realism to the models and allow to simulate market dynamics at the root of container transport. This is very helpful when aiming to capture how stakeholders adapt and respond to different changes, such as new technologies or policies, economic fluctuations, and so on.

In this thesis, we adopt a market perspective to model the hinterland transport system, see Figure 1.2. On the supply side, the *carriers*, or *transport operators*, propose transport services to move cargo through the network. These services are purchased by *shippers* that want to send their goods, thus forming the demand side. Note that, shippers often delegate the management of their transport operations to freight forwarders. They can also delegate the logistics management to third-party logistics providers. Although they act as intermediate between shippers and carriers, these stakeholders can be assimilated in the demand side too. Indeed, they are also requesting transport services from the carriers. For the sake of simplicity, the term "shipper" will be used to refer to the demand side as a whole (also including the aforementioned intermediary agents).

The supply and demand sides are constantly interacting with each other. For example, a shipper may call for bids to transport their cargo, some contract negotiations may occur between the shipper and the chosen carrier, eventually they will also arrange the operational details of the transport. But interactions also occur between carriers through competition or co-operation, as well as among shippers (e.g.: pooling of assets, shipments consolidation).

All these interactions take place in a multifaceted environment, which obviously consists of the physical transport network (waterways, railways, roads, terminals, etc.); but we can also mention the digital environment allowing information exchange, the

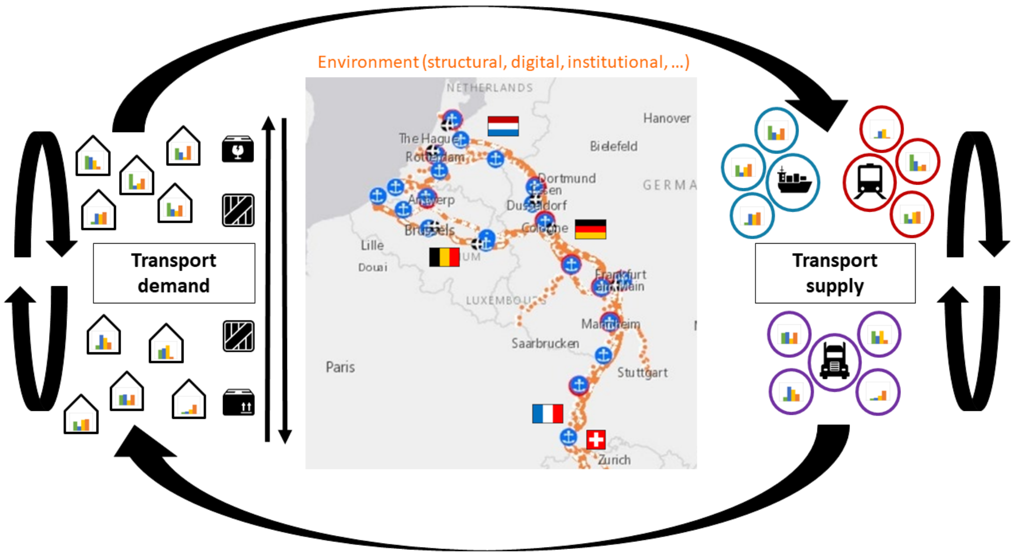

Figure 1.2: Schematic view of the freight transport market.

institutional frame, or the climatic conditions. Although they are not explicitly depicted in the market representation, governments, port authorities and infrastructure managers play an important role in shaping the environment in which shippers and carriers are interacting. They indeed define regulations and policies that the actors must comply with to use the infrastructure. Terminal operators are also an integral part of the environment, acting as interfaces between transportation modes. Terminal operations have a significant impact on the time, cost and reliability of intermodal transport and are, therefore, shaping the environment as well.

Based on the proposed supply-demand representation, the next section explores how hinterland transport systems have been modeled in the existing literature. A particular emphasis is put on the behavior, heterogeneity and interactions of the involved stakeholders.

1.2 Literature overview

Freight transport modeling is a topic of great interest both for practice as well as academia. Multiple reviews have been conducted on the subject, see for example: Archetti et al. (2022); Comi et al. (2013); Crainic et al. (2018); de Jong et al. (2013). Our focus is on the methodologies used to model operations in an intermodal transport system and to support decision-making in this context. To this aim, we initially concentrate on the decisions of supply and demand sides individually, followed by an exploration of models that capture their interactions. This will allow to identify existing research challenges and to later outline the contributions of this thesis.

1.2.1 Demand models

In this section, we review the existing literature on modeling the decisions of shippers. As mentioned earlier, some shippers delegate transport decisions to intermediary agents, that will assign the incoming shipment requests to available transport services. Those problems are referred to as shipment matching (Guo et al., 2020), container allocation (van Riessen et al., 2015), or intermodal routing (Chang, 2008). They have been extensively addressed in the recent literature, see for example the theses of Zhang (2023) and Guo (2020): therefore, this thesis will not focus further on these problems, but instead on decisions made by the shippers themselves.

Many of these decisions are influenced by the available transport supply. For example, the location of a production facility will depend of the suppliers' and customers' location, as well as the potential transport connections and their costs (Şahin & Süral, 2007). Another example is the shipment sizing decision, which involves a trade-off between the inventory costs and the costs of the available transport possibilities (Piendl et al., 2017). For a more thorough overview of these logistics decisions, the reader is referred to Tavasszy et al. (2020a). The remainder of this section will concentrate on shippers' decisions that are directly related to the services provided by the carriers: namely the mode/carrier choice.

Mode/carrier choice

The mode choice can be considered as a simplification of the carrier selection. Indeed, it is often difficult to obtain data regarding each individual carrier due to confidentiality and distinguishing attributes between carriers operating the same transport mode may be cumbersome. Moreover, the same carrier can operate multiple modes of transport. On the other hand, each transport mode has distinct attributes and more data are available. It is then not surprising that mode choice has been more studied in the existing literature than carrier selection (Tavasszy et al., 2020a).

Multiple methods have been used to identify the decision factors playing a role in the mode choice and their hierarchy. Regardless of the methodology employed (e.g.: survey, content analysis, multi-criteria analysis) or the year of the study, it is consistently observed that three elements exert a dominant influence on the mode choice: cost, time and reliability. This is illustrated by the distinct works of McGinnis (1979);

Cullinane & Toy (2000); Tavasszy et al. (2020b), each separated by a 20-year interval and respectively using the three different methodologies stated above: they all come up with cost, time, and reliability as the most influential attributes for mode choice. Besides, other attributes such as transport flexibility, safety, traceability, and frequency are also often considered (de Jong, 2013; Li et al., 2020). Despite the crucial societal importance of sustainability, the CO_2 emissions are most of the time considered as less important than the other attributes by industry professionals (Tavasszy et al., 2020b). Finally, the mode choice decision is also influenced by the characteristics of the shipper (e.g.: size and location) and of the shipment, such as its size, its value and the commodity type (de Jong, 2013; Keya et al., 2019; Samimi et al., 2011).

The most commonly used method to estimate the mode choice is through the utility maximization of the shipper[1]. This means that the aforementioned attributes are embedded in a utility function for each mode, which also includes an error component accounting for the unobserved characteristics of the mode and of the decision-maker. The shipper then selects the mode with the highest expected utility (Winston, 1983). The error component of each utility function is expressed as a random variable, whose distribution is assumed by the modeler. In the deterministic part of the utility, the different attributes are weighted by some coefficients that are estimated using the available data. These coefficients can be generic, mode-specific or even shipper-specific. This brings us to the first research challenge:

RC1: Data availability and heterogeneity representation

The quality of a mode choice model heavily relies on the data used to estimate it. Therefore, the more detailed and abundant input data is available, the more reliable will be the resulting mode choice model. Acquiring such data is nevertheless difficult as companies are often reluctant to share information about the transport of their shipments (de Jong, 2013). It is then challenging to come up with accurate values for the attributes of each mode, especially for reliability, which is hard to estimate (Holguín-Veras et al., 2021). When limited disaggregate data are available, it is also problematic to depict the heterogeneous preferences of shippers in terms of mode choice. As mentioned above, a shipper's decision is influenced by their characteristics. Therefore, two different shippers may not have the same sensitivity to cost or travel time. Including this heterogeneity within a mode choice model makes it more representative and accurate, but usually requires detailed shipment data. The limited amount of detailed shipment data makes it difficult to come up with a precise mode choice model and to account for the heterogeneity inherent to the decision process.

[1]The reader interested in other estimation methods is referred to de Jong (2013).

1.2.2 Supply models

In this section, we now review the existing literature on modeling the decisions of carriers. Similarly to the previous section, various decisions faced by the transport operators depend on the demand they meet, or expect to meet. The latter is mostly related to strategic decisions (e.g.: fleet sizing or terminal location), while the former concerns operational decisions such as routing or load planning of vehicles (Caris et al., 2008).

The reviews of Crainic & Laporte (1997); Gorman et al. (2014); SteadieSeifi et al. (2014) give a detailed outline of the various planning models for freight transport. The rest of this section will focus on the decisions of carriers that directly impact the shippers, i.e., service network design and pricing (or revenue management) problems.

Service Network Design

This problem tackles the tactical decisions of a carrier. In particular, Service Network Design (SND) answers the following questions (Crainic, 2000): "What type of service to offer? How often over the planning horizon to offer it? What traffic itineraries to operate? What are the appropriate terminal workloads and policies?". The SND problem is modeled as an optimization problem, whose main decision variables are: the itineraries that are served, the frequency of these services and the demand allocation to these services. The way a SND problem is formulated depends on how services are defined. Three main representations are distinguished (SteadieSeifi et al., 2014):

- Arc-based: each service is associated to a single arc in the network;
- Path-based: each service is made of a series of arcs;
- Cycle-based: each service is defined as a sequence of arcs, starting and ending at the same location.

In the last two formulations, paths and cycles typically have to be generated a priori. Andersen et al. (2009) show that a cycle-based formulation is solved faster than its arc-based counterpart, but this advantage decreases when the network size increases as the cycle generation becomes computationally more demanding.

Elbert et al. (2020) further classify SND models along three characteristics:

1. Given or variable network structure: the former has a predefined service offering and the decision is the assignment policy of the incoming demand to the services, while the latter aims at determining which services to operate on top of the assignment policy;

2. Dynamic or static, depending on whether the time dimension is included or not: if it is considered, then the variable indicating the frequency of a service may be replaced by the departure time of the service (Crainic, 2000);
3. Deterministic or stochastic, whether it considers given or uncertain parameters: stochastic SND models mostly include demand or travel time uncertainty.

A vast majority of the SND models have cost minimization as their objective function, only a handful of studies include the revenue of fulfilling orders and even less consider the pricing decision of the operator (Elbert et al., 2020). Nevertheless, the price has a strong influence on demand as shippers proceed to a trade-off between transport price and service level (such as speed, reliability or frequency) when choosing their transport option (Duan et al., 2019). Including the demand response of the customers in SND models can lead to very different solutions than assuming fixed demand and applying a pure cost minimization. Therefore, considering the pricing decision within SND models can increase the profits of the carrier by addressing the trade-off between demand and price (Elbert et al., 2020).

Pricing/revenue management

Despite the critical importance of this business decision, relatively few works addressed intermodal transport pricing and those studying it apply simple assumptions (Tawfik & Limbourg, 2018). This tendency is also observed in practice, where companies often simply apply a fixed profit margin to their costs to set their prices (Boin et al., 2020). Such approach has also been used in some works: the demand is then assumed fixed and known (Dandotiya et al., 2011; Li et al., 2015a). Quite a few studies include revenue management considerations by inputting transport requests with given revenue. The carrier's decision is then to serve a request or not, see for example: Luo et al. (2016); Kapetanović et al. (2018); van Riessen et al. (2017).

In all aforementioned works, the pricing and revenue management processes of the carrier are quite simplified for at least three reasons:

1. The pricing decision is not really addressed, as price is either determined as a multiple of the costs or inputted as fixed fare class;
2. The impact of price on the demand is neglected;
3. The competition faced by the carrier is not considered.

These points can be addressed using an analytical demand function which is dependent on the price set by the carrier: some studies do not include competing carriers (Li & Tayur, 2005; Li & Zhang, 2020; Liu & Yang, 2015), while others use game theory to account for competition (Mozafari & Karimi, 2011; Tamannaei et al., 2021).

Some works started addressing the aforementioned shortcoming of SND models by combining service design with pricing decisions. The pricing is either made by selecting a fee from a discrete set of rates (Scherr et al., 2022), or by introducing directly a continuous variable for the service's prices (Martin et al., 2021; Qiu et al., 2021; Tawfik & Limbourg, 2019). Since these models are still in their early stages, the following challenge needs to be tackled:

RC2: Including detailed and heterogeneous preferences of customers in supply models

In the works of Martin et al. (2021) and Scherr et al. (2022), the behavior of shippers is not explicitly included. Instead, an assumption is made on their willingness to pay for a given level of service. In the works of Qiu et al. (2021) and Tawfik & Limbourg (2019), a bilevel setting is considered: the carrier acts as the leader and shippers as the followers, whose objective is to minimize their costs. Nevertheless, the structure of the costs is kept relatively simple, as it consists in the sum of costs of transport and of capital (or storage). In particular, the influence of service level attributes (such as frequency or reliability) on the demand is not considered. Moreover, the shippers are assumed homogeneous, i.e., they all share the same cost sensitivity; whereas in reality, shippers may have different willingness to pay depending on their characteristics. The outcomes of supply models greatly depend on the assumptions made about the demand. This is particularly true for pricing models, where information about the willingness to pay is crucial to make accurate decisions. To summarize, the existing models combining SND and pricing only consider a uniform influence of cost on the demand: the influence of level of service attributes and the demand heterogeneity is thus overlooked. The addition of these elements is challenging, as it will lead to more complex models that are computationally more expensive to solve. Nevertheless, including level of service considerations and heterogeneity into supply models will result in improved services, not only for the transport operators but also for their customers and the overall transport system.

1.2.3 Supply-Demand models

In this section, we review the literature on the interactions between shippers and carriers, regarding the decisions introduced in Section 1.2.1 and 1.2.2. On the one hand, most of the works combining supply and demand decisions use a multilevel setting and/or the user equilibrium principle, see: Li et al. (2021); Meng & Wang (2011); Taheri & Tamannaei (2023). The advantage of these models is that the demand reactions can be expressed analytically. However, these models rely on simplifying assumptions, which can impede the reliability of the results, as explained in Section 1.2.2.

On the other hand, there are experimental economics, where results are derived directly from observed behavior. A good example is the work of Holguín-Veras et al. (2011), which studies shipper-carrier interactions by making volunteers play a profit maximization game. Such works depict much better the human decisions in supply-demand interactions, however they are costly to build up as a considerable amount of time is needed to design the method, find participants, conduct the experience, and extract the results.

In between these two methods, we find agent-based simulations. They allow to explicitly describe the decision-making of the stakeholders by integrating them as "cognitive" agents following a given behavioral pattern (Tavasszy, 2020). These models are interesting to represent the system's functioning that emerges from individual behaviors (de Jong et al., 2016) and relationships. The existing agent-based simulations mostly cover the mode choice decision of shippers and the assignment of cargo on the network (Baindur & Viegas, 2011; Liedtke, 2009; Mommens et al., 2020). More detailed aspects can also be included, such as the production decisions of firms (Holmgren et al., 2012) or the pricing mechanisms of carriers (Cavalcante & Roorda, 2013). Regardless the degree of detail, a major drawback of the existing models is that the level of intelligence of the agents is kept relatively low (Crainic et al., 2018). Most agents are assumed to follow a rational cost or profit optimization approach or some simple heuristics. A few models account for other decisions than costs, but they assume homogeneous agents that follow identical decision-making processes.

Finally, some works overcome these limitations by considering heterogeneous agents competing with each other and following a more complex decision-making pattern. In particular, the works of Adler (2005); Park & Min (2017); Wang et al. (2014) address the network design and pricing problem mentioned above and use game theory to model the competition between carriers. However, those models have limitations too, as they assume that demand is exogenous and that the carriers have perfect information on the demand function. The last two references also assume that both competitors have exact knowledge about each other. But some attributes, such as the price that the competitors are applying, cannot be known perfectly.

Following this discussion, a third research challenge is identified that needs to be addressed:

RC3: More detailed decision-making, demand representation and information level in supply-demand models

Various methods can be used to model supply-demand interactions. Each method comes with its own advantages and limitations. While game theory and multilevel programming address more complex problems, the demand representation is very simplified. Often, the demand response is overlooked and decision-makers are assumed to have perfect information, which is not realistic (Park & Min, 2017). On the other hand, agent-based simulations explicitly represent the reactions of shippers with respect to carriers' decisions and vice versa. Moreover, the degree of information available to the agents can be controlled (Le Pira et al., 2017). But the decision-making process of the agents is often very simplified. The challenge is to develop methods able to cover both complex decision-making problems and detailed demand representation, while allowing for different levels of information. Such methods will be able to better capture the dynamics between supply and demand, therefore the impact of any change on the transportation system can be more accurately evaluated.

1.2.4 Evaluation of improvement measures

The aforementioned research challenges lead back to the main purpose of this thesis: assess the impact of improvement measures on the intermodal transport system, considering the behaviors and interactions of the stakeholders. Since a ready-to-use evaluation framework with these elements does not exist, the last research challenge arises:

RC4: Consideration of the behaviors and interactions of stakeholders for the evaluation of improvement measures

As mentioned in Section 1.1, good models are essential to get an accurate evaluation of policies, investments, or innovations. In the existing models, behavioral aspects are often overlooked (Meersman & Van de Voorde, 2019; Tavasszy, 2020): by neglecting these aspects, such models will produce results that are at best incomplete, if not totally erroneous. There is, therefore, a need for models considering the behaviors and relationships of the different stakeholders in the freight transport system. Given the scarcity of such models, an evaluation framework needs to be developed.

1.3 Research questions and approach

In light of the research challenges identified above, this thesis aims at addressing the main research question: **How to improve decision-making in freight transport by considering the heterogeneous actors and their interactions?** To tackle it, this main question is partitioned into four research questions, each focusing on one particular research challenge:

RQ1: How can the transport demand be accurately modeled taking heterogeneity into consideration?

This question addresses **RC1** in Chapter 2 by proposing a weighted mode choice model to estimate the heterogeneous preferences of shippers directly from aggregate data.

RQ2: What is the impact of including mode choice decisions of shippers in the decision-making of intermodal carriers?

This question addresses **RC2** in Chapter 3 by proposing a choice-driven Service Network Design and Pricing model incorporating the aforementioned mode choice model.

RQ3: How shall the supply-demand interactions be modeled to accurately represent the freight transport market?

This question addresses **RC3** in Chapter 4 by proposing a competitive Service Network Design and Pricing model extending the aforementioned choice-driven method.

RQ4: What insights does the consideration of actors and their behavior bring in the evaluation of an improvement measure?

This question addresses **RC4** in Chapter 5 by applying the three aforementioned models to a case study consisting of a Modular Terminal concept to improve the container handling process in seaports.

1.4 Contributions

This thesis contributes to the fields of intermodal transport and operation research by proposing methods combining advanced choice models and optimization problems covering tactical decisions. The main contributions are as follows:

- Development of a mode choice model estimating the heterogeneous preferences of shippers directly from aggregate data, see Chapter 2 and Nicolet et al. (2022).
- Inclusion of mode choice models considering heterogeneity and unobserved attributes into a Service Network Design and Pricing problem, see Chapter 3 and Nicolet & Atasoy (2024a).
- Development of a price and service competition framework between two carriers considering demand response and imperfect information, see Chapter 4 and Nicolet & Atasoy (2024b).
- Design of an optimization model to determine the configuration of Modular Terminals maximizing time savings and application of the aforementioned methods to estimate the potential impacts on the transport system, see Chapter 5 and Nicolet et al. (2023).
- Evaluation, validation and analysis of the proposed methods using data from a real intermodal transport network, see Chapters 2-5 and Nicolet et al. (2022); Nicolet & Atasoy (2024a,b); Nicolet et al. (2023).

1.5 Thesis outline

The outline of this dissertation is illustrated in Figure 1.3. It follows the supply-demand structure as introduced above.

In Chapter 2, we introduce a demand model representing the shippers side of the freight transport market. It covers the mode choice of shippers taking into account their heterogeneous preferences. The methodology is then applied to the European Rhine-Alpine corridor to represent the mode choice for containerized goods.

This demand model is then embedded into the decision-making problem faced by an intermodal carrier in Chapter 3 to design and price their services. We thus come up with a choice-driven Service Network Design and Pricing model. The proposed model is used in case study along the same corridor to improve the decisions of an inland waterway operator.

In Chapter 4, we develop a competition framework, where two intermodal transport suppliers compete on the price and frequency of their services and react to the demand response. The framework also captures the various degree of information that carriers have about each other and their demand. A similar case study as in the previous chapter is used, but this time with two competing inland waterway operators.

Chapter 5 presents the Modular Mobile Terminal concept as an improvement measure for inland waterway transport along the Rhine-Alpine corridor. A time savings optimization model is used to determine the optimal configuration of this innovation. This configuration is then used in the choice-driven models presented in the three previous chapters to evaluate the potential impact of the Modular Mobile Terminal on the intermodal corridor.

Finally, Chapter 6 concludes the thesis and proposes directions for future research.

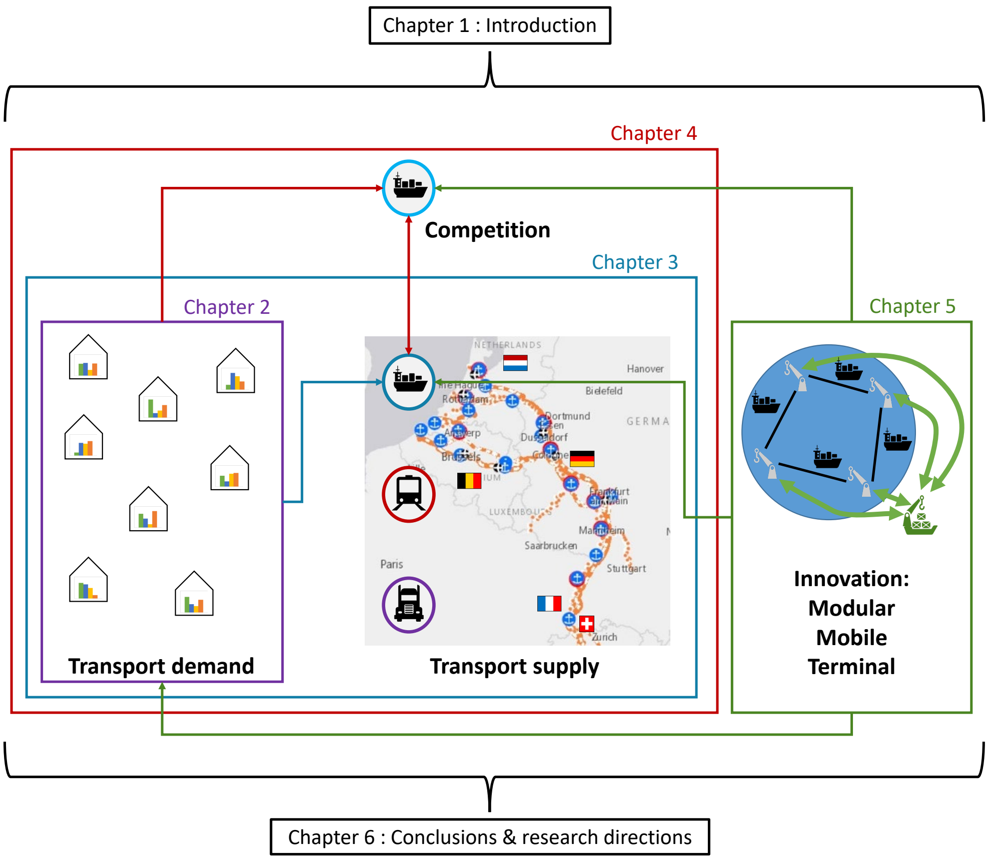

Figure 1.3: Outline of this thesis.

Chapter 2

Estimation of shippers behavior considering heterogeneity

Chapter 1 of this thesis has highlighted the challenge to estimate accurate transport demand models with limited shipment data. It is particularly difficult to capture the heterogeneous preferences of shippers. In this chapter, we thus propose a Weighted Logit Mixture methodology to estimate heterogeneous mode choice preferences directly from aggregate data. This chapter addresses RQ1: How can the transport demand be accurately modeled taking heterogeneity into consideration?

This chapter is structured as follows: Section 2.1 provides some background regarding mode choice modeling. In Section 2.2, a literature review is provided, after which we describe the model and its characteristics in Section 2.3. The proposed methodology is then applied to a concrete case study, introduced in Section 2.4 and we present the main results in Section 2.5. Finally, conclusions are provided in Section 2.6.

Parts of this chapter have been published as a journal article: Nicolet, Negenborn, & Atasoy (2022) "A logit mixture model estimating the heterogeneous mode choice preferences of shippers based on aggregate data", *IEEE Open Journal of Intelligent Transportation Systems*, 3, pp. 650-661.

2.1 Introduction

International freight transport plays a significant role in the worldwide CO_2 emissions. Its share has been estimated to be more than 7% of global emissions in 2015 (International Transport Forum, 2015). Regarding land transport, the road is by far the most used modality. In Europe, freight transport on the road represented more than 70% of the tonnes-kilometers traveled in 2018 (European Commission, 2020a). Therefore, modal shift to rail or water freight transport is a key objective of the European Green New Deal to move toward sustainable mobility (European Commission, 2019; European Environment Agency, 2021). Beside the use of new policies or regulations, the attractiveness of waterborne and rail transport can be enhanced through innovations, e.g. smart navigation or coordinated lock scheduling. These can address several aspects of the transport, such as cost reduction or time savings. In order to take appropriate action, it is crucial to accurately represent and understand the modal split, its drivers and its potential evolution. Since the 1980s, various freight mode choice models have been developed following similar methodologies as for passenger transport (de Jong et al., 2004). The outcome of these models is typically the probability for choosing a given alternative to ship a good from origin to destination. A so-called alternative can consist of a single mode but can also be more complex, e.g. a combination of modes, a mode chain or a specific route.

Depending on the scale observed, aggregate and disaggregate models are differentiated. Aggregate models refer to situations where the Origin-Destination (OD) flows of cargo between regions are observed, whereas disaggregate models make use of shipment data (Winston, 1983). The latter then present a greater level of detail and depict better the preferences of the decision-maker (Tavasszy et al., 2000), however shipment data are often difficult to acquire due to their commercially-sensitive nature (de Jong, 2013). Furthermore, an international scope necessitates that companies active in different regions share their data with researchers and that the number and variety of firms are sufficient to be representative for the whole population. This requires a laborious data collection process, with no guarantee of success.

On the other hand, aggregate models make sense in an international freight transport context since modal share is strongly influenced by the geography and the commodity mix (Vassallo & Fagan, 2007). One can reasonably assume that firms belonging to the same industry sector with identical available transport infrastructure and services will exhibit similar behaviors. Therefore, OD flows between regions, especially when segmented into commodity types, are considered to be representative for the whole population (Rich et al., 2009). However, there remains underlying heterogeneity since it is impossible to observe all factors influencing the mode choice process, all the more with aggregate data.

The main contribution of this work is to consider heterogeneity explicitly in the aggregate mode choice model without the need of disaggregate shipment data or additional data handling. Instead of assuming that the same behavior is shared by the whole population, we allow the preferences to be randomly distributed. Therefore, the inherent heterogeneity is taken into account in the modal share estimation process. Moreover, the methodology is applied to real-world data along the European multimodal Rhine-Alpine corridor.

2.2 Related work

This section gives an overview of the existing freight mode choice models, focusing on aggregate models that have been applied to a real-world situation. For a thorough review of freight mode choice models, the reader is referred to the following works: de Jong (2013); de Jong et al. (2004); Gray (1982).

2.2.1 Aggregate mode choice models

At early stages, mode choice was estimated through regression models based on cost and demand functions for freight transport (Oum, 1979). Several optimization models have been developed later to assign the flows to their corresponding mode and route in the freight transport network (Beuthe et al., 2001; Guelat et al., 1990; Macharis & Pekin, 2009; Tavasszy et al., 1998; Zhang et al., 2015). They aim at minimizing the costs and are solved employing shortest path algorithms. This cost minimization can also be used as a control rule within a freight transport network simulation (Larsen et al., 2021; Li et al., 2015b). But the most prevalent model to estimate the mode choice in freight transport is the Multinomial Logit (MNL), or one of its variations (de Jong, 2013).

The MNL is based on the Random Utility Maximization (RUM) principle applied to the context of discrete choice (Ben-Akiva & Lerman, 1985; McFadden, 1982). Although designed for disaggregate models, this methodology can also be applied to aggregate mode choice models (de Jong et al., 2004; Rich et al., 2009). Some studies estimate their model directly with OD flows, while others proceed to a disaggregation of the flows before applying the model. The latter can be seen as a hybrid technique: the mode choice model is generally estimated with disaggregate data (through a survey of shippers or a Commodity Flow Survey, like the one gathered by the US Bureau of

Transportation Statistics (Margreta et al., 2009)), then the model can be used for modal share estimation by disaggregating the OD flows into shipment inputs. Zhang et al. (2008) use a shippers' survey to estimate the coefficients of a binary Logit model. The two considered alternatives are truck only and intermodal transport. To compute modal shares with the estimated model, the aggregate freight flows in tons are then decomposed into smaller units, such as twenty-foot equivalent units (TEU), using a predetermined distribution of the weight per TEU. The Aggregate-Disaggregate-Aggregate (ADA) methodology, proposed by Ben-Akiva & de Jong (2013), pushes the concept further by converting zone-to-zone flows into firm-to-firm flows and combining transport chain choice with other logistics decisions (e.g. shipment size, type of loading unit). The choice model itself is estimated on a Commodity Flow Survey with generalized costs as a "disutility" function. The authors mention that the estimation of the model is also feasible with only OD data: it can be achieved by setting these data as targets and iteratively calibrating the parameters until the model's output is close enough to the targets.

The aforementioned "hybrid models" between aggregate and disaggregate models present the advantage that they are estimated with data from real decision-makers (shippers, firms). The models are thus perfectly consistent with the RUM theory, as they compute the (dis)utility of concrete individuals. Nevertheless, only aggregate data are available when the models are used for forecasting: shipment surveys are indeed not available for each year and every region. Data at the firm or shipment level are then produced using predefined probability distributions.

Other authors use directly the available data (OD flows) to estimate their mode choice models. From a theoretical point of view, this is more debatable since data do not relate to a concrete agent capable of decision. However, this approach presents the advantage of not handling the data before applying the model. The Weighted Logit methodology proposed by Rich et al. (2009) proposes that OD pairs and commodity groups are representative of the population. During model estimation, the flow on each pair and for each commodity group is then used to weigh the importance of the respective pair and group. Their Logit model is applied to the crossing of the Øresund region (Denmark-Sweden) and evaluates the choice between truck, ship, train and combinations of truck with the two other modes. Jourquin & Beuthe (2019) also apply a Weighted Logit to compute cost and time elasticities at a trans-European level. They especially focus on the Benelux region to evaluate the impact of geographical aggregation (NUTS-2 vs. NUTS-3)[1] on the elasticities for three modes, namely road, rail and inland waterways transport (IWT). Jourquin (2021) further applies Box-Cox transfor-

[1]The NUTS (Nomenclature of Territorial Units for Statistics) is the official division of the EU and the UK for regional statistics (European Commission, 2020b)

mations (Box & Cox, 1964) to the cost, time and distance variables within a Weighted Logit model. Indeed, these attributes are often correlated with each other in an aggregate mode choice context. The study's results show that the Box-Cox transforms can improve the validity and accuracy of the model's estimates. Albert & Schaefer (2013) present a standard MNL to determine the modal split between air, truck and rail in the US. Instead of estimating the model through a likelihood maximization (as in Jourquin (2021); Jourquin & Beuthe (2019); Rich et al. (2009)), it is performed via the ordinary least squares methodology. A similar procedure is used by Nuzzolo et al. (2015) to simulate the modal split of Italian import and export flows between four alternatives (road, road-railway, road-sea, air).

As stated in the introduction, the choice alternatives can also be a transport chain, i.e. a sequence of multiple transport modes. This occurs if the cargo is transshipped from one mode to another along the way from origin to destination. In WORLDNET (Newton, 2008) – a simulation of international cargo flows – a MNL is applied to assign the OD flows to transport chains in the network. To avoid taking into account every feasible alternative, they restrict the choice to be between the k cheapest chains, with k being modifiable to allow reasonable computation time. However, there is no transport chain data available but only uni-modal OD flows. The model is then estimated iteratively by adjusting its coefficients and adding shadow prices to the network until the model's output fits the data. In the freight transport model BasGoed (de Bok et al., 2018), the unavailability of transport chain data is remedied by constructing multi-modal chains from uni-modal data. This is done with heuristics based on practical assumptions.

We notice that there exist several types of aggregate mode choice models coming with different degrees of data handling. For "hybrid models", data at disaggregate level need to be generated from the available aggregate data with some chosen probability distributions. Similarly, when transport chains are used as alternatives, these chain data have to be built using some heuristics on the available data. In contrast, the Weighted Logit methodology does not require any data handling.

2.2.2 Heterogeneity representation

A key challenge of freight mode choice models is to capture the heterogeneous preferences (Román et al., 2017). In the context of aggregate mode choice, there are at least two aspects of heterogeneity to consider. Firstly, a shipper's behavior can significantly vary given the type of commodity that is transported (Zhang et al., 2008), and its value. For example, bulk cargo does not require the same transport conditions as containerized cargo; likewise, the lead time is a more important criterion for perishable commodities than for building materials. The second aspect concerns geography: indeed, regional particularities might impact the mode choice process due to different transport infrastructure (Rich et al., 2009), transport services or culture. Heterogeneity is also present within a region as all the established shippers will not behave identically (Arunotayanun & Polak, 2011). However, this last point cannot be captured explicitly because of the aggregate nature of the data.

Under the RUM theory, two advanced variants of the MNL allow capturing heterogeneity: the Logit Mixture Model and the Latent Class Model. The former allows the coefficients of the utility functions to be randomly distributed instead of fixed (McFadden & Train, 2000), whereas the latter splits the population into classes with coefficients that differ from one class to another (Greene & Hensher, 2003).

Among the works reviewed previously, the ADA methodology is the most flexible to take heterogeneity into account as it allows the use of a Mixture model to capture variations of preferences or correlation between alternatives (Ben-Akiva & de Jong, 2013). The method also estimates various coefficients according to the commodity type being shipped. Other studies also perform segmentation with respect to the commodity type (Jourquin, 2021; Jourquin & Beuthe, 2019; Nuzzolo et al., 2015; Rich et al., 2009): the coefficients of the utility functions are then estimated separately for each segment. One of these works (Nuzzolo et al., 2015) goes a step further by also determining different coefficients regarding the shipping direction (import or export). Another model segments the data according to the types of OD pair, namely: hinterland to port, port to hinterland, hinterland to hinterland, and port to port (de Bok et al., 2018). A last study directly considers heterogeneous data sources by modifying the error covariance term in the model's formulation (Albert & Schaefer, 2013).

The existing studies mostly use segmentation on observable data (commodity, geography) to express some heterogeneity. Only the ADA methodology has the possibility to capture heterogeneity with respect to unobserved attributes, however this requires some disaggregate data as well.

2.2.3 Contribution of this study

Within this research, we propose to estimate the mode choice model without making any assumptions on the data. Therefore, a Weighted Logit methodology is adopted (Rich et al., 2009). We express the heterogeneous preferences in the model by introducing a Mixture formulation. The comparison of our approach with the existing models is shown in Table 2.1. The reader can notice the absence of data handling (i.e. no synthetic data are generated) and the expression of preferences' heterogeneity with respect to unobserved attributes, which is allowed by the proposed modeling.

Table 2.1: Comparison of Logit-based Aggregate Mode Choice Models.

Reference	Methodology		Data handling		Heterogeneity wrt. [c]
	Model type [a]	Modes [b]	Flows partition	Transport chain building	
Albert & Schaefer (2013)	MNL	Rd-Rl-A			(g)
Ben-Akiva & de Jong (2013)	MNL+	Rd-Rl-S-A	✓		c, (g), u
de Bok et al. (2018)	MNL	Rd-Rl-IWT		✓	g
Jourquin (2021)	WL	Rd-Rl-IWT			c
Jourquin & Beuthe (2019)	WL	Rd-Rl-IWT			c
Newton (2008)	MNL	Rd-Rl-IWT-S		✓	-
Nuzzolo et al. (2015)	MNL	Rd-Rl-S-A			c, g
Rich et al. (2009)	WL	Rd-Rl-S			c
Zhang et al. (2008)	BL	Rd-Rl	✓		-
Our model	WLM	Rd-Rl-IWT			g, u

[a] MNL = Multinomial Logit, MNL+ = Multinomial Logit and others, WL = Weighted Logit, BL = Binary Logit, WML = Weighted Logit Mixture.
[b] Rd = road, Rl = (intermodal) rail, IWT = inland waterway transportation, A = air, S = (short-)sea.
[c] c = commodity, g = geography, u = unobserved attributes.

The only assumption to be made concerns the probability distribution of a given parameter among the population, then the parameters are estimated directly from the data. This method will allow revealing the underlying heterogeneity in the population. We thus propose a Weighted Logit Mixture (WLM) model that aims at staying as close as possible to the actual situation, so as to depict it accurately.

Table 2.1 contains some other models, that directly use the data at hand without generating any synthetic data, but they do not account explicitly for unobserved heterogeneity. The ones that consider some kind of heterogeneity use a deterministic segmentation most of the time according to the commodity. The Mixture methodology proposed in this research allows to go a step further by depicting heterogeneity within the segments themselves, thus extracting more information from the aggregate data.

2.3 Estimation method

The proposed WLM aims at combining the advantages of the Weighted Logit methodology (Rich et al., 2009) and the Mixture modeling (McFadden & Train, 2000). The former allows estimating the mode choice model directly from aggregate OD flows, whereas the latter enables the introduction of heterogeneous preferences among the population. We first describe the Weighted Logit method, on which our approach is based and that we will use as benchmark, and then we explain how the Mixture formulation is introduced.

2.3.1 Weigthed Logit Model

In our context of intermodal transport, we only consider the long-haul transport and neglect any pre- and post-haulage trips. Therefore, the choice set on each OD pair is made of the three main transport modes: IWT, road, and rail (provided that they are available on the pair). The model's inputs are the OD matrices for each mode, which can be discretized in various ways depending on the case study, as well as the attributes related to each mode on each OD pair (e.g.: cost, time, accessibility). In practice, these attributes would vary per container given its weight, due time, precise origin and destination, etc. However, due to the unavailability of shipment data, it is considered that all containers shipped on the same OD pair share the same mode attributes.

We formulate a utility function U_{m,q_s} for each container s on OD pair q and for each available mode m, which can be expressed according to the following formula:

$$U_{m,q_s} = V_{m,q_s} + \varepsilon_{m,q_s} \tag{2.1}$$

where V_{m,q_s} is the systematic component of the utility function and ε_{m,q_s} is the random component which is assumed to follow an Extreme Value distribution. In our study, the latter is assumed independent across m and q_s but this assumption can be relaxed by considering correlations between modes (e.g. IWT and rail are both scheduled modes) or between OD pairs. The systematic part can be derived from the set I of considered attributes for each mode:

$$V_{m,q_s} = \alpha_m + \sum_{i \in I} \beta_{i,m} X_{i,m,q} \quad \forall s. \tag{2.2}$$

This formulation contains an alternative specific constant α and a sum expressing the impact of each attribute's value X on the utility. This impact is expressed by the related coefficient β, which can be mode-specific or identical for all modes. In the absence of segmentation, the same α and β parameters are assumed to be shared by the whole population. Note that the right-hand side in (2.2) is identical for all containers due to the assumption that shipments share the same mode attributes on a given OD pair. As a result, the container index s can be dropped and the probability to choose mode m among the set of available modes M on OD pair q is computed using the following expression:

$$P_q(m) = \frac{e^{\mu V_{m,q}}}{\sum_{k \in M} e^{\mu V_{k,q}}} \tag{2.3}$$

where μ is a "scale parameter" generally normalized to one. The estimation of the α and β parameters is performed through a maximum likelihood estimation, in which the log-likelihood LL is defined as:

$$LL = \sum_{q \in Q} \sum_{m \in M} \sum_{s \in S_q} y_{m,q_s} \ln(P_q(m)) \tag{2.4}$$

with Q the full set of OD pairs, S_q the full set of shipments on OD pair q and y_{m,q_s} a dummy variable equal to one if mode m is chosen for container s on OD pair q.

Since the mode choice probability is independent of s, (2.4) can be rewritten as:

$$LL = \sum_{q \in Q} \sum_{m \in M} \ln(P_q(m)) \sum_{s \in S_q} y_{m,q_s} = \sum_{q \in Q} \sum_{m \in M} \ln(P_q(m)) w_{m,q} \tag{2.5}$$

where $w_{m,q}$ is the total volume (in TEUs) shipped by mode m on OD pair q, which acts as a weight of the log-likelihood function.

2.3.2 Weighted Logit Mixture formulation

The proposed Weighted Logit Mixture method is based on the approach described above but without assuming that the β parameters are identical for the whole population. Indeed, shippers may exhibit different sensitivities especially regarding the costs: some may be willing to spend as few as possible for the transport, while others may agree to spend more in exchange of additional transport services. The Mixture formulation accounts for different sensitivities by defining one or several of the β coefficients as following a random distribution ψ with mean $\overline{\beta}$ and variance σ^2_β.

Unlike in (2.3), the expression of the probability has no closed-form this time: thus, the likelihood maximization cannot be performed analytically. Monte Carlo simulation shall be used to obtain a "simulated likelihood". The simulation executes R draws within a given distribution ψ to approximate $P_q(m)$ with:

$$\tilde{P}_q(m) = \frac{1}{R}\sum_{k=1}^{R} P_q(m, r_k) \tag{2.6}$$

where r_k is the result of the kth draw in ψ. The simulated log-likelihood $\widetilde{LL}$ to be maximized is then expressed as:

$$\widetilde{LL} = \sum_{q\in Q}\sum_{m\in M} \ln(\tilde{P}_q(m))w_{m,q}. \tag{2.7}$$

2.4 Case study

We apply the proposed methodology to represent the mode choice for containerized goods along the European multimodal Rhine-Alpine (RA) corridor, focusing on the Rhine section of the corridor (see Figure 2.1) where 3 transport modes are accessible: road, rail and IWT.

Figure 2.1: The Rhine section of the RA corridor (European Commission, 2021), covering 5 countries with 3 transport modes available: road, rail and IWT.

Attributes used in freight mode choice typically consist of the cost, time, reliability, flexibility, frequency, tractability, emissions, number of transshipments, probability of damage (de Jong, 2013; Mangan et al., 2001; Ramos et al., 2020). In addition, the availability (or accessibility) of a mode represents an influential driver of the mode choice (Evers et al., 1996; Ramos et al., 2020). For intermodal transport, the proximity of terminals is an important decision factor (Elbert & Seikowsky, 2017): existing models use a dummy variable indicating if rail tracks and quays are accessible to a firm (Abate et al., 2019; de Jong & Ben-Akiva, 2007) or a qualitative evaluation of the access to intermodal facilities (Samimi et al., 2011). The accessibility of road transport can also be included, for example with the highway density of a zone (Keya et al., 2019), which impacts positively the utility of road transport, or with a dummy variable indicating high traffic OD pairs (Mohri et al., 2019), whose impact on road utility is negative.

In this study, we consider the accessibility a expressed as the number of terminals in both zones of origin and destination for IWT and rail and as the number of highway junctions in both zones for road. These data have been manually collected through the RA corridor info system (Interregional Alliance for the Rhine-Alpine Corridor EGTC, 2021). Moreover, the weekly frequency f of IWT and rail services on the OD pair is included. These data have been collected within the NOVIMOVE project (Majoor et al., 2021) and completed using the operators' websites.

The costs c of transporting and handling a container from origin to destination, expressed in thousands of euros per TEU, are issued from a conference paper (Shobayo et al., 2021). In this work, the transport costs per container are estimated between NUTS-2 regions for each mode[2]. For road transport, costs are expressed as a sum of distance- and time-based costs (expressed in euros per km and euros per hour). The former include fuel, maintenance and tires; the latter mainly consist of labour, depreciation and insurance. These costs are then respectively multiplied by the distance and the time from origin to destination. The cost structure for rail transport is also composed of distance- and time-based costs, but some fixed costs are added in the computation to account for the related shunting operations. For IWT, the transport costs comprise voyage costs (i.e. fuel, port dues and infrastructure charges) and operating costs. The latter are further divided into maintenance costs and crew costs, that are proportional to the duration of the voyage.

Finally, the model also includes a dummy variable p equal to one if either origin

[2]Beside transport costs, other cost components are estimated in the paper such as reliability costs. However, they are not usable for our model because of their limited variability: they are either estimated using fixed values or strongly correlated to the transport costs.

or destination zone contains a seaport[3]. It is added in the utility function of IWT: the idea is that having a port in the origin or destination will facilitate the use of waterway transport and that no road haulage will be needed.

A key note is that time could not be directly included in the model. Several estimations have been conducted with the time attribute, but the associated coefficient was consistently not significant. This is because the costs are estimated from travel times in the considered paper (Shobayo et al., 2021), as described above. Cost and time are then strongly correlated to each other and the model cannot be estimated with these attributes together. Nevertheless, the omission of the time attribute in our model does not mean that it does not play a role but rather does so (to some extent) through the cost attribute.

We evaluate a standard Weighted Logit to serve as a benchmark. The container volume data are issued from the ASTRA model (Fiorello et al., 2010): OD matrices are available for each mode and several years. They represent the annual cargo flows between European regions at the NUTS-2 level. Based on (2.2), the following systematic utility functions are defined for each mode (the index for OD pair q is omitted for the ease of notation):

$$V_{\text{IWT}} = \alpha_{\text{IWT}} + \beta_{c,\text{Inter}} c_{\text{IWT}} + \beta_{a,\text{Inter}} a_{\text{IWT}} + \beta_{f,\text{Inter}} f_{\text{IWT}} + \beta_{p,\text{IWT}} p \tag{2.8}$$

$$V_{\text{Rail}} = \alpha_{\text{Rail}} + \beta_{c,\text{Inter}} c_{\text{Rail}} + \beta_{a,\text{Inter}} a_{\text{Rail}} + \beta_{f,\text{Inter}} f_{\text{Rail}} \tag{2.9}$$

$$V_{\text{Road}} = \alpha_{\text{Road}} + \beta_{c,\text{Road}} c_{\text{Road}} + \beta_{a,\text{Road}} a_{\text{Road}} \tag{2.10}$$

with α_{IWT} being normalized to zero, thus setting the reference level. In the proposed formulation, two different β coefficients for cost and accessibility are estimated: one for the road alternative and one for intermodal alternatives (rail and IWT)[4]. Regarding cost, this allows considering a different cost sensitivity with respect to the mode that is considered. For accessibility, this is because this attribute is measured differently for road than for intermodal transport.

2.4.1 Heterogeneity representation

Based on the benchmark formulation, we estimate a WLM by allowing the cost coefficient β_c to be randomly distributed among the population. We assume that it follows a Lognormal distribution with parameters μ_c and σ_c^2. The semi-infinite support of this

[3] The considered seaports are Amsterdam, Rotterdam, Antwerp and Zeebrugge.

[4] A formulation with distinct β coefficients for each of the three modes was also investigated. However, the estimation revealed that the β coefficients for rail and IWT were not significantly different from each other. The same remark holds for frequency.

distribution ensures that the estimated value of the cost coefficient will have a negative sign. This a priori assumption is commonly used because a positive cost coefficient is inconsistent with the theory of rational economic behavior (Hess et al., 2005). Indeed, it is unrealistic that a cost raise for a given mode (everything else being equal) would cause an increase in its utility. Under the defined Lognormal distribution, β_c is then expressed as:

$$\beta_c = -e^{\mu_c + \sigma_c Z} \tag{2.11}$$

with Z a standard normal variable, in this case ψ is thus $\mathcal{N}(0,1)$. The following expressions:

$$\overline{\beta_c} = -e^{\mu_c + \sigma_c^2/2} \tag{2.12}$$

$$\sigma^2_{\beta_c} = (e^{\sigma_c^2} - 1)e^{2\mu_c + \sigma_c^2} \tag{2.13}$$

are used to obtain the mean $\overline{\beta_c}$ and variance $\sigma^2_{\beta_c}$ of the cost coefficient. We use a maximum simulated likelihood estimation with 10'000 draws in $\mathcal{N}(0,1)$ to determine the values of the WLM parameters. Both the Weighted Logit (benchmark) and the WLM are estimated and validated using the software package Biogeme (Bierlaire, 2020).

2.4.2 Validation of the models

We proceed to out-of-sample validation using flow data of two different years based on a procedure described by Jourquin (2021). We first compute the predicted modal shares on the whole corridor for both models and compare them with the actual shares. Then we assess the accuracy at the OD level: this is done by computing the correlation coefficient between the container volumes returned by our WLM (or the benchmark) and the actual ones on every OD pair for each mode[5].

Beside this, we compute the (point) cost elasticities for the benchmark and the WLM that represent how a change in the transport cost influences the probability to choose a given modality. The point elasticity $E^{c_{k,q}}_{P_q(m)}$ of the probability $P_q(m)$ to choose mode m on an OD pair q with respect to the cost of mode k is expressed as:

$$E^{c_{k,q}}_{P_q(m)} = \frac{\partial P_q(m)}{\partial c_{k,q}} \frac{c_{k,q}}{P_q(m)} \tag{2.14}$$

[5]The third step in the approach of Jourquin, i.e. comparing volumes on the network's segments, cannot be performed in our case since the network assignment task is not included in the present study.

If $k = m$, the direct cost elasticity is obtained; otherwise, we get the cross cost elasticity. When it is computed for the WLM, $P_q(m)$ is replaced by the simulated probability $\tilde{P}_q(m)$.

To obtain elasticity values for the whole corridor, we proceed to an aggregation of elasticities (Bierlaire, 2017):

$$E_m^{c_k} = \sum_{q \in Q} E_{P_q(m)}^{c_{k,q}} \frac{w_q P_q(m)}{\sum_{q \in Q} w_q P_q(m)} \tag{2.15}$$

where w_q is the total volume (in TEUs) on OD pair q. The resulting estimates are then assessed by comparison with elasticity values from previous studies.

2.4.3 Addition of Value of Time

Once the proposed WLM is validated, we investigate the impact of the Value of Time (VoT) on the mode choice. By Value of Time, we mean the capital costs incurred while transporting the cargo. We make use of the VoT proposed by Hintjens et al. as 1.12 € per hour per TEU. This figure is based on the average value transported per TEU with a depreciation of four years (Hintjens et al., 2020). This value is then multiplied by the total travel time for each mode, including the pre- and post-haulage for intermodal transport, and added to the transport costs c. We finally re-estimate the WLM with these new costs. This will allow us to consider the influence of time on the model's coefficients and on shippers' heterogeneity.

2.5 Results

In this section, we present the key results of the models' estimation and compare the performance of both methods. The model is estimated with the container flow data of the year 2017 and the data of years 2016 and 2019 will be used for out-of-sample validation purposes[6]. The resulting coefficients for our WLM and the benchmark are displayed in Table 2.2 together with the log-likelihood.

Regarding the parameters, the estimated β coefficients for both models have the expected signs: negative for the costs, as an increase in the costs will impact the utility negatively; and positive for the accessibility, frequency and port coefficients. Indeed, the utility of intermodal transport increases together with the number of existing terminals in the origin and destination zones and the utility of road with the number of

[6] The year 2018 is not considered since a major drought occurred on the Rhine, thus disrupting the IWT flows compared to the year 2017.

Table 2.2: Estimation results for the Weighted Logit and our WLM, using 10'000 draws.

	Benchmark			WLM		
Parameter	Value	Standard error	p-value	Value	Standard error	p-value
α_{Rail}	0.693	0.655	0.290	1.04	0.835	0.213
α_{Road}	1.96	0.78	0.0120	2.52	1.14	0.0272
$\beta_{p,\text{IWT}}$	1.28	0.353	2.77e-04	1.41	0.456	0.00199
$\beta_{f,\text{Inter}}$	0.0219	0.00729	0.00273	0.0271	0.00877	0.00203
$\beta_{a,\text{Road}}$	0.0442	0.0237	0.0622	0.0491	0.0295	0.0958
$\beta_{a,\text{Inter}}$	0.138	0.0578	0.0171	0.156	0.0737	0.0343
$\beta_{c,\text{Road}}$	-4.79	0.744	1.22e-10	-10.1	4.71	0.0311
$\overline{\beta}_{c,\text{Inter}}$	-7.32	3.21	0.0226	-19.8		
$\sigma_{\beta_{c,\text{Inter}}}$				20.6		
$\mu_{c,\text{Inter}}$				2.62	0.586	7.94e-06
$\sigma_{c,\text{Inter}}$				0.856	0.300	0.00426
LL	-1.19e+08			-1.18e+08		

highway junctions. The same reasoning applies to the frequency coefficient. For the port coefficient, it means that having a seaport in either the origin or destination zone will increase the utility of IWT. Regarding the variation of the parameters between the two models, we notice that the ratio between $\overline{\beta}_{c,\text{Inter}}$ and $\beta_{c,\text{Road}}$ is increased when passing from the benchmark to the WLM (1.55 for the benchmark and 1.95 for the WLM). This means that the relative cost sensitivity of intermodal transport versus road is augmented when the cost coefficient of intermodal transport is allowed to be distributed.

Concerning the alternative specific constants, α_{Road} is compliant to what is expected along the RA corridor: road is preferred to intermodal transport, all else being equal. The positive value of α_{Rail} is unexpected, but this should be nuanced as, in both models, it is not very significant, i.e. different from zero. This last point suggests that our models have a satisfying predictive power. Indeed, the alternative specific constant represents the mean effect on the utility of other attributes that are not included in the utility function. When the value of α gets closer to zero, it means that the influence of these other attributes is decreased, or formulated differently, that the deterministic part of the utility function has an improved descriptive power. For the other coefficients, only $\beta_{a,\text{Road}}$ exhibits a p-value higher than the 5% threshold, but it falls under the 10% limit in both models.

2.5.1 Heterogeneity representation

Concerning the variability of the cost coefficients, we had also estimated Mixture specifications where both $\beta_{c,\text{Road}}$ and $\beta_{c,\text{Inter}}$, or only $\beta_{c,\text{Road}}$ were log-normally distributed, but results were unreliable since several parameters were not statistically significant. In the proposed WLM, however, the $\sigma_{c,\text{Inter}}$ estimates is statistically significant which means that there exists a variation of the cost sensitivity regarding intermodal transport among the population. The magnitude of the standard deviation estimates reveals that the preferences concerning the intermodal transport costs vary substantially. The probability distribution of $\beta_{c,\text{Inter}}$ is depicted in Figure 2.2.

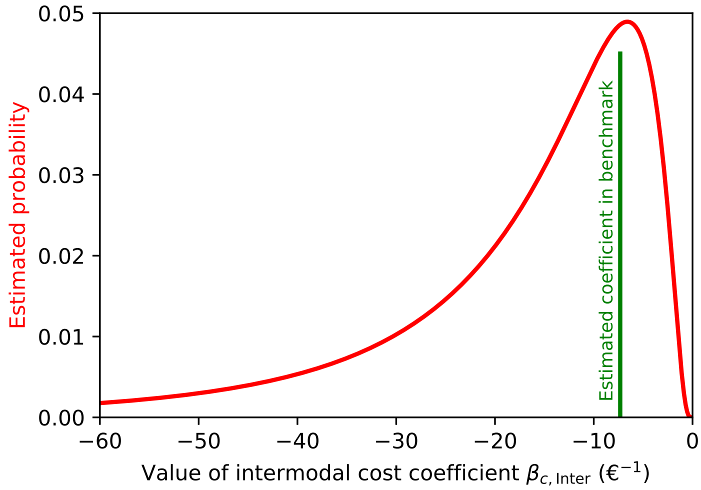

Figure 2.2: Probability distribution of the cost coefficient for intermodal transport $\beta_{c,\text{Inter}}$, together with its fixed value estimated in the benchmark.

We immediately notice that the mode of the distribution of $\beta_{c,\text{Inter}}$ (which equals -6.6) is close to the fixed coefficient estimated in the benchmark. But a great share of the population exhibits a lower cost coefficient: the mean of the distribution is indeed almost -20. This means that the benchmark underestimates the influence of intermodal transport cost for a significant part of the population. The WLM enables to explicitly capture this part of the population with a low cost coefficient, or equivalently, a higher sensitivity. This explains why, as noticed above, the relative cost sensitivity of intermodal transport compared to road is increased in the WLM.

2.5.2 Validation of the models

The proposed WLM is further compared to the benchmark with an out-of-sample validation, which is performed at the corridor and OD pair levels. Moreover, we compute the cost elasticities from our models and compare them to existing works.

Corridor level

We estimate the market shares of each mode for years 2016 and 2019 with both models. The predicted modal shares are then compared with the ones measured from the existing data in Table 2.3.

Table 2.3: Actual Modal Shares Compared to Estimated Shares.

		2016			2019		
		Actual	Benchmark	WLM	Actual	Benchmark	WLM
Modal shares	IWT	28.96%	29.08%	28.83%	30.04%	29.79%	29.60%
	Road	68.52%	68.41%	68.48%	67.47%	67.70%	67.73%
	Rail	2.52%	2.51%	2.69%	2.49%	2.51%	2.67%
Difference	IWT		0.12%	-0.13%		-0.25%	-0.44%
	Road		-0.11%	-0.04%		0.23%	0.26%
	Rail		-0.01%	0.17%		0.02%	0.18%

The benchmark shares are generally closer to the actual ones, except for the share of road for year 2016. However, the relative differences remain modest for both models. The greatest absolute difference between actual and estimated shares for both the benchmark and the WLM happens for the share of IWT in year 2019. This difference is -0.25% and -0.44% respectively, which represents a relative error around 1%. We nevertheless notice that the WLM tends to overestimate the share of rail with a relative error of approximately 7%. Other than this, the relative differences remain small for both models: it is then necessary to further compare them at a more disaggregate level.

OD pair level

We now compare the actual container flows to the ones estimated by both models on every OD pair and for each mode. To do so, the correlation coefficients between actual and estimated volumes for years 2016 and 2019 are computed. To further evaluate the models' performance, we also compute the correlation factors obtained when OD pairs from Rotterdam to Antwerp and vice versa are not included. The resulting correlation coefficients are presented in Table 2.4.

Table 2.4: Correlation Coefficient between Actual Container Volumes and Estimates.

		2016		2019	
		Benchmark	WLM	Benchmark	WLM
All OD pairs	IWT	0.974	0.976	0.976	0.978
	Road	0.945	0.950	0.939	0.945
	Rail	0.496	0.504	0.474	0.489
Without OD pairs Rotterdam $\leftrightarrow$ Antwerp	IWT	0.796	0.810	0.807	0.821
	Road	0.950	0.955	0.944	0.949
	Rail	0.534	0.511	0.514	0.497

The results show that the models are both very successful to estimate the container volumes transported by IWT and road, but much less when it comes to rail transport. Several reasons might explain this limited performance: firstly, the cost estimation for rail is less detailed than for the other modes (Shobayo et al., 2021). Secondly, rail transport is less available (or, at least, less data are reported) along the RA corridor. This means that the estimation is performed on less data points than for road and IWT. Finally, even when rail transport data are available, the container volumes are significantly lower than for the two other modes. In a Weighted Logit context, low volumes imply less weight in the estimation process: thus, the resulting estimators may be less accurate.

The influence of the Weighted Logit methodology on the predictive power is particularly visible when the OD pairs from/to Rotterdam to/from Antwerp are not considered in the correlation coefficient computation. In that case, both models perform better regarding road and rail transport but much worse for IWT. Indeed, as these two OD pairs are the only ones linking two seaports, they have at least two characteristics that distinguish them from others:

1. The number of transported containers is considerably higher (see Figure 2.3 hereafter). The yearly volumes reported in the dataset are around 1.5 million TEUs for Rotterdam $\rightarrow$ Antwerp and around 700'000 TEUs in the other direction. As a comparison, the third busiest OD pair has a yearly volume of around 350'000 TEUs.

2. The modal split is remarkably different. Table 2.5, which displays the modal shares corresponding to the particular cases in Table 2.4, show this difference in modal split between the Rotterdam $\leftrightarrow$ Antwerp pairs and the remaining ones.

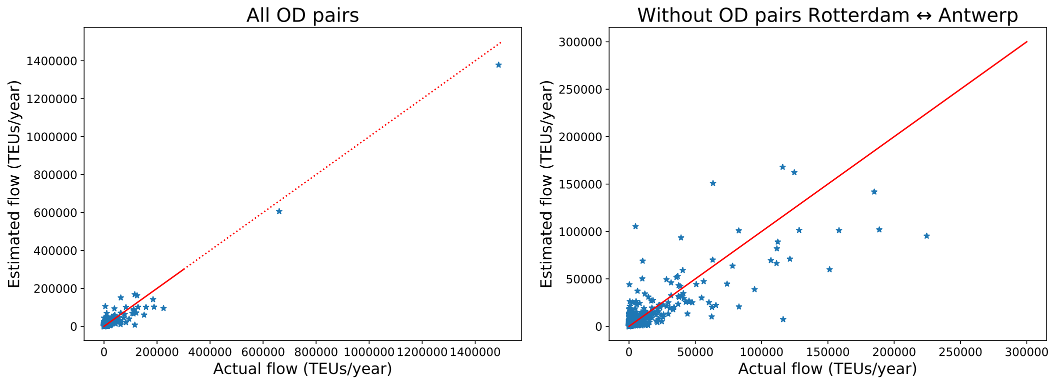

Figure 2.3: Actual volumes vs estimates from WLM for inland waterway transport (year 2019): on the left figure, all OD pairs are considered; on the right, all but Rotterdam ↔ Antwerp are considered. Each dot represents one OD pair, whereas the line is the identity function. The scale difference appears clearly between the two plots.

The consequence of these considerations is that it leads to large relative errors when the proposed models are used to estimate the container flows on these two OD pairs. Figure 2.3 illustrates the difference in scales between the Rotterdam ↔ Antwerp pairs and all the other ones for IWT. Together with Table 2.5, it also shows that, for the Rotterdam ↔ Antwerp pairs, the number of containers are underestimated for IWT, and overestimated for road and rail. All of this reveals that a different model (or, at least, different coefficients) should be used to estimate the "seaport-to-seaport flows". It also legitimates the approach proposed by de Bok et al. (2018), which consists in segmenting data according to the type of OD pair.

Finally, this analysis offers more insights on the comparison of the two models than the corridor level analysis. Indeed, in Table 2.4, the correlation coefficients of the WLM are almost always greater than the ones of the benchmark, suggesting that the WLM returns better estimations than the benchmark. This is supported by Table 2.5 where the shares estimated by our WLM are systematically closer to the actual ones compared to the benchmark. These results at the OD pair level highlight the benefits of our Mixture approach compared to the standard Weighted Logit method.

One question still remains: if the shares of our WLM are more accurate than the ones of the benchmark when looking at the Rotterdam ↔ Antwerp pairs and the remaining ones separately, then why is it not the case at the aggregate level? This is due to the compensation of the differences observed in Table 2.5: for almost all modes, the share differences have an opposite sign for the Rotterdam ↔ Antwerp pairs compared

Table 2.5: Actual Modal Shares Compared to Estimated Shares (specific cases).

		2016			2019		
		Actual	Benchmark	WLM	Actual	Benchmark	WLM
Rotterdam	IWT	92.50%	85.72%	86.82%	92.47%	85.72%	86.82%
↔	Road	7.26%	12.29%	12.24%	7.29%	12.29%	12.24%
Antwerp	Rail	0.24%	1.99%	0.94%	0.24%	1.99%	0.94%
	IWT		-6.78%	-5.68%		-6.75%	-5.65%
Difference	Road		5.03%	4.98%		5.00%	4.95%
	Rail		1.75%	0.70%		1.75%	0.7%
Other	IWT	22.83%	23.62%	23.25%	23.67%	24.09%	23.77%
OD pairs	Road	74.43%	73.82%	73.90%	73.61%	73.35%	73.39%
	Rail	2.74%	2.56%	2.85%	2.72%	2.56%	2.84%
	IWT		0.79%	0.42%		0.42%	0.10%
Difference	Road		-0.61%	-0.53%		-0.26%	-0.22%
	Rail		-0.18%	0.11%		-0.16%	0.12%

to the other pairs. Also, the former represents a container volume of 9%, whereas the latter account for 91% of the considered corridor. If we take IWT for year 2016 as an example, the differences are compensated as follows:

- For the benchmark: $-6.78\% * 9\% + 0.79\% * 91\% = 0.11\%$
- For the WLM: $-5.68\% * 9\% + 0.42\% * 91\% = -0.13\%$

which leads to the same differences, except for a rounding, as reported in Table 2.3. These results would suggest that the benchmark is more accurate than the WLM, although the WLM shares are closer to the actual ones for both the Rotterdam↔Antwerp pairs and the other ones.

These considerations show that, even if a model seems to perform better at the aggregate level, it does not mean its predictions at the OD pair level will be more accurate. And it is the latter that really matters for a mode choice model. Hence, conclusions cannot be drawn from a comparison at the aggregate level. A validation at the OD pair level is required as it is more informative on the predictive performances of the models. In our case, the WLM has then proven to give more accurate share predictions than the benchmark.

Cost elasticity

Table 2.6 contains the resulting cost elasticities of the benchmark and the WLM. We notice great variations between the models, especially regarding the direct elasticities that are displayed in bold. Indeed, the WLM exhibits much higher direct elasticity values (in absolute value). This is because the WLM has higher cost coefficients (in absolute value) than the benchmark, as depicted in Table 2.2.

Table 2.6: Direct and Cross (point) Elasticities with respect to Transport Costs.

wrt.	Benchmark			WLM		
↱	IWT	Road	Rail	IWT	Road	Rail
IWT	**-0.43**	0.54	0.07	**-1.57**	1.15	0.05
Road	0.17	**-0.26**	0.05	0.24	**-0.56**	0.05
Rail	0.34	0.70	**-2.08**	0.48	1.71	**-6.18**

For both models, the direct elasticity of road is lower than for intermodal transport: meaning that the impact of a cost increase on the resulting mode share will be less important for road. Significant variations between both models also occur regarding the cross elasticities of intermodal transport probability with respect to costs of the road alternative. Once again, elasticities are significantly higher for the WLM than for the benchmark.

To put these elasticity values into perspective, they are compared to the cost elasticities estimated in recent studies, see Table 2.7. The work of Arencibia et al. (2015a) makes use of stated preference data collected from Spanish shippers, whereas the model of Jensen et al. (2019) is estimated using commodity flow surveys. The last two studies estimate the elasticities with a Weighted Logit (the methodology used for our benchmark), as mentioned in the literature review.

Table 2.7: Direct and Cross (point) Elasticities with respect to Transport Costs from existing literature.

	Direct Road	Direct Intermodal	Road wrt. Intermodal	Intermodal wrt. Road
Arencibia et al. (2015a)	-1.79 to -1.53	-2.49 to -1.79	1.31 to 1.70	2.09 to 2.61
Jourquin & Beuthe (2019)	-2.56 to -0.03	-4.82 to -0.02	0.00 to 1.91	0.14 to 3.71
Jensen et al. (2019)	-0.43 to -0.17	-1.36 to -0.38		
Rich et al. (2009)	-0.29 to -0.04	-0.43 to -0.10		

Compared to the values from other studies, the elasticities computed in this chapter seem coherent. They all fall within the range of values proposed by Jourquin & Beuthe, expect for the direct elasticity of rail (due to the data limitations explained above). The provided range is particularly large compared to the other studies, but this might also be due to the fact that they also use a Weighted Logit methodology and that their geographical coverage is close to the one used in our study.

2.5.3 Addition of Value of Time

The resulting coefficients of the WLM with the inclusion of VoT are reported in Table 2.8, together with the coefficients of the previously estimated WLM.

Table 2.8: Results for the WLM and the WLM with the Addition of VoT.

	WLM			WLM with VOT		
Parameter	Value	Standard error	p-value	Value	Standard error	p-value
α_{Rail}	1.04	0.835	0.213	0.713	0.765	0.351
α_{Road}	2.52	1.14	0.0272	2.30	1.06	0.0304
β_p	1.41	0.456	0.00199	1.63	0.402	4.97e-05
β_f	0.0271	0.00877	0.00203	0.0278	0.00829	7.96e-04
$\beta_{a,\text{Road}}$	0.0491	0.0295	0.0958	0.0530	0.0276	0.0543
$\beta_{a,\text{Inter}}$	0.156	0.0737	0.0343	0.157	0.0679	0.0205
$\beta_{c,\text{Road}}$	-10.1	4.71	0.0311	-8.68	3.56	0.0147
$\overline{\beta}_{c,\text{Inter}}$	-19.8			-12.7		
$\sigma_{\beta_{c,\text{Inter}}}$	20.6			9.88		
$\mu_{c,\text{Inter}}$	2.62	0.586	7.94e-06	2.30	0.631	2.64e-04
$\sigma_{c,\text{Inter}}$	0.856	0.300	0.00426	0.690	0.291	0.0179
LL	-1.18e+08			-1.19e+08		

As expected, the addition of VoT does not have an important impact on the value and significance of the β coefficients that are not related to costs. However, it is has a noticeable impact on the values of the cost parameters and the alternative specific constants α. The values of α_{Rail} and α_{Road} (but to a lesser extent) are reduced. This means that adding this new element has improved the predictive power of the deterministic part of the utility functions of these modes.

For the cost coefficients, the absolute values of both $\overline{\beta}_{c,\text{Inter}}$ and $\beta_{c,\text{Road}}$ decrease: this is because the new cost figures have been increased by the addition of VoT. As IWT and rail have higher travel times, this decrease is more important for the intermodal coefficient than for the road. As a result, the two coefficients are closer to each other: the ratio between $\overline{\beta}_{c,\text{Inter}}$ and $\beta_{c,\text{Road}}$ was almost 2, when it is less than 1.5 with VoT included. It means that the relative cost sensitivity of intermodal transport compared to road is decreased when considering the VoT.

Indeed, a major asset of intermodal transport is the lower costs compared to road: when VoT is not considered, shippers may then be much more sensitive to a cost increase for IWT or rail, than for road. However, the lower costs are achieved at the expense of a larger transportation time so that, when VoT is added to the out-of-pocket costs, it acts as a counterbalance. The resulting cost sensitivity with respect to intermodal transport is thus less important, but still significantly more than for road transport.

Regarding the heterogeneity of cost sensitivity, the $\sigma_{c,\text{Inter}}$ estimates remains statistically significant. Figure 2.4 shows the probability distribution of $\beta_{c,\text{Inter}}$ when VoT is included compared to when it is not. The addition of VoT causes a shrinkage of the distribution and a shortening of its tail. Indeed, the value of $\sigma_{\beta_{c,\text{Inter}}}$ is decreased by 52% in Table 2.8. And this is not only due to the change in scale of $\beta_{c,\text{Inter}}$ since its mean $\overline{\beta}_{c,\text{Inter}}$ decreases by only 36% in absolute value. It shows that adding VoT in the model enables to explain the heterogeneity to some extend, yet there remains heterogeneity due to attributes exogenous to the model.

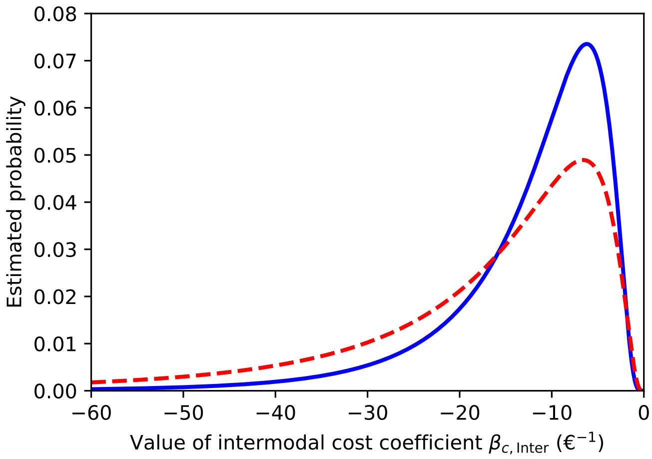

Figure 2.4: Probability distribution of the cost coefficient for intermodal transport $\beta_{c,\text{Inter}}$ when VOT is added, together with its distribution without VoT (dashed line) – as in Figure 2.2.

2.5.4 Discussion

The results demonstrate that the proposed WLM is capable of a better estimation of the characteristics of the shippers' population while achieving a performance at least equivalent to the benchmark. In particular, the WLM reveals two important elements that cannot be captured by the benchmark: there exists a variation of cost sensitivity among the population and this variation is occurring for intermodal transport.

The significant standard deviation of the intermodal cost coefficient implies a variation of the shippers' cost sensitivity. Indeed, the cost coefficient ranges from the extremely cost-sensitive shippers (with very low values of cost coefficient) and shippers that are sensitive to cost but are likely to proceed to a trade-off with some other attributes. The former category of shippers would be ignored by the benchmark since the estimated cost coefficient is relatively close to zero. This issue means that, when the model is used to simulate the demand for freight transport, an entire segment of the population is not represented. There is then a substantial risk to draw inaccurate conclusions and take inappropriate actions.

The fact that data does not reveal sensitivity variation concerning the cost of road could be explained by the higher cost of road transport compared to the intermodal alternatives. Shippers might be much less cost-sensitive regarding transport by truck since it is already an expensive alternative in itself. Road transport may then attract them with other attributes, such as lower transport time or increased availability.

The results also show that the addition of VoT into the WLM reduces the standard deviation of the distribution of the intermodal cost coefficient. This distribution accounts for all the different factors playing a role in shippers' cost sensitivity, but that cannot be explicitly captured in the model. By including more contextual variables into the model (or if better data are collected), then the distribution will become less and less important and the coefficient's estimation will be improved. It thus leads to a model fitting better the real behavior of shippers as it captures more aspects of the mode choice decision.

2.6 Conclusions

In order to address RQ1, this chapter proposes a Weighted Logit Mixture (WLM) model that estimates the variability of cost preferences among the shippers' population using only aggregate flow data, cost estimates and publicly available data. The obtained results show that the WLM is better capable to estimate the population's preferences while exhibiting improved performance compared to the benchmark. This improved performance is not visible at the aggregate level because overestimations on some OD pairs compensate for underestimations on other ones. Nevertheless, results at the OD pair level show that the WLM systematically gives better estimations than the benchmark. The results also demonstrate that there exists a significant variation in the sensitivity regarding intermodal transport costs.

The Weighted Mixture modeling not only gives more information about the mode choice preferences; it also represents the shippers' population more realistically. Indeed, assuming that all shippers share the same behavior would mean that, for a given mode, they would all contract the same carrier, e.g., the cheapest one. If this might be true for some shippers, others also opt for more expensive services, because of contractual relationships or tracking services for example.

That is why it is crucial to analyze behavior in detail by looking into different segments, including as much contextual variables as possible, and considering heterogeneity. With the proposed Weighted Logit Mixture, we provide a way to do it with aggregate data. By considering preferences variation, this approach supports better the implementation of a specific innovation or policy by providing more precise indications concerning the diverse behaviors inherent to a large freight transport network. Similarly, the impacts of the innovation or policy can be analyzed more realistically by taking into account the heterogeneous preferences in the modal share estimations.

Beside policy-makers, the proposed mode choice model can also be used by transport operators to improve their decision-making. In particular, the detailed information about the cost sensitivity of shippers can help operators to optimize the pricing of their transport services. Moreover, the proposed mode choice model informs about other criteria playing a role in shippers' decisions: in particular, the influence of the frequency of services is also considered. This can further help operators to design their services. Therefore, the next chapter proposes a methodology to include mode choice decisions directly into the decision-making process of a transport operator.

Chapter 3

Choice-driven service network design and pricing

In Chapter 2, an aggregate mode choice model has been developed to capture shippers' heterogeneity. This model can now be used by transport operators for the design and pricing of their services. As highlighted in Chapter 1, including more information about customers has the potential to improve the decision-making of carriers. Therefore, we propose a Choice-Driven approach incorporating advanced choice models directly into a Service Network Design and Pricing problem. This chapter addresses RQ2: What is the impact of including mode choice decisions of shippers in the decision-making of intermodal carriers?

This chapter is structured as follows: Section 3.1 defines the Service Network Design and Pricing problem and highlights the importance of the research question through a small example. In Section 3.2, we review the existing literature and we then describe the proposed methodology in Section 3.3. In Section 3.4, the method is applied to a case study and several variations of the model are compared with each other. Finally, Section 3.5 concludes the chapter.

Parts of this chapter have been published as a journal article: Nicolet & Atasoy (2024a) "A Choice-Driven Service Network Design and Pricing Including Heterogeneous Behaviors", *Transportation Research Part E: Logistics and Transportation Review*, 191: 103740.

3.1 Introduction

In intermodal freight transport, planning at the tactical level is of key importance to make the best use of existing infrastructure and available assets and to ensure reliable transport plans. An appropriate way of managing this task is through Service Network Design (SND) problems, as they cover most of the tactical decisions (Crainic, 2000). They can support the decisions of intermodal operators about the itineraries to be served, the offered frequencies and how demand will be assigned to these services.

Until recently, pricing was not explicitly covered in most SND models although it plays a crucial role in the success of the planning (Tawfik & Limbourg, 2018; Li et al., 2015a). As pointed out by Macharis & Bontekoning (2004), intermodal transport pricing is a difficult task as costs must be accurately computed and some knowledge of the market situation has to be gained. Indeed, the costs faced by an intermodal operator are various (Li & Tayur, 2005): some of them, e.g. crew costs or contracts with infrastructure manager, are perfectly known by the operator but other variable costs are set by external companies, such as terminal operators for the handling costs or energy suppliers for the fuel costs. For the latter, not only do they depend on external actors, but also on the transport demand as they increase together with the carried load. Although transport operators have some control on the quantity of transported freight (via contract binding, for example), demand remains mostly stochastic in nature (Combes, 2013). As a result, variable costs can only be estimated from the expected transport demand.

Regarding the pricing decision itself, some knowledge about the targeted demand, such as the willingness to pay or the transport requirements, is also of key importance. Indeed, the cost of transportation is among the main drivers of shippers' mode choice. It would, however, be inadequate to consider that shippers are purely "cost-minimizers" as other factors (e.g., transport time, offered quality, service frequency) play a role in the decision process, see for example Arencibia et al. (2015b) or Ben-Akiva et al. (2013). On top of that, these factors and their importance can vary from shipper to shipper and the final decision of choosing a mode also depends on the available alternatives, hence making the planning and pricing process even more complex. On the other hand, there exists a great variety of mode choice models (see de Jong (2013) for a comprehensive review) that can be used to support the planning of intermodal operators. For example, Duan et al. (2019) include values of time and reliability, that are estimated from a stated preference survey, within the cost minimization of a SND model. This represents a step towards the integration of shippers' preferences within the planning process.

3.1.1 Illustrative example

To highlight the benefits of using a mode choice model for the pricing decision, we consider the case in Figure 3.1, where two shippers, S1 and S2, want to send 200 Twenty-foot Equivalent Units (TEUs) each. To do so, they have two alternatives: Road and Inland Waterway Transport (IWT). Each mode has the following utility function for each shipper i:

$$\begin{cases} V_i^{\text{IWT}} & = \beta_f f + \beta_{c,i} p_{\text{IWT}} = 1 \times 5 + \beta_{c,i} \times x, \\ V_i^{\text{Road}} & = \alpha_{\text{Road}} + \beta_{c,i} p_{\text{Road}} = 15 + \beta_{c,i} \times 15, \end{cases}$$

where α_{Road} is the Alternative Specific Constant (ASC) for Road, equal to 15, and the ASC for IWT is normalized to 0. p_{Road} is the cost of the Road alternative, set to 15 €/TEU, and $\beta_{c,i}$ represents the cost sensitivity of each shipper i: we assume that it is -5 for S1 and -2 for S2. β_f is the weight associated to the frequency of IWT services f, and assumed to be 1 for both shippers.

In this example, the decision-maker is the IWT operator that wants to set up a transport service running each working day (hence: $f = 5$) and to optimize their price x. The operator faces a fixed cost, c_{fix}, of 100 € per round trip and a variable cost, c_{var}, of 1 €/TEU. Assuming that the transport demand of shippers is split according to a logit model, the operator aims at setting a unique price so as to maximize their profits, expressed as:

$$\begin{aligned} \Pi(x) &= \sum_i (200 \times \frac{e^{V_i^{\text{IWT}}}}{e^{V_i^{\text{IWT}}} + e^{V_i^{\text{Road}}}})(x - c_{\text{var}}) - f \times c_{\text{fix}} \\ &= \sum_i (200 \times \frac{e^{V_i^{\text{IWT}}}}{e^{V_i^{\text{IWT}}} + e^{V_i^{\text{Road}}}})(x - 1) - 500 \end{aligned}$$

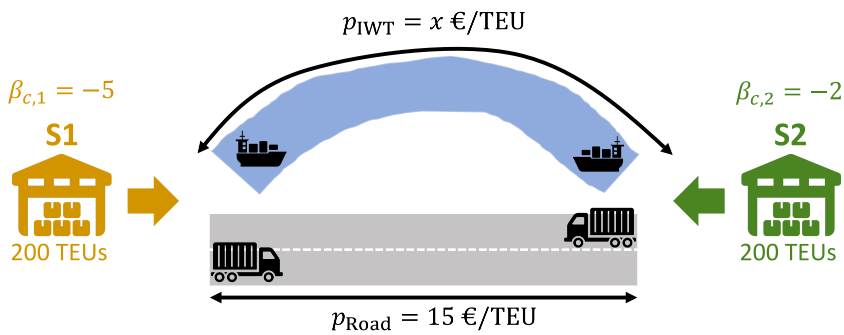

Figure 3.1: Illustrative example with two shippers and two available transport modes.

The operator does not necessarily know the full utility specifications of the shippers. Therefore, it can opt for various demand models, here we consider three of them:

A) Assume that shippers are homogeneous and purely cost-minimizers, the considered utilities may then be: $V_i^{\text{IWT}} = -1x$ and $V_i^{\text{Road}} = -1 \times 15 \; \forall i$;

B) Make more market study to come up with the same utility functions as above, but consider that shippers are homogeneous with a mean cost sensitivity, thus: $\beta_{c,i} = -3.5 \; \forall i$;

C) Consider also the heterogeneity regarding cost sensitivity (ground truth model), thus: $\beta_{c,1} = -5$ and $\beta_{c,2} = -2$.

Finally, let us assume that the operator has a fixed vessel capacity of 20 TEUs. The resulting profits $\Pi(x)$ associated to price x are depicted in Figure 3.2, together with the profits stemming from each individual shipper. Before the price reaches 10 €/TEU, the profits grow linearly. Indeed, IWT is much cheaper than Road so the demand assigned to IWT is equal to the capacity (only 100 TEUs per direction) and the profits only depend on the price.

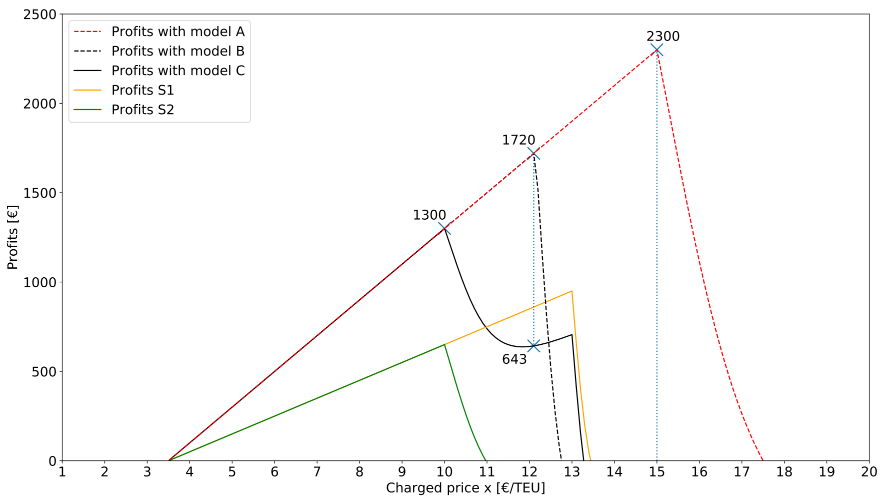

Figure 3.2: Resulting profits for models A (pure cost minimization), B (homogeneous shippers), C (heterogeneous shippers) and individual profits for S1 and S2.

The highest expected profits are reached with model A with a price of 15 €/TEU. Indeed, when only considering costs, the IWT operator can charge a higher amount as the cost of Road is relatively high. If the price exceeds 15 €/TEU, IWT becomes more expensive than Road and the IWT operator faces a rapid decrease of their demand, and thus their profit. Nevertheless, when shippers S1 and S2 will face a price of 15 €/TEU, they will both turn to Road as it has a higher utility. This will then end up in losses for the IWT operator.

The maximal expected profits with model B occur at 12 €/TEU. This is because the cost sensitivity of S2 is overestimated. With model B, it is as if the cost of Road was still too high for S2 despite the other advantages of this transport mode. But in reality, the profits stemming from S2 reach zero for a price of 12 €/TEU because Road advantages (included in α_{Road}) overcome the higher cost, thus making Road much more attractive. Therefore, it will result in profits reduced by half when the price of 12 €/TEU is charged to the actual heterogeneous shippers.

Applying model C returns the highest profits, as it considers the true cost sensitivity of each shipper. In reality, it will of course not be the case. But the purpose of this example is to showcase the potential consequences of using simplifying assumptions in the planning and pricing process of a transport operator. In this example, if they consider that their customers are purely cost-minimizers, then the optimal price under this assumption will eventually cause losses to the operator. When they consider a more detailed representation of shippers (as in model B), the optimal price is still overestimated but, at least, positive profits are achieved. So even if the exact parameters are not known, it is beneficial for the operator to incorporate more information about their customers.

Note that a revenue management strategy would be trivial to implement in this example with only two shippers and simple utility functions, then the optimal solution would be to set different prices for S1 and S2. However, segmentation may be difficult to identify when much more shippers are considered and less detailed information are available. In the remainder of this work, we will not consider revenue management, although we recognize that it can be an effective tool to optimize pricing decisions.

3.1.2 Problem definition

We consider a transport operator as the decision-maker: they have a potential demand made of multiple shippers and face the competition of several other carriers/transport modes. The operator and their competitors operate on a multimodal network. The competition's services are assumed known by the operator, that has to decide which terminals to serve and at which frequency. In addition, the operator has to set a single price for each Origin-Destination (OD) pair that they will charge the shippers. In this work, we aim to exploit the advantage of using advanced choice models in this tactical decision-making setting. For this, we make use of "choice-based optimization" to combine SND and pricing problem with a detailed representation of shippers. Therefore, we develop a Choice-Driven Service Network Design and Pricing (CD-SNDP) model, which includes an existing mode choice model to consider shippers' behavior directly in the decision-making of the transport operator.

3.2 Literature review

Although it has not been applied to SNDP models yet, choice-based optimization is already used for other types of problems. Therefore, we first review the state of literature on SNDP in intermodal transport, then investigate the existing choice-driven methods in related transportation fields and finally present the main contributions of the present work.

3.2.1 Service Network Design and Pricing problems in intermodal transport

The majority of existing studies on SND are formulated as a cost minimization of the transport operator and do not include the revenues of fulfilling the transport orders (Elbert et al., 2020; Wieberneit, 2008). Nevertheless, two models using cost minimization have addressed the pricing decision. Li et al. (2015a) determine the price charged by an intermodal operator using a pre-defined profit margin, expressed as a given percentage of the operational costs. The price is the addition of the costs and the margin and cannot exceed a given market price. Dandotiya et al. (2011) include a target for the minimal profit (per transported unit) to be achieved by an intermodal operator: this translates into a constraint assuring that the applied rate is greater or equal to that target added to the operating costs. The authors also include a cost sensitivity factor representing the willingness to pay for intermodal transport rather than road and enforce that the rate difference between road and intermodal transport has to be greater or equal to this factor.

For the works applying a profit maximization, some of them do not include the pricing decision but rather assume fixed tariffs that are included as parameters into the model. Andersen & Christiansen (2009) apply a SND model to explore new rail services along a Polish freight corridor. The demand is represented as contracts generating a given revenue when served. The operator then decides to serve or not the contracts in order to maximize their profit. It also decides on the services' frequency and the vehicles and demand assignment to these services under vehicle balancing and capacity constraints. Braekers et al. (2013) are interested in designing a barge transport service along a Belgian canal considering empty container repositioning. Their SND model decides at which inland ports to stop and in which sequence as well as the fulfillment of transport demand from different clients. Bilegan et al. (2022) also apply a SND model to barge transport with detailed fleet management and revenue management considerations. Different customer segments are considered as well as two different service levels (standard or express) with a given fare. The operator then decides which services to operate, what percentage of the demand to serve and how to assign the vessels and demand to the services so as to maximize their profits. The model has been developed further to include the possibility of bundling services and penalties for early and late distribution (Taherkhani et al., 2022). Teypaz et al. (2010) treat similar models and propose decomposition algorithms for computational efficiency. Zetina et al. (2019) capture demand elasticity using a gravity model, where the demand is considered inversely proportional to the transport costs faced by the transport operator. The decisions are whether or not an arc (or a path) is used and in which sequence to visit the demand nodes. Finally, Scherr et al. (2022) use SND to conceive a new platooning service of autonomous vehicles. They come up with a two-stage stochastic model considering scenarios to represent the demand variation. The first stage designs the services performed by "manually operated vehicles" and assigns rates to the different customers over all scenarios, whereas the second sets the flow of autonomous vehicles for each particular scenario.

Other works include demand functions in the profit maximization to capture the influence of prices on the transport volumes. Li & Tayur (2005) design a railroad network using a concave inverse demand function. In this case, the demand for each service and each itinerary are the decision variables and the corresponding prices are computed using the inverse demand function. Mozafari & Karimi (2011) represent two competitive road carriers within a non-cooperative game model. Each carrier has to set their price so as to maximize their own profit and the demand is represented as a linear function of the carrier's price and the competitor's price. Shah & Brueckner (2012) also investigate competition between carriers: each of them fix their price, frequency and capacity. The demand of shippers for a given carrier is represented as a function of price and frequency. The inconvenience of demand functions is that they become hard to obtain when the number of shippers or alternatives increase (Li & Tayur, 2005), thus requiring a numerical estimation or some simplifying assumptions.

An increasingly common way to model SNDP problems is using Stackelberg game or bilevel programming. This formulation was first proposed in intermodal freight transport by Tsai et al. (1994). The intermodal operator is the leader and sets the price of their services to maximize their profit. Truck carriers are followers that will adjust their prices based on the leader's decision and the exogenous demand is split between the carriers using a logit model, where the considered attributes are the prices, travel times and reliability. A general formulation for the Joint Design and Pricing (JDP) on a network has been proposed by Brotcorne et al. (2008). The network operator decides on the network design and prices so as to maximize their profits. The network and rates of the competitors are assumed known and exogenous. The followers are the network users that seek to minimize their cost by selecting the services of the operator or those of the competitors. The authors propose an iterative procedure to solve the JDP. Crevier et al. (2012) propose a similar formulation, with the addition of capacity constraints and revenue management considerations. Ypsilantis & Zuidwijk (2013) extend the JDP formulation to include time constraints, as well as capacity constraints. Their model is used to design and price the hinterland barge services of an extended gate operator. In their work, Tawfik & Limbourg (2019) include some level-of-service attributes in the JDP formulation. In particular, the lower level costs are more detailed as they not only consider transport costs but also the cost of capital: each cost component is weighted by a coefficient estimated using a random utility model. An iterative heuristic is later proposed to solve large instances of the JDP (Tawfik et al., 2022). A similar formulation is adopted by Zhang & Li (2019) to design and price rail container transport. The lower level objective is to minimize the generalized costs, made of price, transport time, convenience and security. Only the price is endogenous to the model. The same authors also propose a time varying model (Zhang et al., 2019; Li & Zhang, 2020). A single-level formulation is used and the demand follows a logit model with price as single attribute. The model proposed by Wang et al. (2023) extends the JDP of Tawfik & Limbourg (2019) with the introduction of additional cost components. The transport operator faces some waiting costs and penalty for an under-utilisation of their capacity, while the lower level costs also embed heterogeneous shipper classes through different values of time and reliability.

Finally, there also exist a few different versions of Stackelberg game. A monopoly setting is proposed by Qiu et al. (2021) where a hinterland carrier sets services and prices in multiple planning horizons. The followers are represented by a set of captive consignees that minimize their transport and storage costs. Lee et al. (2014b) consider three different actors as leaders and all shippers as followers. The upper level itself is represented as a three-level program where ocean carriers are leaders of terminal operators which, in turn, are leaders of land carriers (Lee et al., 2014a). At the lower level, shippers set their production, consumption and transportation demand using "spatial price equilibrium".

The relevance of bilevel models is questioned by Martin et al. (2021), especially because of the simplifying assumptions regarding demand modeling (pure cost minimizers and homogeneous preferences). They propose a SNDP model applied to an express shipping service by airplanes and trucks. In their profit maximization problem, the transport operator has to set prices for some given service times that can be selected by their customers. The service time chosen by each customer is the one providing a welfare greater or equal to all the other options.

The novelty of our CD-SNDP is that it includes a stochastic demand model considering heterogeneity, within a bilevel optimization setting. The proposed formulation is inspired by the work of Tawfik & Limbourg (2019), where the cost minimization of shippers is replaced by the maximization of their utility. In our work, beside the costs, the utility functions also consider the transport time, the accessibility of a mode and the frequency of intermodal services. This last element implies that now, both the price and frequency decisions of the transport operator have an influence on the shippers. This CD-SNDP formulation then allows for a more detailed and realistic representation of the shippers' characteristics and behavior towards the prices and services designed by the operator. To include stochasticity and heterogeneity in our model, we make use of choice-based optimization: hereafter are presented some applications of this method to other transportation problems.

3.2.2 Choice-based optimization in transportation

The term "choice-based optimization" refers to optimization problems that explicitly include a discrete choice model into their formulation (Pacheco Paneque, , 2020). That is why works decoupling the optimization from the demand, using iterative procedures such as simulation-optimization, are not considered here (e.g., Liu et al. (2019)).

Although not for freight, choice-based optimization has been used in a few works to model passenger SND problems. Wang & Lo (2008) propose a profit maximization problem to support the design of ferry services, where the operator decides on the itineraries and schedules of the ferries. They assume that the passenger demand is split according to a logit model including two attributes: a given price, and the travel time, which is dependent on the decision variables. Huang et al. (2018) also include a logit model into a profit maximization problem to design a car-sharing network. Among other things, the operator decides on the number of car-sharing stations to open. The utility function of car-sharing is composed of given rental costs and walking access costs. The latter are directly dependent on the number of opened stations. A drawback of these two models is that they are non-linear due to the exponential terms inherent to the logit model. A Mixed-Integer Linear Programming (MILP) including a logit mode choice model is proposed by Hartleb et al. (2021) to design passenger rail services. The main decision is the selection of lines to open. To get rid of the exponential terms of the logit model, the authors precompute the modal shares of rail for each possible solution. This precomputation technique is useful when only binary or integer variables are included in the choice model. However, as mentioned by the authors, the model can become intractable when the instance size increases.

Choice-based optimization has also been applied to facility location and pricing problems. It is used by Lüer-Villagra & Marianov (2013) to set up hubs and prices for an airline company. The demand is split between companies using a logit model with price as unique attribute. A similar modeling approach is adopted by Zhang (2015) to locate retail stores and set selling prices. Zhang et al. (2018) study an intermodal dry port location and pricing problem where the route choice of shippers is determined using a logit model including six attributes, where only transport cost depends on the decision variables. The common point of these three models is that they are all non-linear: therefore, heuristics are required to solve them.

In most of the aforementioned models, the inclusion of discrete choice into an optimization problem results in a non-linear model. In their work, Paneque et al. (2021) propose a general framework to deal with more advanced choice models. In particular, the authors rely on the Sample Average Approximation (SAA) principle to deal with the non-linearities of the choice model and, therefore, come up with a MILP model. The proposed model is then applied to the pricing of parking services using a Mixed logit to represent the demand. The latter comprises price as endogenous attribute and other exogenous attributes. Bortolomiol et al. (2021) develop this framework further to model oligopolistic competition, whereas Schlicher & Lurkin (2022) present a non-linear cooperative game to model collaborative pricing of urban mobility.

The present CD-SNDP is inspired by the work of Paneque et al. (2021) to integrate an existing Mixed logit model within a bilevel setting. Specifically, error terms are included in the utilities to account for the attributes that are not captured by the model but still play a role in the mode choice. Moreover, the coefficient representing cost sensitivity is considered randomly distributed to consider the heterogeneous preferences of shippers. It is assumed that the probability distributions of the error terms and the cost coefficient are known and the resulting CD-SNDP problem is solved using stochastic optimization. The addition of these more detailed behavioral attributes within SND models aims at providing a more realistic representation of shippers' reaction to the proposed services, ultimately helping intermodal operators to make more informed design and pricing decisions.

The following section provides a recap of the main characteristics of the previously reviewed bilevel SNDP models and sums up the contributions of our work.

3.2.3 Contributions

The existing bilevel models for SNDP presented in Section 3.2.1 are sorted in Table 3.1. In particular, it shows whether some constraints regarding the fleet are included (e.g., size limit). It also indicates how the transport demand is modeled: most works assume that shippers are deterministic cost minimizers. Still regarding demand, it can be noticed that no existing model considers unobserved attributes that play a role in the choices of shippers. In addition, only three studies embed shippers' heterogeneity through distinct values of time (or reliability). Finally, only one work considers that frequencies also influence the demand alongside the prices endogenously in the optimization model.

Table 3.1: Summary of existing bilevel models for intermodal Service Network Design and Pricing problems.

Reference	**Fleet constraints**	**Deterministic or Stochastic**	**Demand function** $F(\cdot)^*$	**Hetero-geneity**	**Cross-level variables**
Tsai et al. (1994)	✓	D	$F(c)$		Price
Brotcorne et al. (2008)		D	$F(c)$		Price
Crevier et al. (2012)	✓	D	$F(c, LoS)$	✓	Price
Ypsilantis & Zuidwijk (2013)	✓	D	$F(c)$		Price
Lee et al. (2014b)	✓	D	$F(c, VoT)$	✓	Price
Tawfik & Limbourg (2019)		D	$F(c, VoT)$		Price
Zhang & Li (2019)	✓	D	$F(c, VoT, LoS)$		Price
Qiu et al. (2021)	✓	D	$F(c)$		Price
Wang et al. (2023)		D	$F(c, VoT, VoR)$	✓	Price & Freq.
Proposed CD-SNDP	✓	S	$F(c, f, u)$	✓	Price & Freq.

* c = costs, LoS = level of service, VoT = value of time, VoR = value of reliability, f = frequency, u = unobserved attributes.

The proposed CD-SNDP is a generalization of the model by Tawfik & Limbourg (2019). Firstly, it generalizes the network structure as cycles and services with multiple stops are now allowed. Secondly, the shippers' objective is also generalized as they do not only proceed to a minimization of their costs, but instead maximize their utilities. These utilities contain other attributes beside the costs, such as frequency, accessibility, etc. Thirdly, our formulation generalizes the representation of shippers as it can accommodate some unobserved attributes (via randomly distributed error terms) and shippers' heterogeneity (through the Mixed logit formulation). Because of these features, the proposed CD-SNDP becomes a stochastic problem, as opposed to the previous works that all assumed a deterministic setting. Finally, the service frequency is made endogenous to the optimization model along with the price. A summary of the aforementioned features can be found on the last row of Table 3.1.

The contributions presented in this chapter are summarized as follows:

1. Inclusion of shippers' heterogeneity and unobserved attributes within a SNDP model, which leads to a stochastic optimization model;

2. Consideration of realistic features (service frequency as a cross-level variable alongside the price, fleet constraints, cycle-based formulation), which increases the problem's complexity;

3. Application to a real logistics network, whose data have also been used to estimate and validate the choice model integrated in the SNDP.

3.3 Methodology

As previously mentioned, the present work is inspired by the bilevel JDP formulation proposed by Tawfik & Limbourg (2019). In both the JDP and the proposed model, the upper level represents the decisions of the transport operator and the lower level corresponds to the shippers. Just like in the JDP, the upper level consists of determining the frequency and price of services that maximize the operator's profit. However, the lower level now represents the utility maximization of the shippers, whereas in the JDP, it is assumed that shippers proceed to a minimization of their logistics costs. This change of paradigm brings additional complexity to the problem as the two decision variables of the upper level are now included in the lower level, unlike the JDP where only the price is included but not the frequency.

Concerning the upper level, it differs from the JDP in two aspects. Firstly, the arc-based formulation of services is replaced by a cycle-based multi-leg formulation. The cycle-based formulation is deemed more accurate to represent realistic decision-making. Indeed, most intermodal transport services go back and forth on an itinerary with a defined schedule. The multi-leg representation also enables a more elaborate representation of services as multiple intermediary stops can be added in both directions. In addition, it simplifies the asset management of the operators. In an arc-based formulation, they may need to re-balance the vehicles at the end of the planning horizon; whereas a cycle-based representation ensures that each vehicle ends up at its starting point. It is noteworthy that the arc-based pricing representation is not changed compared to the benchmark. Indeed, shippers will pay only for the transport of their cargo from its origin to its destination, and not for the whole cycle. The second difference is the addition of fleet size and cycle time feasibility constraints. The former restricts the actions of the transport operator as they do not have an infinite number of vehicles at their disposal to satisfy the demand. The latter determines, for each service, the number of cycles that can be performed by one vehicle during the planning horizon given the cycle's duration. Moreover, an heterogeneous fleet is considered.

In the remainder of this chapter, the JDP with fleet constraints will be used as *Benchmark*. The benchmark with cycle-based formulation (instead of path-based) will be further referred to as *SNDP*. Finally, the proposed choice-driven model, which considers utility maximization of shippers, is denoted *CD-SNDP*. The notations for the CD-SNDP are described in the following paragraphs.

3.3.1 Problem formulation

The transport network is represented as a directed graph $\mathcal{G} = (\mathcal{N}, \mathcal{A})$, where $\mathcal{N}$ is the set of terminals and $\mathcal{A} = \{(i, j) : i, j \in \mathcal{N}, i \neq j\}$ the set of arcs between these terminals. Since we use a frequency service network design formulation (Crainic, 2000) and not a scheduled SND, we only represent the physical network and do not include the time dimension.

Upper level

The operator's fleet is heterogeneous, therefore the different vehicle types are denoted by set $\mathcal{K}$. The number of available vehicles per type is V_k and their capacity is Q_k.

The set $\mathcal{S}$ includes all transport services that can be run by the operator. Unlike the benchmark, where each service corresponds to a single arc of $\mathcal{A}$, a service is composed of a sequence of arcs. Each arc in this sequence is called a leg and the whole sequence of legs for a given service s is denoted $\mathcal{L}_s$. Next to the multi-leg representation, the cycle-based formulation of the problem implies that the sequence starts and ends at the same node. This set of services $\mathcal{S}$ coincides with the set of cycles and has to be generated prior to the optimization. For small networks, it can contain all possible services; but for large networks, decision rules have to be implemented to restrict the size of this set (e.g.: enforce minimal/maximal number of stops or travel time per service).

The maximum number of cycles of service s that can be performed by vehicle type k is named W_{sk}: it typically consists of the maximum operating time divided by the cycle time (sum of travel time and time at terminals). Each service s has a fixed cost c_{sk}^{FIX} of operating it with vehicle type k and a variable cost c_{ijsk}^{VAR} per container transported between terminals i and j. Moreover, we introduce the parameter δ_{ijl_s}, which equals one if a container traveling from i to j uses the service leg l_s and zero otherwise.

The transport operator has three decision variables in the upper level problem:

- v_{sk} is the number of vehicles of type k allocated by the operator to service s;
- f_{sk} is the frequency of service s per vehicle type k;
- p_{ij} is the price per container charged to shippers to transport goods from i to j.

Lower level

The shippers are represented as a whole, i.e. their demand is aggregated. The container transport demand between terminals i and j is denoted D_{ij}. Shippers decide to assign demand to the transport operator or their competitors by the maximization of their utility. The deterministic utility function of using the services proposed by the transport operator between i and j is denoted U_{ij}^{O} and is dependent on p_{ij} and f_{sk}, whereas the deterministic utility of using a competing alternative h is given as U_{ij}^{h}. Finally, the decision variables of the lower level consist in the number of containers that are assigned to the operator's services (x_{ijsk}) and to every competing alternative (z_{ij}^{h}). When some demand from i to j is assigned to the transport operator, it is assumed that the operator themselves will determine the services to which the containers will be assigned. Of course, the chosen services have to pass through both i and j and to have enough remaining capacity.

All the sets, parameters and decision variables are listed in Table 3.2.

Table 3.2: Notation.

Sets:	
$\mathcal{N}$	Set of terminals (indices: i, j)
$\mathcal{A}$	Set of arcs (i, j)
$\mathcal{K}$	Set of vehicle types (index: k)
$\mathcal{S}$	Set of potential services (index: s)
$\mathcal{L}_s$	Set of legs of service $s \in \mathcal{S}$ (index: l_s)
$\mathcal{H}$	Set of competing alternatives (index: h)
Parameters:	
V_k	Number of vehicles of type k in the operator's fleet
Q_k	Capacity of vehicle type k [TEUs]
W_{sk}	Maximum possible number of cycles of service s by vehicle type k
c_{sk}^{FIX}	Fixed cost of operating service s with vehicle type k [€]
c_{ijsk}^{VAR}	Variable cost between i and j with service s and vehicle type k [€/TEU]

δ_{ijl_s}	Dummy parameter equal to 1 if container traveling from i to j uses service leg l_s, 0 otherwise
D_{ij}	Aggregated transport demand of shippers between i and j [TEUs]
U_{ij}^{O}	Deterministic utility of using the operator's services between i and j
U_{ij}^{h}	Deterministic utility of using competing alternative h between i and j
Variables:	
v_{sk}	Number of vehicles of type k assigned to service s by the operator
f_{sk}	Frequency of service s operated with vehicle type k
p_{ij}	Price charged by the operator to transport goods from i to j [€/TEU]
x_{ijsk}	Volume using service s with vehicle type k between i and j [TEUs]
z_{ij}^{h}	Volume using competing alternative h between i and j [TEUs]

Mathematical model

The proposed SNDP is expressed as a BiLevel Problem (BLP):

$$(\mathbf{BLP})\ \max_{v,f,p,x,z} \quad \sum_{(i,j)\in\mathcal{A}}\sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}} p_{ij}x_{ijsk} - \sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}} c_{sk}^{\mathrm{FIX}} f_{sk} - \sum_{(i,j)\in\mathcal{A}}\sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}} c_{ijsk}^{\mathrm{VAR}} x_{ijsk} \tag{3.1}$$

$$\text{s.t.} \quad \sum_{s\in\mathcal{S}} v_{sk} \ \leq\ V_k \qquad \forall k\in\mathcal{K} \tag{3.2}$$

$$f_{sk} \ \leq\ W_{sk}v_{sk} \qquad \forall s\in\mathcal{S},\ \forall k\in\mathcal{K} \tag{3.3}$$

$$\sum_{(i,j)\in\mathcal{A}} \delta_{ijl_s}x_{ijsk} \ \leq\ Q_k f_{sk} \qquad \forall l_s\in\mathcal{L}_s,\ \forall s\in\mathcal{S},\ \forall k\in\mathcal{K} \tag{3.4}$$

$$x_{ijsk} \ \leq\ \sum_{l_s\in\mathcal{L}_s} \delta_{ijl_s}D_{ij} \qquad \forall (i,j)\in\mathcal{A},\ \forall s\in\mathcal{S},\ \forall k\in\mathcal{K} \tag{3.5}$$

$$p_{ij} \geq 0 \qquad \forall (i,j)\in\mathcal{A} \tag{3.6}$$

$$v_{sk}, f_{sk} \in \mathbb{N} \qquad \forall s\in\mathcal{S},\ \forall k\in\mathcal{K} \tag{3.7}$$

where x and z solve:

$$\max_{x,z} \quad \sum_{(i,j)\in\mathcal{A}} \left(\sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}} U_{ij}^{O}x_{ijsk} + \sum_{h\in\mathcal{H}} U_{ij}^{h}z_{ij}^{h} \right) \tag{3.8}$$

$$\text{s.t.} \quad \sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}} x_{ijsk} + \sum_{h\in\mathcal{H}} z_{ij}^{h} \ =\ D_{ij} \qquad \forall (i,j)\in\mathcal{A} \tag{3.9}$$

$$x_{ijsk} \geq 0 \qquad \forall (i,j)\in\mathcal{A},\ \forall s\in\mathcal{S},\ \forall k\in\mathcal{K} \tag{3.10}$$

$$z_{ij}^{h} \geq 0 \qquad \forall (i,j)\in\mathcal{A},\ \forall h\in\mathcal{H} \tag{3.11}$$

At the upper level, the objective function of the transport operator (3.1) is to maximize their profit. It is computed as the revenues from the transported containers minus the fixed and variable costs of the offered services. Constraint (3.2) is the fleet size constraint for each vehicle type. Constraint (3.3) ensures that the service's frequency is inferior to the maximum number of cycles that can be performed by the assigned vehicles. Constraint (3.4) assures that the total number of containers transported on each leg of every service does not exceed the available capacity of the service, whereas constraint (3.5) ensures that no container can be assigned to a service that does not go through the origin or destination terminal of the container. The domains of the operator's decision variables are defined by constraints (3.6)-(3.7).

Regarding the lower level, shippers seek to maximize their utility (3.8) by assigning their containers either to the operator's services or to the competition. Moreover, constraint (3.9) enforces the total transport demand to be met. Finally, constraints (3.10)-(3.11) define the domain of the decision variables of the shippers.

3.3.2 Model transformation

The proposed bilevel problem can be reformulated as a single level problem and then linearized, for more details on these procedures the reader is referred to Tawfik & Limbourg (2019). For the reformulation, additional variables $\lambda_{ij},\ \forall(i,j) \in \mathcal{A}$ are introduced: they represent the dual variables related to constraints (3.9). The model can then be transformed using the Karush-Kuhn-Tucker conditions. After this process, the following constraints appear:

$$\lambda_{ij} \leq -U^O_{ij} \qquad \forall(i,j) \in \mathcal{A},\ \forall h \in \mathcal{H} \tag{3.12}$$

$$\lambda_{ij} \leq -U^h_{ij} \qquad \forall(i,j) \in \mathcal{A},\ \forall h \in \mathcal{H} \tag{3.13}$$

$$(-U^O_{ij} - \lambda_{ij}) \sum_{s \in \mathcal{S}} \sum_{k \in \mathcal{K}} x_{ijsk} = 0 \qquad \forall(i,j) \in \mathcal{A} \tag{3.14}$$

$$(-U^h_{ij} - \lambda_{ij}) z^h_{ij} = 0 \qquad \forall(i,j) \in \mathcal{A} \tag{3.15}$$

Note that constraints (3.14) and (3.15) are non-linear. To address these, the big M technique is used and binary variables are introduced: y^{I}_{ij} and y^{II}_{ij} for constraint (3.14); $y^{\mathrm{I}h}_{ij}$ and $y^{\mathrm{II}h}_{ij}$ for constraint (3.15).

The only remaining non-linear expression is the first term of the operator's objective function (3.1). To remedy it, the strong duality theorem can be applied to the lower level problem (3.8)-(3.11), as in the work of Tawfik & Limbourg (2019). At optimality, we have:

$$-\sum_{(i,j)\in\mathcal{A}}\left(\sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}}U_{ij}^{O}x_{ijsk}+\sum_{h\in\mathcal{H}}U_{ij}^{h}z_{ij}^{h}\right) = \sum_{(i,j)\in\mathcal{A}}D_{ij}\lambda_{ij} \tag{3.16}$$

In addition, the following form is considered for the utility function of the transport operator:

$$U_{ij}^{O} = \bar{U}_{ij}^{O}+\beta_c p_{ij}+\beta_f f_{ij} = \bar{U}_{ij}^{O}+\beta_c p_{ij}+\beta_f\sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}}\phi_{ijs}f_{sk} \tag{3.17}$$

where $\bar{U}_{ij}^{O}$ is the part of utility depending on attributes exogenous to the model, β_c and β_f are the coefficients respectively weighting the importance of price and frequency in the utility function, and ϕ_{ijs} is a dummy equal to one if both terminals i and j are contained in service s and zero otherwise. Then, using equations (3.16) and (3.17), the first term in (3.1) can be expressed as:

$$\begin{aligned}\sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}}p_{ij}x_{ijsk} = -\frac{1}{\beta_c}\Big(D_{ij}\lambda_{ij}+\sum_{h\in\mathcal{H}}U_{ij}^{h}z_{ij}^{h}\\ +\sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}}x_{ijsk}(\bar{U}_{ij}^{O}+\beta_f\sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}}\phi_{ijs}f_{sk})\Big)\end{aligned} \tag{3.18}$$

Because we now have x_{ijsk} multiplying the sum of f_{sk}, we still did not completely eliminate non-linearity. This new term is nevertheless more convenient as the order of magnitude of the frequency is more limited than that of the price. Let us first define the frequency per OD pair: $f_{ij}=\sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}}\phi_{ijs}f_{sk}$. This term can then be represented in base 2 conveniently: $f_{ij}=\sum_{b=0}^{B_{ij}-1}2^b f_{ijb}$, where f_{ijb} are binary variables and B_{ij} an upper bound of $\log_2 f_{ij}$. The product term in (3.18) can ultimately be linearized using the well-known technique for the product of binary and continuous variables. The variable representing the product is referred to as a_{ijskb}.

The final MILP is then formulated as follows:

$$
\begin{aligned}
(\mathbf{MILP})\ \max_{v,f,p,x,z} \quad & \sum_{(i,j)\in\mathcal{A}} -\frac{1}{\beta_c}\Big(D_{ij}\lambda_{ij} + \sum_{h\in\mathcal{H}} U_{ij}^h z_{ij}^h + \sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}} \bar{U}_{ij}^O x_{ijsk} \\
& + \sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}} \beta_f \sum_{b=0}^{B_{ij}-1} 2^b a_{ijskb}\Big) - \sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}}\Big(c_{sk}^{\mathrm{FIX}} f_{sk} + \sum_{(i,j)\in\mathcal{A}} c_{ijsk}^{\mathrm{VAR}} x_{ijsk}\Big)
\end{aligned} \tag{3.19}
$$

s.t. constraints (3.2) − (3.7) & (3.9) − (3.11)

$$
\begin{aligned}
a_{ijskb} &\le D_{ij} f_{ijb} && \forall (i,j)\in\mathcal{A},\ \forall s\in\mathcal{S},\ \forall k\in\mathcal{K},\ \forall b\in\mathcal{B} && (3.20)\\
a_{ijskb} &\le x_{ijsk} && \forall (i,j)\in\mathcal{A},\ \forall s\in\mathcal{S},\ \forall k\in\mathcal{K},\ \forall b\in\mathcal{B} && (3.21)\\
a_{ijskb} &\ge x_{ijsk} - D_{ij}(1-f_{ijb}) && \forall (i,j)\in\mathcal{A},\ \forall s\in\mathcal{S},\ \forall k\in\mathcal{K},\ \forall b\in\mathcal{B} && (3.22)
\end{aligned}
$$

$$
\sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}} \phi_{ijs} f_{sk} = \sum_{b=0}^{B_{ij}-1} 2^b f_{ijb} \qquad \forall (i,j)\in\mathcal{A} \tag{3.23}
$$

$$
\lambda_{ij} \le -(\bar{U}_{ij}^O + \beta_c p_{ij} + \beta_f \sum_{b=0}^{B_{ij}-1} 2^b f_{ijb}) \qquad \forall (i,j)\in\mathcal{A} \tag{3.24}
$$

$$
-(\bar{U}_{ij}^O + \beta_c p_{ij} + \beta_f \sum_{b=0}^{B_{ij}-1} 2^b f_{ijb}) - \lambda_{ij} \le M_{ij}^{\mathrm{I}} y_{ij}^{\mathrm{I}} \qquad \forall (i,j)\in\mathcal{A} \tag{3.25}
$$

$$
\sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}} x_{ijsk} \le M_{ij}^{\mathrm{II}} y_{ij}^{\mathrm{II}} \qquad \forall (i,j)\in\mathcal{A} \tag{3.26}
$$

$$
y_{ij}^{\mathrm{I}} + y_{ij}^{\mathrm{II}} \le 1 \qquad \forall (i,j)\in\mathcal{A} \tag{3.27}
$$

$$
\begin{aligned}
\lambda_{ij} &\le -U_{ij}^h && \forall (i,j)\in\mathcal{A},\ \forall h\in\mathcal{H} && (3.28)\\
-U_{ij}^h - \lambda_{ij} &\le M_{ij}^{\mathrm{I}h} y_{ij}^{\mathrm{I}h} && \forall (i,j)\in\mathcal{A},\ \forall h\in\mathcal{H} && (3.29)\\
z_{ij}^h &\le M_{ij}^{\mathrm{II}h} y_{ij}^{\mathrm{II}h} && \forall (i,j)\in\mathcal{A},\ \forall h\in\mathcal{H} && (3.30)\\
y_{ij}^{\mathrm{I}h} + y_{ij}^{\mathrm{II}h} &\le 1 && \forall (i,j)\in\mathcal{A},\ \forall h\in\mathcal{H} && (3.31)
\end{aligned}
$$

$$
\begin{aligned}
& f_{ijb} \in \{0,1\} && \forall (i,j)\in\mathcal{A},\ \forall b\in\mathcal{B} && (3.32)\\
& y_{ij}^{\mathrm{I}}, y_{ij}^{\mathrm{II}}, y_{ij}^{\mathrm{I}h}, y_{ij}^{\mathrm{II}h} \in \{0,1\} && \forall (i,j)\in\mathcal{A} && (3.33)\\
& \lambda_{ij} \in \mathbb{R} && \forall (i,j)\in\mathcal{A} && (3.34)\\
& a_{ijskb} \in \mathbb{N} && \forall (i,j)\in\mathcal{A},\ \forall s\in\mathcal{S},\ \forall k\in\mathcal{K},\ \forall b\in\mathcal{B} && (3.35)
\end{aligned}
$$

3.3.3 Stochastic formulation

In equation (3.17), we set the generic form of the utility function U_{ij}^{O}. In particular, it was assumed to be fully deterministic, but in reality this is not the case. Firstly, the utility traditionally contains a random term (also called "error term"), representing the unobserved attributes playing a role in the mode choice. Secondly, one or several β coefficients can be assumed as randomly distributed, to account for heterogeneous preferences. Note that these remarks also hold for U_{ij}^{h}.

With these considerations, the CD-SNDP model becomes a stochastic optimization problem. We then come up with a SAA formulation to solve it. In this formulation, shippers are not represented as a whole anymore; on the contrary, the population is represented as a sample $\mathcal{R}$ composed of R individual shippers. The total demand per OD pair (i, j) is equally divided among the shippers, so that term D_{ij} is replaced by D_{ij}/R in the MILP formulation above. For every shipper r, the utility function of the transport operator becomes:

$$U_{ijr}^{O} = \bar{U}_{ijr}^{O} + \beta_c^r p_{ij} + \beta_f^r f_{ij} + \varepsilon_r^{O} \tag{3.36}$$

where ε_r^{O} is the error term representing unobserved attributes influencing the choice of shipper r toward the transport operator. Similarly, the utility of competing modes also becomes shipper-dependent: $U_{ijr}^{h}(\beta^{hr}, \varepsilon_r^{h})$. For each shipper r of the sample $\mathcal{R}$, a draw is performed in the distributions of β^r and ε_r and the corresponding utility functions are computed. Since utility functions now differ per shipper r, this impacts the mode choice such that the decision variables x_{ijskr} and z_{ijr}^{h} become dependent on the sampling. This is also true for the dual variables λ_{ijr}. It means that all constraints dependent on these variables need to hold for each shipper r. Nevertheless, the decision variables of the transport operator (p_{ij}, v_{sk}, f_{sk}, f_{ijb}) are fixed once and for all, independently of the sampling. Finally, the objective function is modified so as to maximize the sum of the profits over all shippers r in the sample $\mathcal{R}$.

3.3.4 Predetermination heuristic

To speed up the solution time of the stochastic formulations, we propose a "predetermination heuristic". As its name suggests, it consists in determining the operator's utility based on given price and frequency values before the optimization. To compute the operator's utility, discrete sets of predefined prices $\mathcal{P}$ and frequencies $\mathcal{F}$ are considered. It is also assumed that the sampling of the shippers' population is already performed so that the utilities of competing alternatives U^h_{ijr} can be computed. Along with the predefined prices p and frequencies ψ, it allows to pre-compute the demand faced by the operator $d^{\psi p}_{ij}$ for each OD pair.

To compute the resulting profit on an OD pair ij, the fixed and variable costs per vehicle type k are needed. However, the available cost parameters are expressed per service s and not directly per OD pair. Therefore, only the direct service between terminals i and j is considered. Since the variable cost is also dependent on i and j, we simply select the variable cost of the direct service for each vehicle type $\hat{c}^{\text{VAR}}_{ijk}$. For the fixed cost $\hat{c}^{\text{FIX}}_{ijk}$, we select the fixed cost of the direct service for each vehicle type and divide it by two (to get the cost for only one service leg). For a given frequency ψ and OD pair ij, we further consider the set Ξ^{ψ}_{ij} of all the possible combinations of frequencies per vehicle type ψ_{ijk}, such that $\sum_{k\in\mathcal{K}}\psi_{ijk} = \psi$ and that the fleet size and cycle time feasibility constraints are respected. Algorithm 3.1 shows the steps to compute the resulting profit for a given combination of ψ_{ijk} and a specific price p knowing the demand $d^{\psi p}_{ij}$.

For each combination $\xi \in \Xi^{\psi}_{ij}$, it is then possible to determine the price $P^{\xi}_{ij\psi}$ generating the most profit. The steps to obtain this value for every OD pair ij and predefined frequency ψ are given in Algorithm 3.2.

Algorithm 3.1: Profit computation per OD pair ij

Rank the vehicle types in increasing order of $\hat{c}^{\text{VAR}}_{ijk}$ to form the set $\mathcal{K}'$;
for $k' \in \mathcal{K}'$ **do**
  Define the capacity $\Theta_{ijk'} = \psi_{ijk'}Q_{k'}$;
  Define the payload per vehicle type $q_{ijk'} = \min(d^{\psi p}_{ij}, \Theta_{ijk'})$;
  Update the demand left to assign $d^{\psi p}_{ij} = d^{\psi p}_{ij} - q_{ijk'}$
end
Return the profit: $\sum_{k'\in\mathcal{K}'}(pq_{ijk'} - \psi_{ijk'}\hat{c}^{\text{FIX}}_{ijk'} - q_{ijk'}\hat{c}^{\text{VAR}}_{ijk'})$

Algorithm 3.2: Price determination method

for $(i,j) \in \mathcal{A},\ r \in \mathcal{R}$ **do**
  Determine $U'_{ijr} = \max_{h \in \mathcal{H}} U^h_{ijr}$, and $h'_{ijr} = \arg\max_{h \in \mathcal{H}} U^h_{ijr}$;
end
for $(i,j) \in \mathcal{A},\ \psi \in \mathcal{F}$ **do**
  for $p \in \mathcal{P}$ **do**
    $d^{\psi p}_{ij} = 0$;
    for $r \in \mathcal{R}$ **do**
      Compute $U^O_{ijr}(\psi, p)$ according to (3.36);
      if $U^O_{ijr}(\psi, p) \geq U'_{ijr}$ **then**
        $d^{\psi p}_{ij} = d^{\psi p}_{ij} + \frac{D_{ij}}{|\mathcal{R}|}$;
      end
    end
    for $\xi \in \Xi^{\psi}_{ij}$ **do**
      Compute the associated profit $\pi^{\xi p}_{ij\psi}$ using Algorithm 3.1;
    end
  end
  for $\xi \in \Xi^{\psi}_{ij}$ **do**
    $P^{\xi}_{ij\psi} = \arg\max_{p \in \mathcal{P}} \pi^{\xi p}_{ij\psi}$;
  end
end

Once Algorithm 3.2 has been used to compute demand values $d^{\psi p}_{ij}$ and price values $P^{\xi}_{ij\psi}$, they can then be used as parameters to solve an auxiliary optimization problem (AP). This problem consists in determining, for a given sample $\mathcal{R}$, the optimal frequencies for fixed prices $\tilde{p}_{ij}$:

$$\begin{aligned}(\mathbf{AP})\ \max_{v,f,g,x,z} \frac{1}{|\mathcal{R}|} \sum_{r \in \mathcal{R}} \Bigg(& \sum_{(i,j) \in \mathcal{A}} \sum_{s \in \mathcal{S}} \sum_{k \in \mathcal{K}} \tilde{p}_{ij} x_{ijskr} \\ & - \sum_{s \in \mathcal{S}} \sum_{k \in \mathcal{K}} \Big(c^{\text{FIX}}_{sk} f_{sk} + \sum_{(i,j) \in \mathcal{A}} c^{\text{VAR}}_{ijsk} x_{ijsk} \Big) \Bigg)\end{aligned} \tag{3.37}$$

$$\text{s.t.} \quad \sum_{s\in\mathcal{S}} v_{sk} \;\leq\; V_k \qquad \forall k\in\mathcal{K} \tag{3.38}$$

$$f_{sk} \;\leq\; W_{sk}v_{sk} \qquad \forall s\in\mathcal{S},\ \forall k\in\mathcal{K} \tag{3.39}$$

$$\sum_{r\in\mathcal{R}}\sum_{(i,j)\in\mathcal{A}} \delta_{ijl_s}\frac{x_{ijskr}}{|\mathcal{R}|} \;\leq\; Q_k f_{sk} \qquad \forall l_s\in\mathcal{L}_s,\ \forall s\in\mathcal{S},\ \forall k\in\mathcal{K} \tag{3.40}$$

$$x_{ijskr} \;\leq\; \sum_{l_s\in\mathcal{L}_s} \delta_{ijl_s}D_{ij} \qquad \forall (i,j)\in\mathcal{A},\ \forall s\in\mathcal{S},\ \forall k\in\mathcal{K},\ \forall r\in\mathcal{R} \tag{3.41}$$

$$\sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}} x_{ijskr} + z_{ijr} \;=\; D_{ij} \qquad \forall (i,j)\in\mathcal{A},\ \forall r\in\mathcal{R} \tag{3.42}$$

$$\sum_{\psi\in\mathcal{F}} g_{ij\psi} \;\leq\; 1 \qquad \forall (i,j)\in\mathcal{A} \tag{3.43}$$

$$\sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}} \phi_{ijs}f_{sk} \;=\; \sum_{\psi\in\mathcal{F}} \psi g_{ij\psi} \qquad \forall (i,j)\in\mathcal{A} \tag{3.44}$$

$$\sum_{r\in\mathcal{R}}\sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}} \frac{x_{ijskr}}{|\mathcal{R}|} \;\leq\; \sum_{\psi\in\mathcal{F}} g_{ij\psi}d_{ij}^{\psi\tilde{p}} \qquad \forall (i,j)\in\mathcal{A} \tag{3.45}$$

$$v_{sk}\in\mathbb{N} \qquad \forall s\in\mathcal{S},\ \forall k\in\mathcal{K} \tag{3.46}$$

$$f_{sk}\in\mathbb{N} \qquad \forall s\in\mathcal{S},\ \forall k\in\mathcal{K} \tag{3.47}$$

$$g_{ij\psi}\in\{0,1\} \qquad \forall (i,j)\in\mathcal{A},\ \forall s\in\mathcal{S},\ \forall \psi\in\mathcal{F} \tag{3.48}$$

$$x_{ijskr}\geq 0 \qquad \forall (i,j)\in\mathcal{A},\ \forall s\in\mathcal{S},\ \forall k\in\mathcal{K},\ \forall r\in\mathcal{R} \tag{3.49}$$

$$z_{ijr}\geq 0 \qquad \forall (i,j)\in\mathcal{A},\ \forall r\in\mathcal{R} \tag{3.50}$$

This auxiliary problem contains additional elements that deserve some discussion. First, the objective (3.37) is now formulated as a SAA function and the decision variables x and z are now dependent on r. Constraints (3.40) to (3.42) are modified accordingly. A new binary variable $g_{ij\psi}$ is introduced: it is equal to one if the predefined frequency ψ is chosen for OD pair (i,j), and zero otherwise. Constraint (3.43) ensures that at most one frequency ψ is chosen per OD pair. The value of ψ is then linked to the decision variable of services frequency f through constraint (3.44). Finally, constraint (3.45) aggregates the decision variables x_{ijskr} of cargo assigned to the operator over the whole sample and bounds it with the precomputed demand $d_{ij}^{\psi p}$ defined in Algorithm 3.2. This last constraint allows to keep the utility functions out of the optimization problem. As a result, the variable z_{ijr} is now independent of the competing modes h. Once the optimization is performed, the corresponding value of z^*_{ijr} can be assigned to the competing mode h'_{ijr} with the maximum utility as computed in Algorithm 3.2.

Algorithm 3.3: Predetermination heuristic

Use Algorithm 3.2 to pre-compute $d_{ij}^{\psi p}$ and $P_{ij\psi}^{\xi}$;
Define the set of visited solutions $\Omega = \emptyset$;
Set each $\tilde{p}_{ij}$ with arbitrary prices contained in $\mathcal{P}$;
Set each $\tilde{f}_{sk}$ to zero;
while $(\tilde{p}_{ij}, \tilde{f}_{sk}) \notin \Omega$ **do**
    Solve (AP) to get f_{sk}^* and $g_{ij\psi}^*$, i.e. the chosen frequency ψ corresponding to predefined prices $\tilde{p}_{ij}$;
    Update each $\tilde{f}_{sk}$ with f_{sk}^*;
    for $(i, j) \in \mathcal{A}$ **do**
        for $k \in \mathcal{K}$ **do**
            Compute $\psi_{ijk} = \sum_{s\in\mathcal{S}} \phi_{ijs} f_{sk}^*$
        end
        Find the combination $\xi \in \Xi_{ij}^{\psi}$ corresponding to the values ψ_{ijk};
        Update $\tilde{p}_{ij}$ with the value $P_{ij\psi}^{\xi}$;
    end
    Add $(\tilde{p}_{ij}, \tilde{f}_{sk})$ to the set Ω;
end
Return the solution $(\tilde{p}_{ij}, \tilde{f}_{sk})$;

Getting rid of the utilities and the pricing decision in the optimization allows to considerably decrease the solving time. Indeed, the variables p_{ij}, f_{skb}, a_{ijskb}, λ_{ij}, y_{ij}'s are not used anymore, and only the variables $g_{ij\psi}$ are added. The number of constraints is also drastically reduced. The idea of the heuristic is to exploit this advantage to solve the auxiliary problem iteratively, as described in Algorithm 3.3.

The performance of the heuristic is highly dependent on the size of sets $\mathcal{P}$ and $\mathcal{F}$. The more values they contain, the better is the approximation at the cost of additional computational resources. These sets should then ensure a good coverage of the search space in order for the heuristic to return satisfying solutions.

3.4 Case Study

The proposed CD-SNDP is applied to container transport on a small stretch of the European Rhine-Alpine (RA) corridor consisting of 3 nodes: Rotterdam (RTM), Duisburg (DUI) and Bonn (BON). The network is further extended to 9 nodes, as depicted

Figure 3.3: Network of the case study: the Rhine part of the RA corridor (Rivermap, 2024) together with the considered terminals.

in Figure 3.3. We consider an inland vessel operator competing with two other modes (Road and Rail) and another IWT carrier.

3.4.1 Overview

The operator's fleet is composed of 2 vessel types : 24 vessels of type M8 and 12 vessels of type M11 with a maximal capacity of 180 TEUs and 300 TEUs, respectively. Each vessel type has a maximal operation time, T^{max}, of 120 hours per week. The transport demand inputs are based on the NOVIMOVE project (Majoor et al., 2021), whereas the costs for IWT and the two competing modes as well as the sailing time t^{sail} and the time spent in ports t^{port} are estimated using the model of Shobayo et al. (2021). Based on these inputs, the computation of the maximum number of cycles is straightforward: $W_{sk} = T^{max}/(t^{sail}_{sk} + t^{port}_{sk})$.

Regarding demand modeling, the utility functions for each shipper r are formulated as follows:

$$U^{O}_{ijr} = \alpha^{\mathrm{IWT}} + \beta^{\mathrm{Inter}}_{a} a^{\mathrm{IWT}}_{ij} + \beta^{\mathrm{IWT}}_{q} q_{ij} + \beta^{\mathrm{Inter},r}_{c} (\boldsymbol{p_{ij}} + \mathrm{VoT} t^{\mathrm{IWT}}_{ij}) + \beta^{\mathrm{Inter}}_{f} \boldsymbol{f_{ij}} + \varepsilon^{O}_{ijr} \quad (3.51)$$

$$U^{h=\mathrm{IWT}}_{ijr} = \alpha^{\mathrm{IWT}} + \beta^{\mathrm{Inter}}_{a} a^{\mathrm{IWT}}_{ij} + \beta^{\mathrm{IWT}}_{q} q_{ij} + \beta^{\mathrm{Inter},r}_{c} (p^{\mathrm{IWT}}_{ij} + \mathrm{VoT} t^{\mathrm{IWT}}_{ij}) + \beta^{\mathrm{Inter}}_{f} f^{\mathrm{IWT}}_{ij} + \varepsilon^{\mathrm{IWT}}_{ijr} \quad (3.52)$$

$$U^{h=\mathrm{Rail}}_{ijr} = \alpha^{\mathrm{Rail}} + \beta^{\mathrm{Inter}}_{a} a^{\mathrm{Rail}}_{ij} + \beta^{\mathrm{Inter},r}_{c} (p^{\mathrm{Rail}}_{ij} + \mathrm{VoT} t^{\mathrm{Rail}}_{ij}) + \beta^{\mathrm{Inter}}_{f} f^{\mathrm{Rail}}_{ij} + \varepsilon^{\mathrm{Rail}}_{ijr} \quad (3.53)$$

$$U^{h=\mathrm{Road}}_{ijr} = \alpha^{\mathrm{Road}} + \beta^{\mathrm{Road}}_{a} a^{\mathrm{Road}}_{ij} + \beta^{\mathrm{Road}}_{c} (p^{\mathrm{Road}}_{ij} + \mathrm{VoT} t^{\mathrm{Road}}_{ij}) + \varepsilon^{\mathrm{Road}}_{ijr} \quad (3.54)$$

where, for each mode, α is the alternative specific constant, a is an accessibility metric, t is the total travel time in hours, p is the cost for shippers in thousand of euros per TEU, and f is the weekly frequency for intermodal transports (i.e. IWT and Rail). Moreover, q_{ij} is a dummy equal to one if a seaport is located at i or j and VoT is the Value of Time expressed in 1000€/TEU/hour. Each attribute is weighted by a coefficient β and each mode has a random error term ε. Although they have similarities, it is assumed that the vessel operator and the IWT carrier alternatives are not correlated. The same assumption holds between all alternatives. Therefore, in the remainder of this work, all the error terms ε_{ijr} are considered independent and identically distributed (iid).

Within the CD-SNDP context, all the terms contained in the utilities of the competing modes (IWT, Rail and Road) are exogenous to the optimization model and are thus treated as parameters. Regarding the utility of the operator, only the terms in bold (p_{ij} and f_{ij}) are endogenous while the other terms are also parameters. p_{ij} is the decision variable on pricing and f_{ij} corresponds to the term $\sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}}\phi_{ijs}f_{sk}$, as introduced in equation (3.17).

The model's coefficients were estimated with aggregate data using a Weighted Logit methodology. It is named "weighted" because, during the estimation, the log-likelihood function is weighted by the yearly cargo flows on each OD pair (Rich et al., 2009). It thus gives more importance to the OD pairs with high volumes. For more details, the reader is referred to Nicolet et al. (2022). One noteworthy characteristic of the data on which the coefficients were estimated is that the frequency for IWT does not exceed 35 services per week. Therefore, the following constraint is added to our CD-SNDP problem to guarantee consistency between the results and the mode choice model:

$$f_{sk} \leq 35 \qquad \forall s \in \mathcal{S},\ \forall k \in \mathcal{K} \quad (3.55)$$

We use this case study to compare the results of 3 deterministic and 2 stochastic models. The former consist in the benchmark (i.e.: with cost minimizing shippers and single-leg services), the SNDP (i.e.: with cost minimizing shippers and cycle-based services) and the proposed CD-SNDP, which uses only the deterministic part of the utility functions in equations (3.51) to (3.54), without error terms ε_{ijr} and with the same cost coefficients $\beta_c^{\text{Inter},r}$ for all shippers. The latter two are stochastic variations of the CD-SNDP:

- Multinomial Logit (MNL): with iid error terms ε_{ijr}, following an Extreme Value distribution;
- Mixed Logit: full utility specification as in equations (3.51) to (3.54), i.e. with random $\beta_c^{\text{Inter},r}$ following a Lognormal distribution of parameters μ_c^{Inter} and σ_c^{Inter} (representing the heterogeneous cost sensitivity of shippers) together with the iid error terms ε_{ijr}.

3.4.2 Evaluation through out-of-sample simulation

In order to assess the solutions returned by these models, we simulate the demand response using an out-of-sample population. Indeed, the profit returned by the optimization is the one expected based on the SAA and the model's assumptions, but it gives no indication on how well the solution will perform with actual shippers. The idea is to be able to compare the mode shares and profits that are obtained by the optimization, with the ones that are effectively realized in the out-of-sample simulation. In the remainder of this chapter, we will refer to "expected" profit and modal shares for the ones computed in the optimization, and "actual" for the ones returned by the simulation. This out-of-sample simulation also allows to compare the different models with each other. The procedure is as follows:

1. For each OD pair, generate a population of 1000 shippers (i.e. perform 1000 draws of ε_{ijr} and $\beta_c^{\text{Inter},r}$, note that these draws are different than the ones used in the SAA) and divide the demand D_{ij} equally among the shippers;
2. For each shipper, compute their utilities by plugging the drawn ε_{ijr} and $\beta_c^{\text{Inter},r}$, as well as the frequencies and prices returned by the model, into equations (3.51) to (3.54);
3. Allocate the shipper's containers to the alternative with the maximal utility;
4. When all containers have been allocated, compute the actual modal shares and profit for the inland vessel operator.

3.4.3 Coefficients of utility functions

For the out-of-sample simulation, we directly make use the coefficients of the Weighted Logit Mixture model estimated in Nicolet et al. (2022). However, these true utility functions of the shippers are not known by the operator. The same coefficients cannot, therefore, be used in the CD-SNDP. To alleviate this issue, we use the Weighted Logit Mixture to generate synthetic choice data, from which utility coefficients can be estimated by the operator. This process ensures that the true utility functions remain hidden from the operator, as they only have access to the choice realizations of shippers. It should be noted that the Mixture model structure is still the same for the out-of-sample simulation and the CD-SNDP. The purpose is to study the impact of having the correct structure of the utility functions, but not the true coefficients. And to compare the performance of such a model to models that do not have the correct utility functions.

The available inputs are the OD matrices and the attributes related to IWT, Rail and Road on each OD pair along the RA corridor. To generate a choice instance for a given OD pair using the Weighted Logit Mixture, we first draw the value of $\beta_c^{\text{Inter},r}$ and each mode's ε_{ijr} in their respective distributions. Then, they are plugged, along with each mode's attributes, into equations (3.52) to (3.54). Finally, the mode with the highest utility is selected and we get one synthetic choice instance. This process is then repeated for all OD pairs. To remain consistent with the Weighted Logit methodology, the number of generated choice instances per OD pair is set proportional to its cargo volume. In particular, each OD pair get at least one choice instance and an additional instance is generated per 10'000 TEUs circulating yearly on the OD pair. As a result, we end up with a synthetic dataset composed of 8676 choice instances, from which the MNL and Mixed Logit models can be estimated.

The coefficients of the Weighted Logit Mixture model are presented in Table 3.3, along with the coefficients of the Mixed Logit and MNL estimated using the synthetic dataset (note that α_{IWT} is normalized to zero). The mean value of β_c^{Inter} is also presented.

Table 3.3: Coefficients of the mode choice models, estimated using 10'000 draws.

	Actual population	Synthetic data	
Parameter	Weighted Logit Mixture	Mixed Logit	MNL
α^{IWT}	0	0	0
α^{Rail}	0.713	0.816	0.338
α^{Road}	2.30	2.35	2.06
β_q^{IWT}	1.63	1.60	1.49
β_f^{Inter}	0.0278	0.0262	0.0229
β_a^{Road}	0.0530	0.0506	0.0469
β_a^{Inter}	0.157	0.173	0.141
β_c^{Road}	-8.68	-8.73	-4.81
β_c^{Inter}			-5.76
μ_c^{Inter}	2.30	2.40	
$\sigma_c^{\mathrm{Inter}}$	0.690	0.618	
$\bar{\beta}_c^{\mathrm{Inter}}$	-12.65	-13.34	-5.76

3.4.4 3-node network results

In this section, we present and discuss the results of these various models applied on the 3-node network, starting with the deterministic ones.

CD-SNDP vs. Benchmark and SNDP

In order to compare the decisions of the different models, the weekly frequencies for both vessel types and the charged prices together with the total demand on each OD pair are reported in Table 3.4. The table also displays the prices of the competing alternatives, so as to better understand the pricing decision. For the benchmark and SNDP, the optimal prices are set at the same level as the cheapest competing alternative (in our case, IWT). This is because of the assumption that shippers are purely cost-minimizers and the deterministic nature of the models: if the vessel operator charges just 0.001 € less than the cheapest alternative, then the models will consider that all shippers will choose the services of the vessel operator instead of the competition. In the CD-SNDP, shippers are assumed to consider other attributes beside cost to perform their mode choice: the optimal prices then differ from the cheapest alternative.

Regarding the optimal frequencies, allowing to visit more than 2 terminals per service provides additional flexibility to the SNDP compared to the Benchmark. The

Table 3.4: Solutions of deterministic models with prices of the competing alternatives.

		Benchmark	SNDP	CD-SNDP	Competition IWT	Competition Road	Competition Rail
Prices [€]	RTM-DUI (6500 TEUs)	68	68	120	68	252	203
	DUI-RTM (8400 TEUs)	69	69	133	69	251	203
	RTM-BON (1900 TEUs)	76	76	88	76	317	214
	BON-RTM (1500 TEUs)	74	74	58	74	315	214
	DUI-BON (6700 TEUs)	46	46	-	46	136	152
	BON-DUI (6500 TEUs)	46	46	-	46	136	152
Weekly frequencies [M8 vessels | M11 vessels]	RTM-DUI	16|12	0|13	0|16			
	RTM-BON	0|5	0|5	5|2			
	DUI-BON	32|3	20|0	0|0			
	RTM-DUI-BON	-	19|0	19|0			

SNDP takes advantage of this consolidation opportunity which results in higher expected profits. Figure 3.4 displays the expected profits versus the actual ones returned by the out-of-sample simulation: it shows that the SNDP also returns higher simulated profits. The reason is that the vessel operator is able to attract more demand with this 3-stop service. This is seen in Figure 3.5, which represents the expected and actual modal shares for each deterministic model.

For the CD-SNDP, the expected profits increase significantly compared to the two other models, although the OD pair DUI-BON is not served anymore by the vessel operator. The distance between these two terminals is indeed relatively short so, as the CD-SNDP takes multiple factors in consideration for the mode choice of shippers, it is evident that Road becomes the preferred option for this OD pair. Nevertheless, the expected profits are higher because the optimal price on the busiest OD pair (RTM-DUI) is twice as high as in the other two models. Since the choice-driven model also considers frequency in the mode choice, it is able to charge more on this pair. Indeed, the operator's utility remains competitive with the one of the IWT alternative due the higher proposed frequency (35 services per week) between these two terminals. Although the vessel operator gets smaller market shares than with the Benchmark and SNDP (See Figure 3.5), the CD-SNDP returns actual profits that are almost two times higher.

These deterministic results already suggest that significant gains can be achieved with the Choice-Driven SNDP. More efficient services and pricing can be designed, thus resulting in considerably increased profits.

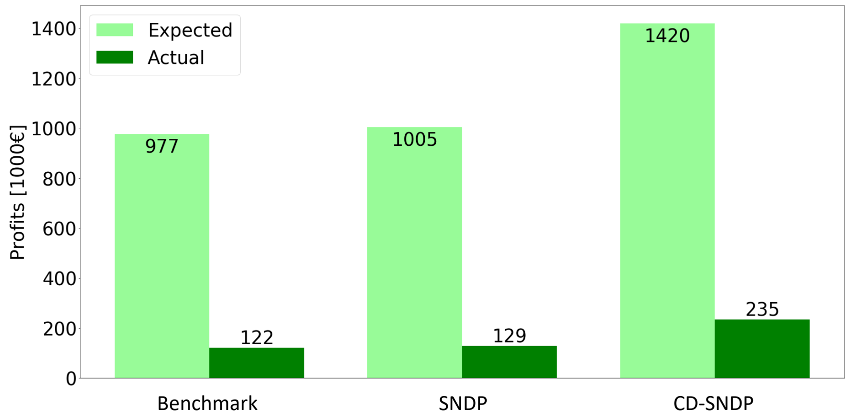

Figure 3.4: Comparison of profits obtained with the deterministic models.

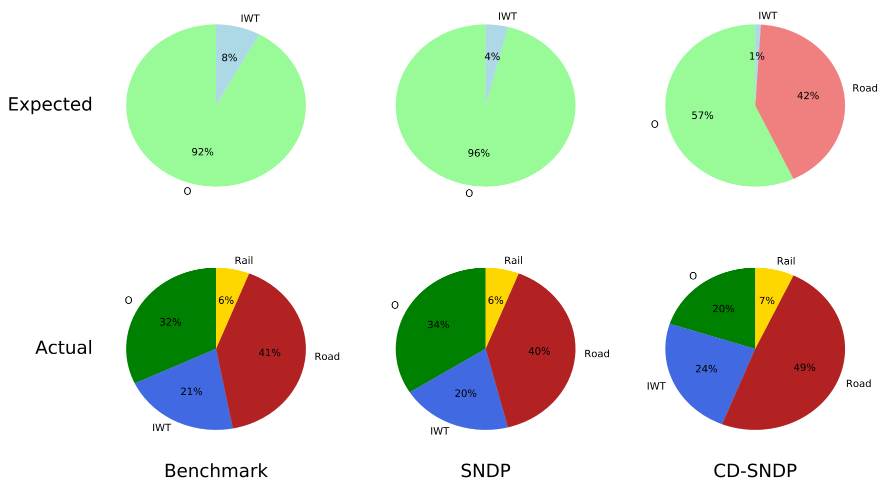

Figure 3.5: Comparison of modal shares returned by the deterministic optimization models (upper row) and by the out-of-sample simulation (lower row).

Stochastic variants with exact method

In this section, the results of the stochastic versions of the CD-SNDP are described. Two random utility formulations are compared: MNL (with random error terms ε) and Mixed Logit (with ε and distributed cost sensitivity β_c^{Inter}).

The two versions are solved through SAA with a sample size of $R = 500$, i.e. 500 draws are performed in the distributions of ε (and of β_c^{Inter}, for the Mixed Logit). For each variant, we run 20 replications with 20 different random seeds, thus generating 20

Table 3.5: Solutions of stochastic models with the commercial solver (500 draws).

		MNL			Mixed Logit		
		Min.	Average	Max.	Min.	Average	Max.
Weekly	RTM-DUI	0|11	0|12	0|14	0|0	0|5	1|13
frequencies	RTM-BON	0|0	0|0	0|0	0|0	0|0	0|0
[M8 vessels |	DUI-BON	0|1	7|2	12|2	0|0	6|2	12|2
M11 vessels]	RTM-DUI-BON	21|0	22|0	24|0	12|0	21|0	24|0
Prices [€]	RTM-DUI	188	248	302	129	172	239
	DUI-RTM	188	247	314	135	167	235
	RTM-BON	191	253	316	140	201	284
	BON-RTM	166	235	286	146	189	283
	DUI-BON	139	202	282	106	175	328
	BON-DUI	142	202	282	106	176	328
Computation time [hours]		27	58	72	72	72	72
Optimality gap		0%	3%	7%	29%	39%	60%

different samples. The aggregated statistics of the obtained solutions and computation time are presented in Table 3.5. Note that a time limit of 72 hours has been applied, that is why the statistics of the optimality gap are also presented.

The pricing decision is very variable from one replication to another. The variation is slightly more pronounced for the MNL case than for the Mixed Logit, but the main takeaway is that the MNL results in higher prices than the Mixed Logit. Also, both variants find higher prices than the deterministic CD-SNDP. The frequency decision also varies between replications, but the ranges in the MNL case are quite similar to the Mixed Logit.

The influence on the expected and actual profits is depicted in the boxplots of Figure 3.6. The higher prices set by the MNL lead to greater expected profits compared to the Mixed Logit. But this difference is canceled out when comparing the simulated profits as the MNL profits fall at a very slightly lower level than the ones of the Mixed Logit. Nevertheless, the actual profits for both variants are substantially higher than for the deterministic CD-SNDP. In fact, they provide an additional 90% gain compared to the deterministic case. This is because the modal shares can be estimated much better during the optimization due to the more detailed choice models. Indeed, Figure 3.7 shows the average expected modal shares against the actual ones. These shares are close to each other for both the MNL and the Mixed Logit, whereas the deterministic model highly overestimates the share of the vessel operator.

Comparing the MNL with the Mixed Logit, the accuracy of their modal share estimation is nearly equivalent, but the MNL tends to overestimate the operator's share

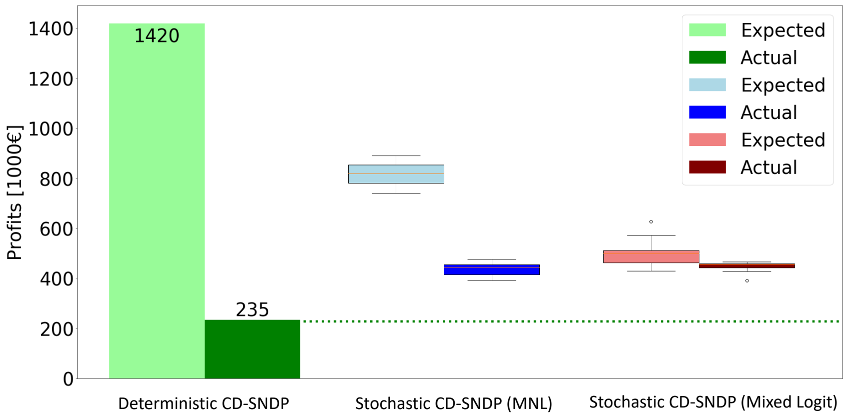

Figure 3.6: Comparison of profits by the stochastic models solved with the commercial solver and the deterministic CD-SNDP.

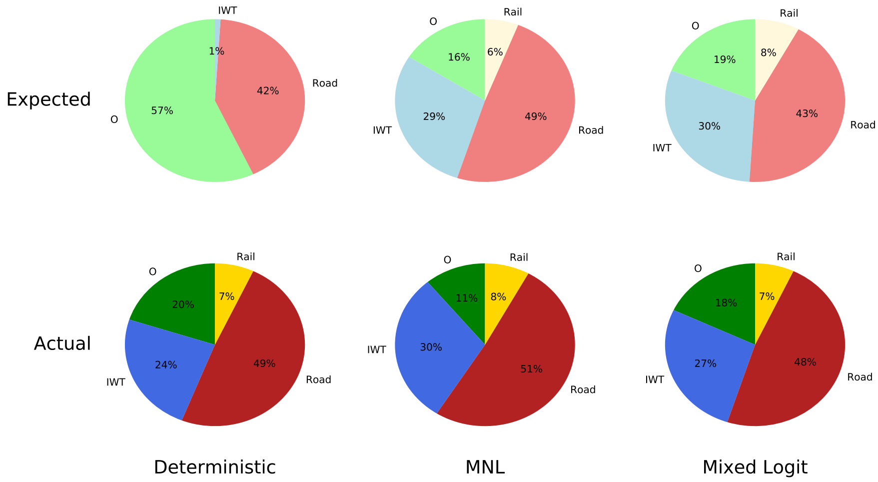

Figure 3.7: Comparison of average modal shares returned by the stochastic optimization models solved with the commercial solver (upper row) and by the out-of-sample simulation (lower row).

during the optimization process. The expected profits in Figure 3.6 are then significantly higher than the actual ones, whereas the expected profits with the Mixed Logit are in line with the actual ones. This is because the MNL used in the CD-SNDP has a much lower cost coefficient β_c^{Inter} in absolute value than in the actual population (see Table 3.3). On the other hand, the Mixed Logit has coefficients that are more in line with the actual population. The cost sensitivity of the shippers is then underestimated by the MNL, which results in prices that are higher than with the Mixed Logit. The CD-SNDP with MNL then expects that high profits will be realized, whereas in reality there will be less demand than expected due to the higher prices: thus resulting in a decrease of profits.

Nevertheless, the large optimality gaps reported for the Mixed Logit in Table 3.5 prevent any conclusion at this stage. Even though the addition of stochasticity in the CD-SNDP provide more gains, it is done at the expense of computing time. In order to remedy this, we make use of the predetermination heuristic presented in Section 3.3.4.

Stochastic variants with predetermination heuristic

The two stochastic variants are solved using the same samples as for the exact method. We use the following set of predefined prices: $\mathcal{P} = \{10k | k \in \mathbb{N} \cap [0, 50]\}$, and the set of predefined frequencies: $\mathcal{F} = \mathbb{N} \cap [0, 35]$ in accordance with (3.55). The statistics of the heuristic solutions are reported in Table 3.6 together with the computation time.

Compared to the exact method, the predetermination heuristic is remarkably faster. When the computation was in the order of days for the exact method, it is now reduced to a few minutes. Most of these minutes are spent precomputing the demand and price values with Algorithm 3.2. With the heuristic, there is also little difference in solving time between the two stochastic variants. Regarding the quality of the solutions, the prices and frequencies found with the heuristic are not identical but they remain consistent with the ones returned by the exact method. The comparison between the profits obtained with the exact method and with the predetermination heuristic is shown in Figure 3.8.

Table 3.6: Solutions of stochastic models with predetermination heuristic (500 draws).

		MNL			Mixed Logit		
		Min.	Average	Max.	Min.	Average	Max.
Weekly frequencies [M8 vessels | M11 vessels]	RTM-DUI	0|11	0|12	0|14	0|0	0|7	0|14
	RTM-BON	0|0	0|0	0|0	0|0	0|0	0|0
	DUI-BON	0|0	4|6	12|2	0|0	8|2	22|0
	RTM-DUI-BON	21|0	22|0	24|0	10|0	21|0	24|0
Prices [€]	RTM-DUI	180	248	320	130	166	230
	DUI-RTM	190	247	310	120	161	230
	RTM-BON	190	251	310	140	199	270
	BON-RTM	160	230	290	140	199	320
	DUI-BON	140	206	320	110	177	330
	BON-DUI	140	207	320	100	181	330
Computation time [hours]		0.04	0.05	0.05	0.05	0.05	0.05

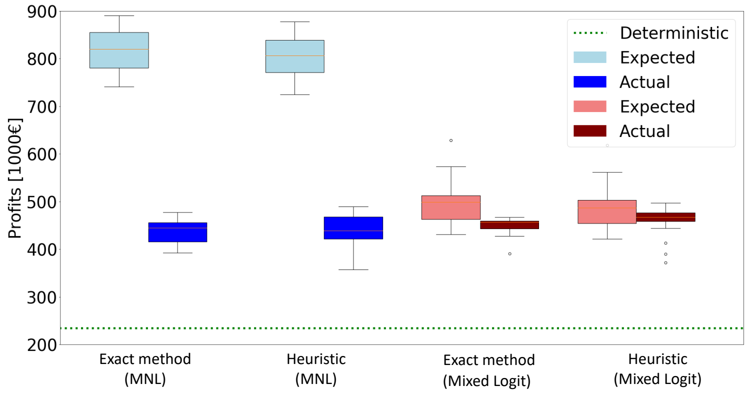

Figure 3.8: Comparison of profits by the stochastic models solved with the commercial solver and the heuristic.

The profit ranges found by the heuristic are similar to the ones with the exact method. The optimal value of the objective function found by the heuristic is on average only 2% lower than the exact solution, while achieving much higher computational efficiency. We still observe a significant gap between the expected and actual profits in the MNL case, whereas these two values are at a more similar level for the Mixed Logit.

These results serve to validate the performance of the heuristic in comparison to the exact method. Therefore, we can now evaluate the CD-SNDP on larger instances which will be presented in the next section.

3.4.5 9-node network results

In this section, we present and discuss the results of these various models applied on the 9-nodes network depicted in Figure 3.3, starting with the deterministic ones.

CD-SNDP vs. Benchmark and SNDP

The optimal service design for the three deterministic models is shown in Figure 3.9. The solution of the benchmark focuses on busy OD pairs, as it allows to serve eight out of the ten pairs with most demand in the network (see Table 3.7). Allowing cycles in the SNDP enables to redeploy some vessels: in particular, a service to Strasburg and Basel is added and the frequency on the OD pairs RTM-DUI and AND-MAI is increased.

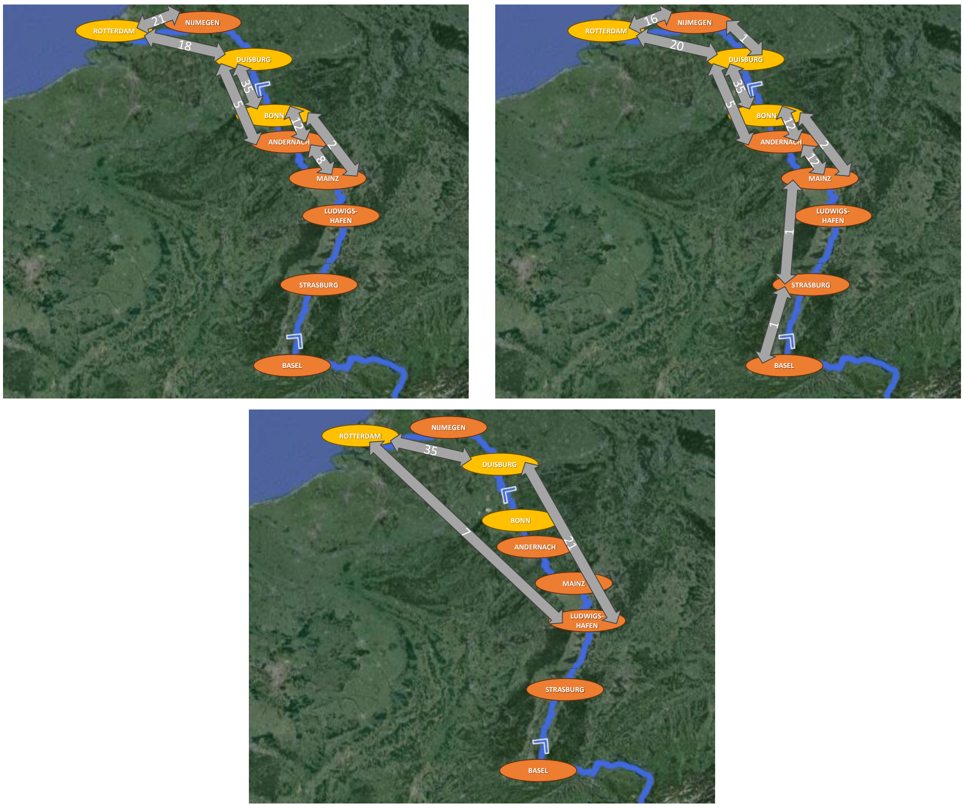

Figure 3.9: Optimal weekly frequencies for the Benchmark (top-left), the SNDP (top-right), and the deterministic CD-SNDP (bottom).

While the benchmark and SNDP serve as much high demand OD pairs as possible, the CD-SNDP only serves two out of the ten pairs with most demand (RTM-DUI and RTM-LUH). These two pairs are also the ones with the most TEU-kilometers, far ahead of the others: this indicates that the CD-SNDP proceeds to a trade-off between the potential demand that can be attracted and the distance on the OD pair. Indeed, water transport tends to become more attractive to shippers for long distance transport. Regarding the pricing decisions, the observations remain similar to the 3-node results.

Table 3.7: Ten OD pairs with the most demand.

Rank	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
OD	RTM-DUI	DUI-BON	RTM-NIJ	RTM-LUH	BON-AND	AND-MAI	RTM-BON	RTM-BSL	DUI-AND	RTM-MAI
Demand [TEUs]	14’900	13’200	10’600	6’400	4’200	3’600	3’400	2’000	1’800	1’200
Distance [km]	230	120	130	590	40	110	360	850	170	520

RTM = Rotterdam, DUI = Duisburg, BON = Bonn, NIJ = Nijmegen, LUH = Ludwigshafen, AND = Andernach, MAI = Mainz, BSL = Basel.

The expected and actual profits resulting from the three deterministic models are illustrated in Figure 3.10. Similarly to the 3-node case, the CD-SNDP returns higher profits (both from the optimization and the out-of-sample simulation). This is due to the more accurate estimation of the demand, as depicted in Figure 3.11. Indeed, the benchmark assumes that the whole demand will go to IWT (be it the operator or the competitor), as it is the cheapest mode; but after simulation, it turns out that only 44% of the demand was assigned to IWT.

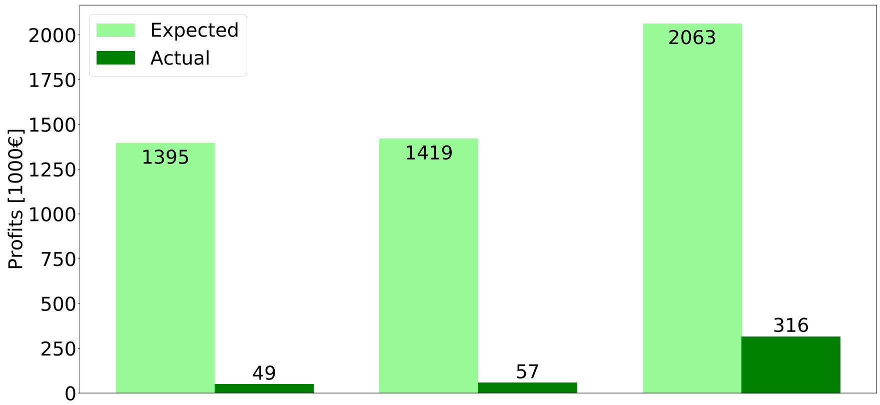

Figure 3.10: Comparison of profits obtained with the deterministic models.

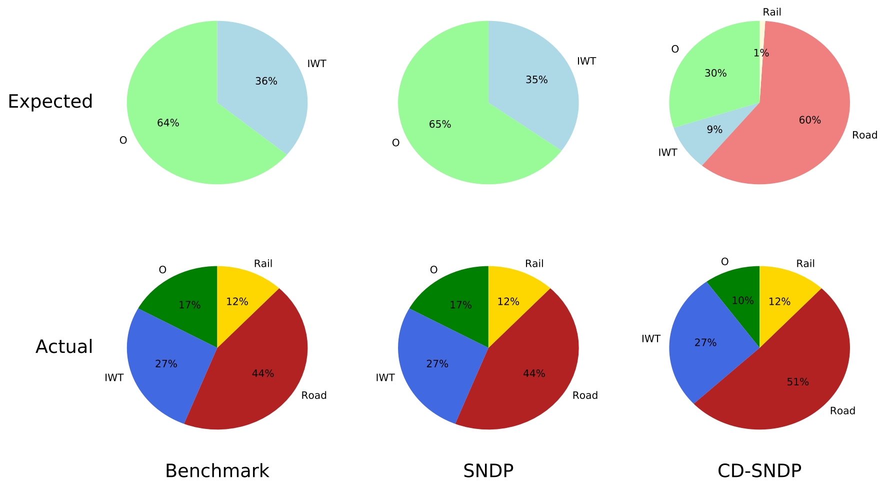

Figure 3.11: Comparison of modal shares returned by the deterministic models (upper row) and by the out-of-sample simulation (lower row).

On the other hand, the CD-SNDP estimates that only 39% of the demand will be assigned to IWT, whereas the simulated IWT share is 37%. For the sake of comparison, the measured shares on these OD pairs are 38% for IWT, 55% for Road and 7% for Rail.

A better demand estimation allows to charge a higher price then the models using the cost-minimization assumption because the other factors influencing the mode choice are also considered. It is also able to target more adequately the OD pairs to serve in priority as it can proceed to a trade-off between the total demand and the attractiveness of water transport on a given OD pair. This allows the operator to make better decisions as the resulting profits are increased by a factor of ten compared to the benchmark.

Stochastic variants

Table 3.8 presents the minimum, maximum and average service frequencies on the ten OD pairs with most demand along with the computation time of the 20 replications. On average, both stochastic models return very similar solutions. The first and third busiest OD pairs have frequencies set at (or close to) the maximum of 35. The rest of the vessels are mostly deployed on the RTM-BON and DUI-BON OD pairs as well as the RTM-LUH OD pair, while a frequency of one service per week is set on the remaining OD pairs. For each model, the differences in maximum and minimum frequencies are explained by the small number of draws (500) relatively to the size of the model. This

Table 3.8: Frequencies on OD pairs with most demand of stochastic models (500 draws).

		MNL			Mixed Logit		
		Min.	Average	Max.	Min.	Average	Max.
Weekly frequencies	RTM-DUI	34	35	35	5	33	35
	DUI-BON	0	14	28	1	12	31
	RTM-NIJ	34	35	35	2	31	35
	RTM-LUH	3	5	16	3	5	6
	BON-AND	0	1	3	0	1	1
	AND-MAI	0	1	3	0	1	1
	RTM-BON	0	14	28	1	12	31
	RTM-BSL	1	1	2	0	1	2
	DUI-AND	0	1	3	1	1	1
	RTM-MAI	0	1	3	1	1	2
Computation time [hours]		4.0	8.8	13.8	3.3	8.3	13.7

difference is also visible in the computation times, that range from three to fourteen hours. However, the time does not change significantly between the two models.

Regarding the pricing decisions, the observations remain similar to the 3-node results. The resulting profits obtained with the two stochastic models are shown in Figure 3.12, together with the profits of the deterministic CD-SNDP.

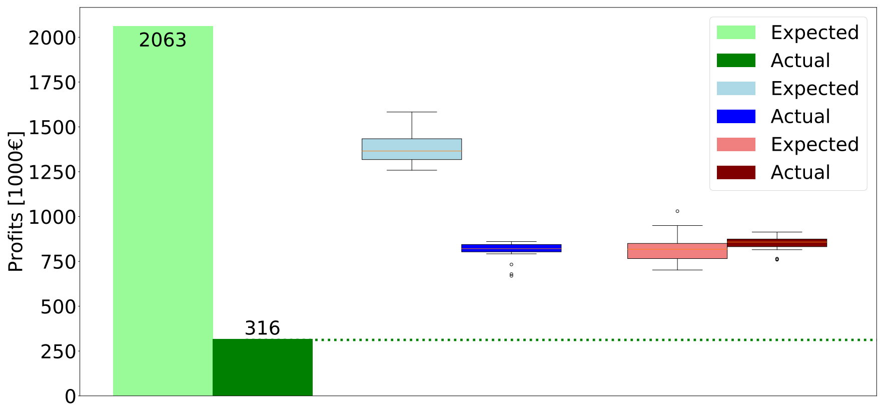

Figure 3.12: Comparison of profits obtained with the two stochastic models against the deterministic CD-SNDP.

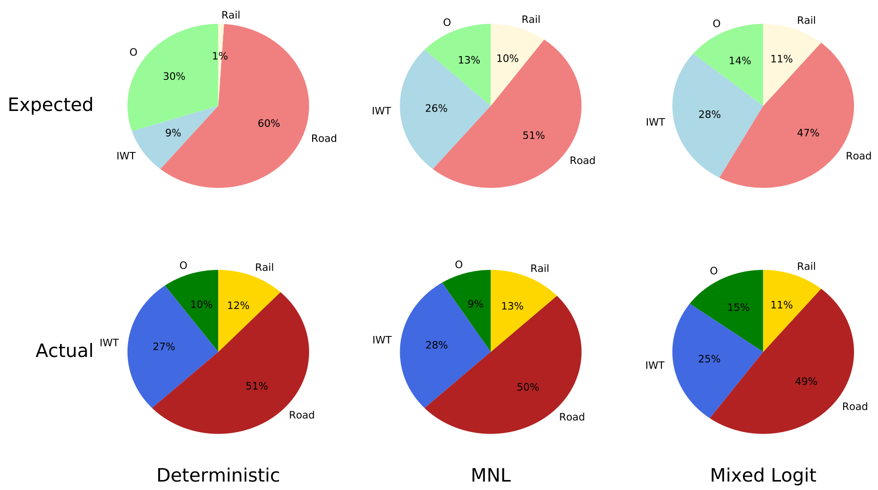

Figure 3.13: Comparison of modal shares returned by the two stochastic models and the deterministic CD-SNDP (upper row) and by the out-of-sample simulation (lower row).

The expected profits (resulting from the optimization) are decreased compared to the deterministic case, whereas the actual ones (obtained through the out-of-sample simulation) are 60% higher. This is once again because the stochastic models are able to better estimate the modal split, hence the potential demand of the transport operator. This is particularly true for the model with Mixed Logit, where the expected profits almost match the actual ones. The modal shares estimated by the models are shown in Figure 3.13 together with the ones obtained through the simulation.

3.4.6 Key insights

Several take-aways can be gathered from the results presented above. First, a cycle-based formulation, together with a multi-leg representation of the SND problem is more efficient in terms of asset usage as the operator can use consolidation opportunities. This results in both reduced costs and increased demand.

Secondly, it is highly beneficial for the transport operator to include the information they have about the demand during the design of their services. The CD-SNDP results have shown that, even with a simple deterministic model, the solution of the SNDP problem is able to generate actual profits that are nearly three times higher than the benchmark. This is because the benchmark's assumption that shippers are purely cost-minimizers neglects other attributes that still play a role in the decision-making of shippers, such as the service frequencies. The utility functions also include the arbitrage between these attributes through the weighting coefficients. As a result, the estimation of modal shares during the optimization stage is much more accurate. Indeed, the cost-minimizing assumption used in the benchmark overestimates the demand assigned to the operator. This can also be observed in the Rail shares obtained in the paper presenting the benchmark Tawfik & Limbourg (2019).

Thirdly, making use of stochastic CD-SNDP exploits further the potential of the model. Indeed, perfect and complete information about the shippers is not available to the operator, so that their demand model will miss some aspects that play a role in the shippers' choices. These aspects can indirectly be accounted for by adding random error terms in the model. Including this uncertainty into the model enables gains exceeding 50% compared to the deterministic CD-SNDP. Therefore, the stochastic formulation of the CD-SNDP is one convenient way to account for imperfect information endogeneously to the model.

Finally, quantifying and incorporating the heterogeneous preferences of shippers allows for a more accurate estimation of the profits. Indeed, except for the stochastic CD-SNDP with Mixed Logit, all models presented above substantially overestimate the profits. This can lead to very bad surprises for the operator if they expect a given amount of profit in their budget, but end up realizing much less. On the other hand, the formulation with Mixed Logit expects profits in line with the ones that are realized. Considering heterogeneity then allows to get a better prevision of the profits.

It should be noted that the decisions (pricing and frequency) of the choice-driven SNDP highly depend on the underlying representation of shipper's behavior. Namely, the range of improvement is closely linked to the elasticity of demand. Therefore, the utility functions need to be carefully studied for the context at hand. In our case, we base them on a study that makes use of real aggregate data on the same network to estimate the parameters and validates the results against real market shares.

3.5 Conclusions

This chapter proposes a Service Network Design and Pricing problem that incorporates the mode choice behavior of shippers. We thus address RQ2 by developing a so-called Choice-Driven Service Network Design and Pricing problem that directly includes utility-based mode choice models into a bilevel optimization problem, which can then be reformulated as a single level linear problem. The random nature of utility-based models, such as the Multinomial Logit, allows to account for missing information about attributes playing a role in the mode choice. Opting for a Mixed Logit formulation further allows to consider the heterogeneous preferences of shippers, thus getting a more realistic representation of the shippers' population. Due to the randomness, the problem becomes stochastic, which makes it computationally expensive to solve with an exact method. To overcome this issue, we develop a predetermination heuristic that computes utilities prior to the optimization.

The results show that the heuristic is able to considerably reduce the computational time: solving a stochastic instance with 500 draws takes hours for the exact method, while it only takes a few minutes for the predetermination heuristic. Meanwhile, the optimal solutions returned by the heuristic are on average only 2% lower than the exact ones.

Regarding the proposed model itself, it is compared to a benchmark where shippers are assumed purely cost-minimizers. We show that the profits achieved by our model are substantially higher. Even if the embedded mode choice model is simply deterministic, the obtained profits can potentially be multiplied by a factor ranging from 2 to 5 depending on the network's size. All in all, including more information about the shippers while designing and pricing the services suggests considerable gains for the transport operator. Even if the exact model or parameters are not known, it is still far better than not using the available information.

Nevertheless, the information about the competing alternatives may not be available to the transport operator. Some attributes can be found, e.g., the frequency of services or travel times. But the price that the competitors are applying cannot be known perfectly: at best it can be estimated. The choice-driven model should then be developed further to account for this imperfect information. In addition, the competition is assumed exogenous and fixed meaning that they will not react to the operator's new services. But the competitors will also seek to improve their services and profits, even more so if they lose market share to the operator. These limitations are addressed in the next chapter, where a competitive version of this problem is presented.

Chapter 4

Supply-demand interactions and competition

In Chapter 3, we developed a Choice-Driven Service Network Design and Pricing model and demonstrated its potential on a real logistics network. However, the proposed model relies on two strong assumptions: first, that the competitors will not react to the services proposed by the operator; second, that the operator has perfect information about the services of their competitors. As mentioned in Chapter 1, there is a need to include imperfect information in supply-demand models. Therefore, we propose a Competitive Service Network Design and Pricing model, which is represented as a Nash game using the Choice-Driven model developed in Chapter 3. The present chapter addresses RQ3: How shall the supply-demand interactions be modeled to accurately represent the freight transport market?

This chapter is structured as follows: in Section 4.1, we position our model while highlighting our contributions. Section 4.2 presents the adopted methodology. It is then applied to a particular OD pair in Section 4.3 to verify its functioning. Finally, Section 4.4 concludes the chapter.

Parts of this chapter have been submitted to a conference: Nicolet & Atasoy (2024b) "Competitive Service Network Design and Pricing for Intermodal Transport", *Proceedings of the LOGMS conference 2024, Hamburg, Germany*.

4.1 Introduction

In intermodal freight transport, the Service Network Design (SND) problem is of key importance, as it covers most of the tactical decisions such as the itineraries to be served, the offered frequencies and how demand should be assigned to these services (Crainic, 2000). As mentioned in the earlier chapter, only a handful of works include pricing decisions of transport operators and a detailed representation of shippers (Elbert et al., 2020). Chapter 3 incorporates heterogeneous behavior of shippers into a Service Network Design and Pricing (CD-SNDP) model. However, as in the literature, Chapter 3 assumes fixed and exogenous competitors. This assumption represents a major limitation as the proposed models cannot capture the reactions of competitors to the decisions of the transport operator (Wang et al., 2023).

On the other hand, some studies consider the competition of operators when they design and price their services. In most of them, the demand is assumed deterministic and the demand functions are assumed known by the operators (Zhou & Lee, 2009). Another commonly used assumption is that operators have complete knowledge about each other's decisions (Zhang et al., 2018). However, these assumptions are not met in practice. In particular, operators never have perfect information about the prices of their competitors or all the factors influencing the decisions of shippers. Therefore, the applicability of the existing models remains limited.

With our work, we bridge the gap between the existing SND and competition models by overcoming the aforementioned limitations. Specifically, we propose an extension of our existing CD-SNDP model (Nicolet & Atasoy, 2024a) by considering the competitor's reaction to the services and prices proposed by the transport operator. Moreover, we assume that decision-makers do not have full information about the competitors and the demand: instead, they use the observed market shares as measures of choice probabilities of the shippers (Ivaldi & Vibes, 2008).

4.2 Methodology

In this section, we present the adopted method to represent the service and price competition in intermodal transport.

4.2.1 Problem statement

We consider two IWT operators that are active on the same intermodal corridor. This corridor is represented as a set of terminals $\mathcal{N}$ and a set of arcs linking these terminals

$\mathcal{A} = \{(i, j) : i, j \in \mathcal{N}, i \neq j\}$. Two other transport alternatives are available on the corridor: Road and Rail. These two modes are considered exogenous to the model. Each Origin-Destination (OD) pair has a given number of shippers R_{ij} to serve, with an aggregated demand D_{ij}. To execute their mode choice, each shipper r is assumed to follow the Mixed Logit model, estimated in a previous work (Nicolet et al., 2022).

Both operators have their own fleet made of different vessel types, denoted by the set $\mathcal{K}$. The capacity per vessel type is V_k and the number of vessels owned by IWT operator c is Q_k^c. Each operator has to design their services: the set $\mathcal{S}$ embeds all potential services that can be run. Each service s is made of a sequence of arcs between terminals and forms a cycle (i.e. it starts and ends at the same terminal). Each operator has to set the frequency of their services f_s^c and the price p_{ij}^c they will charge the shippers, so as to maximize their profit Π^c while respecting fleet size and cycle time constraints. To do so, they solve a Choice-Driven Service Network Design and Pricing (CD-SNDP) problem (Nicolet & Atasoy, 2024a). The mathematical formulation of this problem is presented in Chapter 3. The operators do not know the choice model followed by the shippers, but they have their own assumptions about the formulation of the utility function U^c and the associated coefficients.

4.2.2 Competition framework

We propose to model the competition as a Nash game with incomplete information, which is solved using the iterative-method (Wang et al., 2014). In addition, we simulate the market response to the operators' decisions between each iteration. The competition framework, therefore, consists in the following steps:

1. Initial decisions of the operators;
2. Simulation of the shippers;
3. Update of the operators' decisions;

where steps 2 and 3 are repeated until an equilibrium is reached. To do so, an empty set Θ of visited solutions is created. After each iteration of steps 2 and 3, it is checked if the obtained profits are already in the set. If no, then they are added to Θ and the iterations go on; if yes, then the process stops and the current solution is returned. It is then checked if the obtained profits correspond to a unique solution. If so, the resulting situation is then either an equilibrium or a cycle between solutions. An equilibrium can either consist of the two operators proposing their services, or one operator exiting the market (i.e. the returned prices and frequencies are zero) thus giving the other a monopoly situation.

The whole competition framework is illustrated in Figure 4.1, while the following paragraphs describe the three main steps of the competition framework.

Initializing operators

At the beginning of the game, both operators have little information about each other. In particular, they do not know the prices charged by the other one and the frequencies may also be unknown. Based on the information they possess, each operator assumes some starting prices $\hat{p}_{ij}$ and frequencies $\hat{f}_{ij}$ for each OD pair. Each operator can then compute their competitors' utility $\hat{U}^c_{ij}(\hat{p}_{ij}, \hat{f}_{ij})$ given their assumption on the utility and solve the related CD-SNDP.

Shippers simulation

Once services are set by the operators, we simulate the demand reaction to the chosen prices and frequencies. For each shipper, on every OD pair, we determine their mode choice based on the Mixed Logit model introduced in Chapter 2. Each shipper

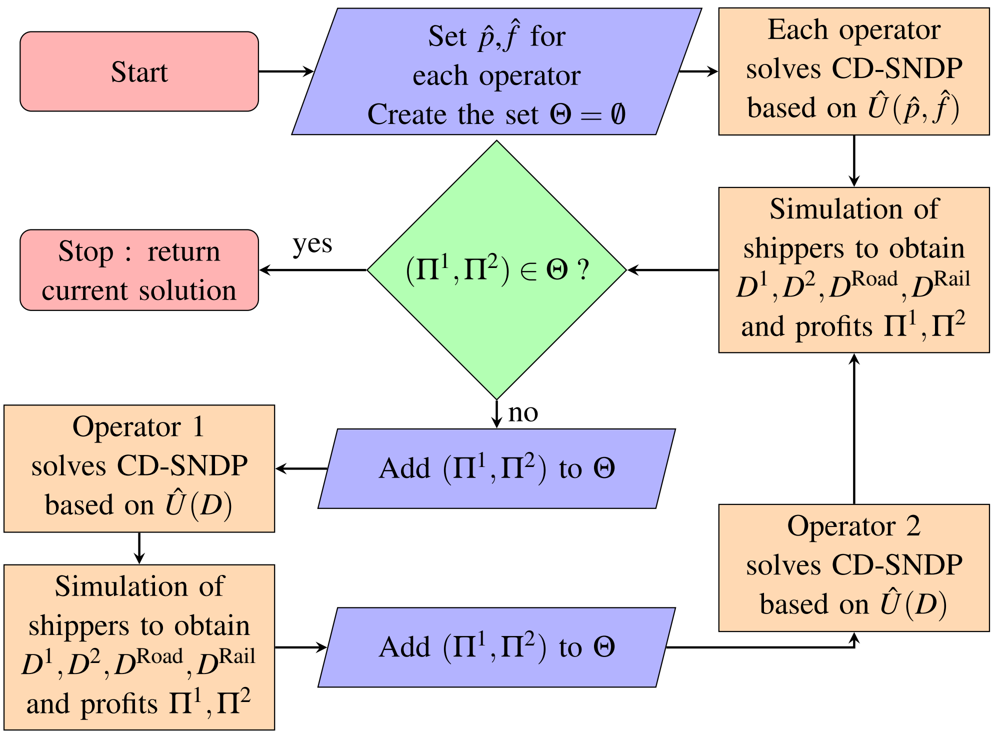

Figure 4.1: Flowchart of the competition model.

will choose between the following alternatives: Road, Rail, IWT operator 1 or IWT operator 2. Road and Rail are assumed to have infinite capacity, while the capacity of IWT operators on each OD pair is determined by the solution of the CD-SNDP. Each shipper will then choose the alternative with the highest utility provided that there is enough remaining capacity. If this is not the case, the corresponding operator is removed from the alternatives for this particular OD pair. Once all shippers have been simulated, we obtain the demand partition between the four alternatives: D_{ij}^{Road}, D_{ij}^{Rail}, D_{ij}^{1} and D_{ij}^{2}. Given this demand assignment, it is then possible to compute the profits that are actually realized by each IWT operator, respectively Π^1 and Π^2.

Updating operator decisions

The demand partition provides each IWT operator with new information. Indeed, they can now observe their market share and the ones of their competitors. This gives them an indication of how attractive they are compared to the competition. Given their assumption about utility, operator 1 can compute their own utility U_{ij}^{1} for each OD pair and deduce the ones of the competing alternatives based on the observed market shares. Assuming a Logit function, the utility of a competing alternative h is determined as follows:

$$\hat{U}_{ij}^{h} = U_{ij}^{1} + \ln(D_{ij}^{h}/D_{ij}^{1}) \tag{4.1}$$

where D_{ij}^{1} is the demand assigned to the operator 1 and D_{ij}^{h} the demand of the competing alternative. Operator 1 then solves the CD-SNDP again, using these updated utility functions[1]. The demand response is then simulated again and operator 2 can now update their decisions following the same procedure.

4.3 Results

We consider two different vessel types: "small" vessels with a capacity of 180 TEUs and big vessels with a capacity of 300 TEUs. The transport demand inputs are based on the NOVIMOVE project (Majoor et al., 2021), whereas the costs and times are estimated using a previously published model (Shobayo et al., 2021).

To verify and validate this competition model, we apply it on the Rotterdam-Duisburg stretch. We examine the influence of the starting assumptions $\hat{p}$ and $\hat{f}$ on the overall results assuming a fixed fleet of 24 small vessels and 18 big vessels for both

[1] If D_{ij}^{1} represents 95% or more of the operator's capacity and $D_{ij}^{h} > D_{ij}^{1}$, the utility function is then not updated. This is to avoid that the operator overestimates their competitor's utility due to the lack of capacity.

operators. Then, we fix $\hat{p}$ and $\hat{f}$ to realistic market values and study the influence of the level of information, the fleet and vessel sizes on the results.

4.3.1 Influence of starting assumptions

The competition model is run multiple times on the Rotterdam-Duisburg stretch using all the combinations of the following starting frequencies $\hat{f} \in [5, 20, 35]$ and prices $\hat{p} \in [30, 60, 90, 120, 150, 180, 210, 240, 270, 300]$. The outcomes of the model are presented in Table 4.1. It contains the following elements:

- The relative difference of profits reached by the two competing operators;
- The resulting prices set by each operator;
- The resulting service frequencies of each operator;
- The total share of IWT (both operators combined) on the studied stretch.

Among all combinations, only one ends up in no IWT services being generated. This happens when $\hat{f}$ is maximal and $\hat{p}$ is minimal: the optimal solution of the CD-SNDP for both operators is to not serve the OD pair, as running services is not profitable. This is because the costs incurred by running high frequency services are high and the prices they assume for their competitor are so low that they cannot align.

For the remaining combinations, the optimal frequency for both operators is always set to the maximum. Moreover, the profit outcomes are always positive, which means that the first player in the Nash game has the advantage. This is because they can make their own decisions (in particular, they are systematically able to charge prices that are slightly higher than their competitor), whereas the second player has to react to the decisions of the first player.

Around the market values of $\hat{f}$ and $\hat{p}$, the resulting profits are more or less balanced between the two operators, as indicated by the profit outcome close to zero. Moreover, for a given $\hat{p}$, the final prices tend to increase as $\hat{f}$ decreases. Indeed, due to the lower value of $\hat{f}$, the operators will assume that their competitor's utility $\hat{U}(\hat{p}, \hat{f})$ is also low. They can then afford to decrease their own utility by setting higher prices and with that, generating more profits. However, for a higher value of $\hat{f}$, the value of $\hat{U}(\hat{p}, \hat{f})$ is also high: the operators will then have less margin to increase their prices and the final prices are then lower. This last situation (high frequencies and low prices) is the most favorable for the attractiveness of the IWT sector, as the modal share of IWT reaches a higher value than for a low value of $\hat{f}$.

Table 4.1: Summary of results of the competition model under different starting assumptions, with profit outcomes : $(\Pi^1 - \Pi^2)/\max(\Pi^1, \Pi^2)$ *and results with realistic market values highlighted in grey.*

		$\hat{p}$ 30	60	90	120	150	180	210	240	270	300
		Profit outcomes									
	5	0.05	0.04	0.03	1	1	1	1	1	1	1
$\hat{f}$	20	0.09	0.05	0.05	0.05	0.03	1	1	1	1	1
	35	-	0.21	0.09	0.05	0.05	0.05	0.03	1	1	1
		Final prices (Operator 1\Operator 2)									
	5	133\130	146\143	134\130	286\0	283\0	284\0	284\0	284\0	284\0	284\0
$\hat{f}$	20	100\97	127\125	138\135	137\134	134\130	288\0	284\0	284\0	284\0	284\0
	35	-\-	80\78	100\97	127\125	138\135	137\134	134\130	288\0	284\0	284\0
		Final frequencies (Operator 1\Operator 2)									
	5	35\35	35\35	35\35	35\0	35\0	35\0	35\0	35\0	35\0	35\0
$\hat{f}$	20	35\35	35\35	35\35	35\35	35\35	35\0	35\0	35\0	35\0	35\0
	35	-\-	35\35	35\35	35\35	35\35	35\35	35\35	35\0	35\0	35\0
		Final IWT share									
	5	68%	66%	66%	28%	28%	28%	28%	28%	28%	28%
$\hat{f}$	20	75%	68%	67%	68%	66%	28%	28%	28%	28%	28%
	35	0%	79%	75%	68%	67%	68%	66%	28%	28%	28%

When $\hat{p}$ exceeds a certain threshold, the profit outcome becomes 1. This means that the first operator bankrupts the other. Indeed, as $\hat{p}$ gets higher, the first operator uses an aggressive competition strategy consisting in massively decreasing their price to attract a lot of demand. The second operator then has to retaliate by lowering their price even further, and this goes on until the second operator cannot follow anymore and drops out of the market. The value of $\hat{p}$ from where this starts happening increases with $\hat{f}$. The reason is that, as explained above, the price levels are generally lower when $\hat{f}$ is high. Lower price levels then prevent an aggressive price competition to happen.

When the second operator drops out of the market, operator 1 has a monopoly situation in the IWT sector and can then set much higher prices. This has a very detrimental effect on the modal share of IWT as it goes from around 70% when both operators are present to 28% in the monopoly situation.

4.3.2 Influence of fleet sizes

The starting assumptions are now fixed to $\hat{f} = 20$ and $\hat{p} = 60$ for both operators. The competition model is run multiple times on the Rotterdam-Duisburg stretch with the following fleet sizes: 14 (8 small vessels + 6 big vessels), 28 (16 + 12), and 42 (24 + 18). The outcomes of the model are presented in Table 4.2.

Table 4.2: Summary of results of the competition model with various fleet sizes, with profit outcomes : $(\Pi^1 - \Pi^2)/\max(\Pi^1, \Pi^2)$.

		IWT operator 2: 14	28	42
Profit outcomes				
IWT operator 1	14	0.00	-1	-1
	28	1	0.07	-0.05
	42	1.08	0.31	0.05
Final prices				
IWT operator 1	14	42\42	0\171	0\189
	28	185\0	106\102	130\148
	42	165\31	101\80	134\131
Final frequencies				
IWT operator 1	14	14\14	0\28	0\35
	28	28\0	28\28	28\35
	42	35\14	35\28	35\35
Final IWT share				
IWT operator 1	14	65%	42%	42%
	28	40%	70%	64%
	42	65%	74%	67%

The profit outcomes show that the operator with the smallest fleet has a disadvantage. This occurs because they cannot provide high frequency services: to remain competitive, they thus have to lower their prices to attract more demand until they make losses. In fact, the operator with 14 vessels almost always go bankrupt when their competitor has a larger fleet. Then, in this monopoly situation, the prices are again higher and the IWT market share diminishes.

When operator 1 has 42 vessels and operator 2 has 14 vessels, the first operator sets high prices. When solving the CD-SNDP, the second operator assumes that they can attract a large share of the demand by setting very low prices and that it is then still profitable to serve the OD pair. However, the simulation of shippers reveals that it would result in losses (i.e. $\Pi^2 < 0$): that is why the profit outcome is greater than 1 in this case.

When both operators have equal fleet sizes, the first player reaches higher profits than the second as the profit outcomes are positive. Even in the case of one operator having 28 vessels and the other 42 vessels: when the first player has the larger fleet, they achieve a much greater difference in profit (0.31) than the second does with the larger fleet (0.05). This highlights once again the advantage of playing first.

4.3.3 Influence of vessel sizes

In this setting, the starting assumptions remain $\hat{f} = 20$ and $\hat{p} = 60$ for both operators and their fleet sizes are fixed to 36, but we vary the share of big vessels in the fleet of both operators. The competition model is run multiple times on the Rotterdam-Duisburg stretch with fleets made of 0%, 25%, 50%, 75% and 100% of big vessels. The outcomes of the model are presented in Table 4.3: interestingly, the final prices of operator 1, prices of operator 2, frequencies for both operators and IWT share are always respectively 134, 131, 35 and 67%. Therefore, Table 4.3 only reports the profit outcomes.

Since they set identical price and frequency, both operators attract the same volumes. However, it is more costly to run 35 weekly services with big than with small vessels. This is why the operator with the smallest share of big vessels always has the advantage and this advantage grows when the difference in shares between the two operators increases[2]. Again, the advantage is more pronounced for the first player than for the second one. Also with identical fleets, the first operator has a small advantage.

Table 4.3: Summary of the results of the competition model with various vessel sizes, with profit outcomes : $(\Pi^1 - \Pi^2)/\max(\Pi^1, \Pi^2)$.

		Big vessels operator 2				
		0%	25%	50%	75%	100%
		Profit outcomes				
Big vessels operator 1	0%	0.04	0.10	0.17	0.24	0.29
	25%	-0.01	0.05	0.13	0.20	0.25
	50%	-0.09	-0.04	0.05	0.13	0.19
	75%	-0.16	-0.11	-0.03	0.05	0.12
	100%	-0.21	-0.17	-0.09	-0.01	0.06

[2] It is worth noting that these results apply because the capacity of both operators is higher than the demand they can potentially attract. If their capacity was a limiting factor, then it would be more interesting to operate larger vessels.

4.3.4 Influence of information levels

The starting assumptions of this last setting are kept to $\hat{f} = 20$ and $\hat{p} = 60$ and the fleet sizes are 24 small vessels and 18 big vessels for both operators. However, we vary the level of information that each operator gets about their competitor. They can either have:

- *Limited information* about the prices and frequencies of the competitor and use Equation (4.1) to estimate their competitor's utility;
- *Full information* and compute their utility by directly plugging the prices and frequencies of the competition into the utility function.

The results of the model are presented in Table 4.4. When the operators have the same level of information, the equilibrium solution is very similar whether they both have limited or full information. This shows that the market shares are a good marker of a carrier's utility. However, when the information level is asymmetric, it reaches different equilibrium points with higher prices overall, which results in a decreased market share for IWT as a whole. In other words, the asymmetric information changes the dynamics of the game and reduces the overall performance of IWT.

In more details, when the first operator has full information but the second operator only limited information, the former is able to bankrupt the latter. With one less

Table 4.4: Summary of results of the competition model with various levels of information, with profit outcomes : $(\Pi^1 - \Pi^2)/\max(\Pi^1, \Pi^2)$.

		IWT operator 2: Limited	IWT operator 2: Full
		Profit outcomes	
IWT operator 1	Limited	0.05	0.05
	Full	1	0.06
		Final prices	
IWT operator 1	Limited	127\125	164\164
	Full	152\0	127\127
		Final frequencies	
IWT operator 1	Limited	35\35	35\35
	Full	35\0	35\35
		Final IWT share	
IWT operator 1	Limited	68%	61%
	Full	50%	68%

operator on the market, the IWT share is then at its lowest. In the opposite case, the full information of the second operator lead them to copy the optimal decisions of the first operator instead of competing. As a result, the game reaches a state of collusion, where both operators can set high prices and still be able to capture a significant share of the demand.

4.4 Conclusions

This chapter addresses RQ3 by introducing a competitive version of the Service Network Design and Pricing problem, which overcomes the main limitations of existing models. It extends our CD-SNDP by taking into account the reaction of operators to each other's services and prices. It also assumes that only limited information is available to the operators: in particular, they only know the market shares but not the exact choice model of the shippers, nor the prices set by the competition. These features contribute to making the model more realistic.

The proposed model is then applied to the Rotterdam-Duisburg stretch, which allows to spotlight the underlying mechanisms and verify the model. In particular, the results highlight the importance of being the first player as they have more decision power compared to the second player, which can only react. Results also show that the equilibrium solution highly depends on the assumptions that are made. For this reason, the assumptions of the model need to be carefully validated when scaling it up to a larger network.

This chapter completes the models' development sequence, which brought us from the demand model proposed in Chapter 2 to this competition model, passing through the supply model of Chapter 3. In the next chapter, the developed models are used to assess the impact of an innovation on the stakeholders in the intermodal transport system.

Chapter 5

Impact assessment of a modular mobile terminal concept

In the previous 3 chapters, models including the behaviors and interactions of actors in the intermodal transport system have been developed. So far, they have been applied to realistic logistics network under usual conditions. However, as explained in Chapter 1, the purpose of this thesis is to improve decision-making by evaluating the influence of policies or innovations on the main actors of the system. In this chapter, we study the impacts of a Modular Mobile Terminal (MMT) concept to improve the container handling for IWT in seaports. Firstly, we propose an optimization model to quantify the time savings that can be achieved with this innovation. The obtained savings, along with estimates of cost variations, are used as inputs for the choice-driven models developed in the previous chapters to further evaluate the MMT concept. This chapter then addresses RQ4: What insights does the consideration of actors and their behavior bring in the evaluation of an improvement measure?

This chapter is structured as follows: Section 5.1 describes the problem that MMTs aim to solve. A review of the related works is provided in Section 5.2, while Section 5.3 describes the MMT concept. The assessment methodology is detailed in Section 5.4 and applied to a case study in Section 5.5. The choice-driven models developed in the previous chapters are applied in Section 5.6 and some conclusions are finally proposed in Section 5.7.

Parts of this chapter have been published as a journal article: Nicolet, Shobayo, van Hassel, & Atasoy (2023) “An assessment methodology for a modular terminal concept for container barging in seaports”, *Case Studies on Transport Policy*, 14: 101103.

5.1 Introduction

Over the years, inland waterway transport (IWT) has significantly contributed to container seaport performance. This is due to the emergence of container transport on water, which brings about efficient accessibility to different hinterland regions. Moreover, this transport mode offers a more sustainable and cost-efficient method of accessing the hinterland and generates higher economies of scale than other transport modes. Given this, it has become more attractive to shippers as it is a better alternative to road transport, especially when a large volume of containers is involved.

Nevertheless, this transport mode still faces different challenges affecting its competitiveness, particularly the high waiting times experienced by container barges in seaports. These can be linked to two main issues: containers spread over several terminals and the low priority of barges at the terminals. Containers are often not bundled but thinly spread over several seaport terminals, thereby leading to inland vessels having to call at several terminals, at times even between six to eight, to collect a few containers at each call. Each of these calls often takes hours before the barges are handled. This is due to the low priority of container barges at each terminal. Since seagoing vessels are prioritized at terminals, inland vessels must wait for available wharf and crane facilities, with waiting time at and sailing between terminals adding up to 60 percent of the total time spent in port (Port of Rotterdam, 2019). Waiting for a slot at large container terminals can quickly increase to one or even several days (van Hassel et al., 2021).

This research examines how to eliminate the identified inefficiencies by reducing port sailing and waiting times for barges without expensive modifications to port infrastructures. To achieve this, a concept named Modular Mobile Terminal (MMT) is proposed, and an assessment methodology is developed to evaluate its potential operational efficiency. Providing a consolidation and distribution station is expected to eliminate the need for the inland container vessels to call at multiple terminals, thereby reducing the waiting times. It is also expected that consolidation will increase the attractiveness of the seaport (Fan et al., 2019). The consolidation and distribution station could be placed on the land. But considering the intensive land use in most ports, developing a floating terminal concept could bridge this gap. The MMT will be the interface where an Inland Waterway Vessel (IWV) can deliver and collect containers to and from the seaport terminals.

This particular Modular Mobile Terminal solution has not been studied before, thus this study constitutes a proof-of-concept and lays the first foundations for assessing the potential of MMTs. Because this innovation is still at an early stage, this work does not claim to provide a business model. Instead, assuming that there exists an independent operator for the MMTs that will charge its services to IWT carriers, the study provides insights into what configuration of the system needs to be investigated further to generate a positive business case based on a holistic assessment framework.

To answer this question, an optimization model is first conceived to determine the number of MMTs generating the most time savings and the target cargo flows. Then, the 3 models developed in the previous chapters are applied to this case study to examine the concept's impacts on actors of the IWT sector.

5.2 Related work

Since the early 2000s, concerns have been raised about substantial delays for container barges in deep-sea ports. In 2004 already, IWT operators experienced up to 60 hours of delays in the seaports of Antwerp and Rotterdam (Vernimmen et al., 2007). The situation has not improved in 2021 since operators reported up to 120 hours of average waiting time in the port of Rotterdam (Contargo GmbH & Co, 2021). Two main issues cause these (van der Horst & de Langen, 2008): the numerous calls of small size and the lack of contractual relationships with terminal operators. Due to the small volume of containers per call, inland barges must call at multiple terminals (typically 6 to 8) to be fully (un)loaded (Ramos et al., 2020). Moreover, terminals prioritize sea-going vessels over inland vessels (Wiegmans, 2005), which must wait for an available berth and crane facility. As a result, the waiting and sailing times of IWVs in the port exceed by far their handling time (Gumuskaya et al., 2020).

Several models have been developed to achieve more efficient IWT operations in the seaport. The barge rotation planning can either be performed by a centralized entity (Li et al., 2017) or within a distributed setting (Douma et al., 2009). Moreover, disruptions (Tong & Nachtmann, 2017) and uncertainties (Gumuskaya et al., 2021) are also included in the models to obtain more robust solutions.

van der Horst & de Langen (2008) report different cooperation mechanisms set up at the ports of Rotterdam and Antwerp and their hinterland to alleviate the existing bottlenecks. It consists of alliances of IWT operators, but they also outline agreements between the barge and terminal operators about time window allocation. Companies can also broaden their scope of services, such as the Extended Gate Model developed by terminal operators or shipping lines. Finally, new concepts, such as a feeder barge equipped with a crane to pick up and deliver containers at a regional scale, are also proposed.

Besides solutions based on information and communication technologies, the Rotterdam port authority also developed infrastructure-based strategies, such as the "container transferium" (Konings et al., 2010). It serves as a consolidation point for cargo coming from the hinterland and going to the port and vice versa. It is suggested that the location of this facility should be in the direct hinterland of Rotterdam. Although its main goal is to serve trucks to decrease congestion on the port's highways, it can also be used by inland shipping. The transport between the transferium and the sea terminals is then assured by shuttle barges. These shuttles would have dedicated quays at sea terminals. They could perform a round trip (visiting all sea terminals) or be assigned to a specific terminal (Froeling et al., 2008). More recently, a Transport and Logistics floating hub not located in the hinterland but at sea was proposed within the Space@Sea project. The feasibility of the concept was assessed by simulating sea-going inland vessels calling at this offshore hub and feeder vessels linking the hub to the sea terminals. It was found that the concept was economically feasible if inland vessels directly go to the hub without stopping at the sea terminals (Assbrock et al., 2020).

Konings (2007) proposed several operational solutions to reorganize container barge services in deep-sea ports to improve the attractiveness of IWT. The main idea was to reduce the number of calls for inland barges by collecting cargo at terminals with dedicated feeder vessels and redistributing it to specific locations. Three potential solutions were investigated: containers of all terminals are grouped at a unique location; containers of "small call-size" terminals are grouped at a location, and inland barges visit "large call-size" terminals themselves; containers of "small call-size" terminals are grouped at "large call-size" terminals that are then visited by inland barges. The author concluded that the second solution was the most promising (even though the third option was slightly more cost-efficient) as it offers a dedicated location for inland barges. It is also underlined that board-to-board transshipment would significantly improve the efficiency of these systems.

This hub-and-spoke idea was developed further for the hinterland of the port of Rotterdam (Konings et al., 2013). Three potential locations are selected at distances from the seaport ranging from 40km to 135km. The authors then compute the potential cost savings for inland vessels of different capacities under three distinct configurations of the feeder barges. The results show that the hub-and-spoke is more beneficial for small hinterland vessels. They also reveal that a greater distance between the hub and the seaport generates more economies of scale. The authors mention that push barges can be used to shuttle between the hub and the seaport because they can serve as floating stacks. The potential of a floating crane is also suggested but not further investigated.

A thorough technical evaluation of the so-called Floating Container Storage & Transshipment Terminal is proposed by (Baird & Rother, 2013). The authors state that the most promising configuration is to fit a crane on a converted container ship. They argue that this concept is technically feasible in a low-wave sheltered environment and that the investment can be covered in much less time than a conventional on-shore terminal.

Malchow (2020) takes the floating crane concept and proposes a Port Feeder Barge for inter-terminal transfers in deep-sea ports. It consists of a self-propelled container barge equipped with a mounted crane. Besides intra-port operations, the author suggests that the Port Feeder Barge can also be used as a floating terminal for inland vessels. The Port Feeder Barge would perform a round trip a day throughout the port to shuttle containers between the various container handling facilities. It can also meet with hinterland barges somewhere at the dolphins to exchange containers. In the course of its daily round voyage, it can collect/deliver the hinterland containers from/among the ocean terminals. Compared to additional land-based facilities, the solution offers advantages regarding implementation costs, simplicity, and environmental impacts. The author nevertheless points out that the defiance of terminal operators represents a significant obstacle as they are reluctant to delegate container handling operations to external actors.

In that sense, the proposed MMT offers a good compromise as the crane module is situated separately, thus not directly interacting with the deep-sea terminals. Containers are stacked on modules that are then conveyed to dedicated terminals that keep the crane handling operations from the modules to the yard. In addition to the evident advantages for IWT operators, this concept allows terminal operators to plan their operations more effectively, as incoming cargo will already be consolidated. Furthermore, with dedicated shuttles, a fixed and regular timeslot can be agreed upon with the terminal. Based on this, the chance of missing the call is much lower than with inland vessels visiting multiple terminals. For these reasons, MMTs would lead to a win-win situation, which is essential to get the commitment of all stakeholders (Caris et al., 2011).

Regarding methodology, the existing works have used several means to assess the efficiency of the proposed solution. Some present a cost-benefit analysis to evaluate the economic possibility of the concept (Konings, 2007; Konings et al., 2013), while others make use of simulations to assess the concept's operational feasibility (Assbrock et al., 2020; Froeling et al., 2008). The other studies mainly focus on the technical components (Baird & Rother, 2013), discuss the offered possibilities and managerial insights without numerical results (Konings et al., 2010), or combine these two approaches (Malchow, 2020).

This work contributes to the body of knowledge through a unified methodology combining technical, operational, and economic aspects. Indeed, an optimization model is proposed to determine which configuration to adopt for the Modular Mobile Terminals and which market to target to generate the highest time savings under some operational constraints. The results are then used in a net benefit analysis to determine the economic feasibility of the MMT concept and financial gains for both the IWT operators and the shippers. The methodology used for this economic analysis is presented in detail in the research article of Nicolet, Shobayo, van Hassel, & Atasoy (2023) and in the thesis of Shobayo (2023). Finally, the potential impacts on the IWT operators and the shippers are estimated through choice-driven methods.

5.3 Concept description

This section presents the most important aspects of the proposed Modular Mobile Terminal concept. For more detailed information, the reader is referred to technical reports of Ramne et al. (2021) and Thill et al. (2022).

The MMT proposed in this study is made up of modules. The modules are configured as a dumb barge that can either be pushed or towed between the mobile terminal handling area and the sea terminals. The MMT modules will be operated in the seaport area and have no reason to move upstream and pass narrow locks. Based on the aforementioned technical reports, the dimensions of the modules are 17m in width and 55m in length. Moreover, a cargo capacity of 138 Twenty-Foot Equivalent Units (TEUs) per module is specified for this concept.

As depicted in Figure 5.1, a Modular Mobile Terminal is composed of 4 modules coupled to a central module with a mounted crane. It is estimated that the crane will make up to 20 container moves per hour. When assembled into a Modular Mobile Terminal, all the modules will have a mooring system that will create a rigid connection between the barges. This rigid connection will increase the stability of the coupled units providing less heeling movements during cargo handling.

The envisaged operation of the system is that inland waterway vessels collect containers from the inland ports. The container cargoes have different destinations, i.e., different seaport terminals. When the IWV reaches the seaport, instead of calling at different terminals to drop and pick up containers as it is currently, the IWV will instead moor at the Export MMT (see Figure 5.2). The crane module will be the center point of the operation, unloading the IWV and distributing the cargo to the shuttle modules. Once the shuttle modules are sufficiently loaded, they are towed/pushed by a push boat to transport the containers to the specified seaport terminal. Each module

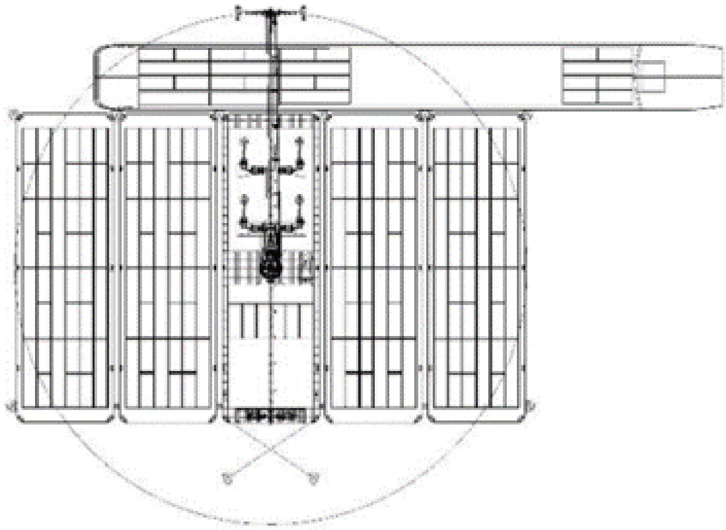

Figure 5.1: Modular Mobile Terminal in action (Thill et al., 2022).

will make a dedicated call to a single seaport terminal where the containers can finally be unloaded. The shuttle modules will also be used to transport import cargoes by transporting containers from the seaport terminal to the import MMT, where the modules are moored. At the import MMT, the crane module will transfer the cargo from the shuttle modules to an IWV for transport to the destination inland port, as shown in Figure 5.2.

As mentioned earlier, the technical feasibility of a floating crane has already been demonstrated in the Port Feeder Barge project. However, the economic factors were not detailed in-depth, and this project suffered from the defiance of terminal operators (Malchow, 2020). Based on this, the concept within the Port Feeder Barge project was not further pursued (Soyka, 2020). The MMT concept proposed in the present work is similar to the Port Feeder Barge. However, to prevent similar a setback, the potential benefits for the logistics actors are carefully highlighted in this study. In particular, this chapter aims to dive further into the logistical aspects of the modular terminal. The expected benefits of this innovation will be demonstrated via time optimization and choice-driven models. The final goal is to understand better this concept's advantages for the involved actors (IWT operators and shippers).

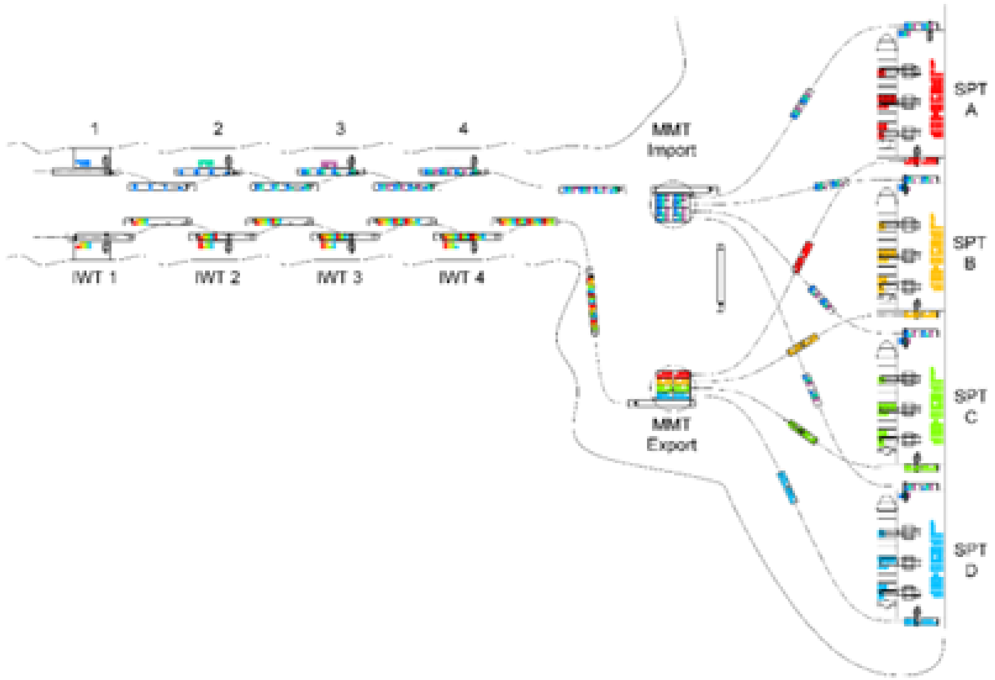

Figure 5.2: Envisaged operation of the MMT concept (Ramne et al., 2021). Although this illustration shows MMTs operating at separate locations, the import and export handling can be arranged at the same location.

5.4 Assessment methodology

The proposed methodology approaches the MMT concept from the time and cost perspective. The MMTs should generate time savings for inland waterway vessels sailing between the deep-sea terminals and the hinterland to be effective. They must also be economically viable for the IWT operators and the shippers. Figure 5.3 shows the main steps of the assessment methodology: firstly, an optimization model computes the number of MMTs, frequency of shuttles, and linked regions that maximize the overall time savings of the vessels. The outputs of this model are then used to compute the related costs and net benefits of using the MMTs, following the procedure described in Nicolet, Shobayo, van Hassel, & Atasoy (2023). Finally, the obtained time savings and net benefits of the IWT stakeholders are inputted into the 3 models developed in the previous chapters to further evaluate the MMT concept.

The following subsections present the modeling of the MMT concept and its operations and introduce the time savings optimization model. The economic analysis

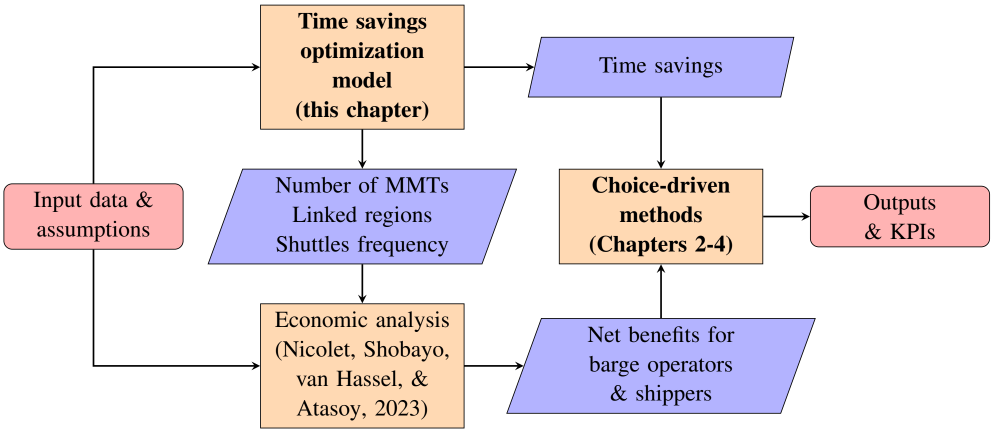

Figure 5.3: Proposed assessment methodology (in bold: the processes that are described in this thesis).

and the choice-driven methods will not be described here: the former is extensively described in the aforementioned reference, whereas the models composing the latter have been presented in the previous chapters.

5.4.1 Modular terminals operations

The MMT concept is applied to a seaport environment, denoted S, and its hinterland. The former is represented as a set of sea terminals I and the latter as a set of regions R. Each region has a given container transport demand via IWT to and from the seaport and some IWT services to satisfy it. Each IWV performs a roundtrip between a given region and the seaport. In the seaport area, it has to sail between multiple sea terminals to load and unload containers.

We consider that the MMTs, denoted $\mathcal{M}$, are located near the seaport area and linked to some of the hinterland regions: then, all inland vessels to and from these regions are handled by the MMTs. For regions not linked to the MMTs, the operations of each IWV does not change compared to the base case. However, the vessels serving the linked regions no longer call at the sea terminals but only at the MMTs. Each MMT module can be detached to be transported to a specific sea terminal using a push barge[1]. This concept is illustrated, together with the base case, in Figure 5.4.

Based on Figure 5.2, the MMTs will operate in pairs: one export MMT and one import MMT. Moreover, each module of an MMT is associated with only one spe-

[1]Since each module is dedicated to a single sea terminal, a fixed and regular timeslot can then be agreed upon with the terminal. It is thus assumed that shuttles will experience no waiting time.

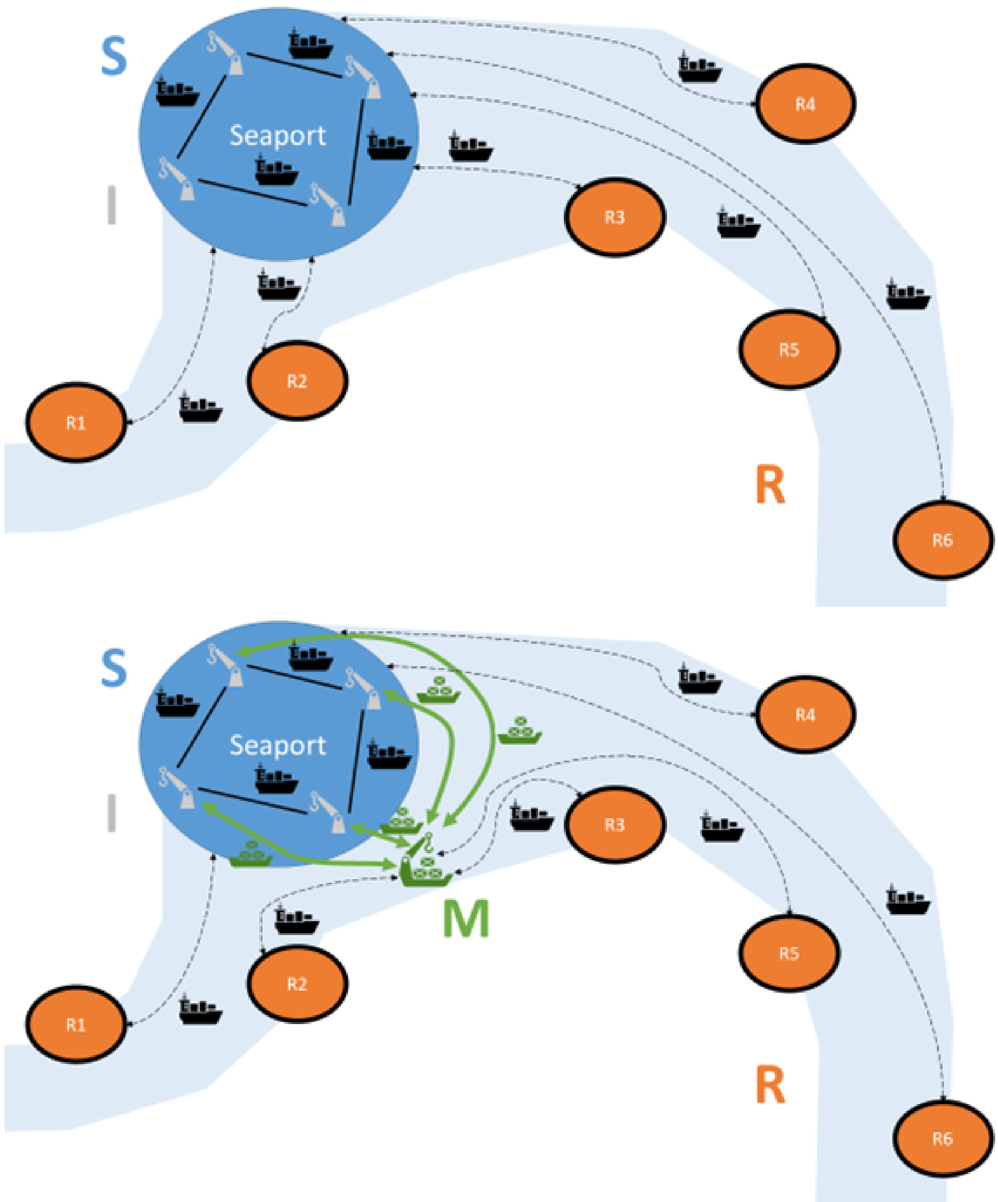

Figure 5.4: Schematic representation of base case scenario (up) and situation with MMTs where regions 2,3,5 are linked (down). The inland vessels serving these regions will no longer call at sea terminals but only at MMTs. There, containers are loaded on barge modules to be shuttled to a dedicated sea terminal (green arrows).

cific sea terminal. The IWVs from the hinterland will first moor at the export MMT to unload their containers. When empty, they can moor to the import MMT, where containers from the seaport to the hinterland can be loaded. Finally, they will unmoor to sail back to the hinterland.

Regarding the shuttles, once a module of the export MMT is full, it is detached and shuttled to its dedicated sea terminal, where the containers are unloaded. Then containers with a destination to the hinterland are loaded, and the module is shuttled back to the import MMT, replacing an empty module. Finally, the empty module is returned and attached to the export MMT.

5.4.2 Time savings optimization

The potential time savings achieved through MMTs are evaluated using a dynamic optimization model to determine which regions should be linked to the MMTs to minimize the total time of all barges in the system. The parameters and decision variables used in the model are presented in Table 5.1. Due to the dynamicity, the variables and some parameters are time-dependent: we thus introduce the index $k \in K = [1, 12]$ to represent the monthly variations.

The objective of the dynamic model is to minimize the total time spent by all barges during a year in the system depicted in Figure 5.4. It is expressed as a sum of several components over twelve months. The first one is the sailing time of IWV between the hinterland and the seaport area:

$$T_k^R = \sum_{r \in R} F_{rk}(t_{rS} + t_{Sr}) \tag{5.1}$$

The three following components are related to the seaport: the service time at terminals $T_k^{S,\text{serve}}$, the time spent waiting to be served at deep-sea terminals for IWVs $T_k^{S,\text{wait}}$ and the time spent by IWVs sailing between deep-sea terminals $T_k^{S,\text{sail}}$:

$$T_k^{S,\text{serve}} = \sum_{r \in R} \sum_{i \in I} t_i^{\text{hand}}(D_{rik} + D_{irk}) \tag{5.2}$$

$$T_k^{S,\text{wait}} = \sum_{i \in I} t_{ik}^{\text{wait}} \sum_{r \in R} (1 - y_{rk}) F_{rk} \tag{5.3}$$

$$T_k^{S,\text{sail}} = \sum_{r \in R} F_{rk} t_S^{\text{sail}} (1 - y_{rk}) |I| \tag{5.4}$$

Table 5.1: Time parameters and decision variables.

Notation	Unit	Description
		Parameters
$\lvert I \rvert$	-	Number of deep-sea terminals in set I
t_i^{hand}	hr/TEU	Handling time at deep-sea terminal i per container
t_S^{sail}	hr	Average sailing time between two sea terminals, incl. maneuverings
t_{ik}^{wait}	hr	Waiting time at deep-sea terminal i for an inland vessel for month k
F_{rk}	-	Number of services between seaport and region r during month k
D_{irk}	TEUs	Transport demand between sea terminal i and region r for month k
D_{rik}	TEUs	Transport demand between region r and sea terminal i for month k
t_{Sr}	hr	Sailing time between seaport area and hinterland region r
t_{rS}	hr	Sailing time between hinterland region r and seaport area
Q	TEUs	Capacity of a MMT module
$t_{\mathcal{M}}^{\text{wait}}$	hr	Waiting time at MMT for an inland vessel
$t_{\mathcal{M}}^{\text{hand}}$	hr/TEU	Handling time at MMT per container
$t_{\mathcal{M}S}^{\text{sail}}$	hr	Sailing time between MMT and seaport area, incl. maneuverings
$t_{\mathcal{M}\mathcal{M}}^{\text{man}}$	hr	Maneuvering time between import and export MMT
$N^{\max}$	-	Maximum number of MMTs allowed in the seaport area
$H^{\max}$	hr	Maximal monthly time of operations for a MMT
		Variables
$x_k^{\text{in}} \in \mathbb{N}$	-	Number of import MMTs operated during month k
$x_k^{\text{ex}} \in \mathbb{N}$	-	Number of export MMTs operated during month k
$y_{rk} \in \{0,1\}$	-	Whether region r is linked to MMTs for month k
$z_{ik} \in \mathbb{N}$	-	Total number of shuttles between MMTs and terminal i for month k

Four additional terms relate to the MMTs: the time for inland vessels being served by MMT $T_k^{\mathcal{M},\text{serve}}$, the waiting time at MMT for inland vessels $T_k^{\mathcal{M},\text{wait}}$, the sailing time of shuttles between MMT and the seaport area $T_k^{\mathcal{M},\text{sail}}$ and the maneuvering time between import MMT and export MMT $T_k^{\mathcal{M}\mathcal{M}}$:

$$T_k^{\mathcal{M},\text{serve}} = t_{\mathcal{M}}^{\text{hand}} \sum_{r\in R}\sum_{i\in I} y_{rk}(D_{rik} + D_{irk}) \tag{5.5}$$

$$T_k^{\mathcal{M},\text{wait}} = 2t_{\mathcal{M}}^{\text{wait}} \sum_{r\in R} y_{rk}F_{rk} \tag{5.6}$$

$$T_k^{\mathcal{M},\text{sail}} = 2t_{\mathcal{M}S}^{\text{sail}} \sum_{i\in I} z_{ik} \tag{5.7}$$

$$T_k^{\mathcal{M}\mathcal{M}} = t_{\mathcal{M}\mathcal{M}}^{\text{man}} \left(\sum_{r\in R} y_{rk}F_{rk} + \sum_{i\in I} z_{ik} \right) \tag{5.8}$$

The objective function of the dynamic model is, therefore[2]:

$$\min \Phi = \sum_{k\in K} T_k^R + T_k^{S,\text{serve}} + T_k^{S,\text{wait}} + T_k^{S,\text{sail}} + T_k^{\mathcal{M},\text{serve}} + T_k^{\mathcal{M},\text{wait}} + T_k^{\mathcal{M},\text{sail}} + T_k^{\mathcal{M}\mathcal{M}} \tag{5.9}$$

The time optimization model is subject to several constraints. The first ones limit the number of hours that each import and export MMT can operate per month. This is represented as:

$$\sum_{r\in R}\sum_{i\in I} y_{rk} D_{irk} t_{\mathcal{M}}^{\text{hand}} \leq H^{\max} x_k^{\text{in}} \qquad \forall k \in K \tag{5.10}$$

$$\sum_{r\in R}\sum_{i\in I} y_{rk} D_{rik} t_{\mathcal{M}}^{\text{hand}} \leq H^{\max} x_k^{\text{ex}} \qquad \forall k \in K \tag{5.11}$$

The second set of constraints imposes the required frequency of shuttles to a sea terminal i given import and export demand, respectively, and the capacity of a module. The shuttles' frequency will then be set in the direction with the most demand:

$$\sum_{r\in R} y_{rk} D_{irk} \leq Q z_{ik} \qquad \forall i \in I, \ \forall k \in K \tag{5.12}$$

$$\sum_{r\in R} y_{rk} D_{rik} \leq Q z_{ik} \qquad \forall i \in I, \ \forall k \in K \tag{5.13}$$

The third set of constraints ensures that the number of shuttles to terminal i is null if there are no regions linked to the MMTs (note that M_{ik} is a large enough positive number):

$$z_{ik} \leq M_{ik} \sum_{r\in R} y_{rk} \qquad \forall i \in I, \ \forall k \in K \tag{5.14}$$

[2]Here, it is assumed that all those time components are equally important. But some weights could also be applied in the objective function to give more or less importance to some components.

The fourth set of constraints determines how many import and export MMTs are needed to make the shuttles' frequency possible. It is assumed that only two modules per MMT per day can be shuttled to the sea terminals, whereas the other two remain at the MMT to hold the incoming/outgoing cargo. The number of MMTs should then equal the rounding up of the shuttles' frequency per day divided by two. The constraints are thus expressed as follows:

$$\frac{\sum_{i\in I} z_{ik}}{30}/2 \leq x_k^{\text{in}} \qquad \forall k \in K \tag{5.15}$$

$$\frac{\sum_{i\in I} z_{ik}}{30}/2+1 \geq x_k^{\text{in}} \qquad \forall k \in K \tag{5.16}$$

$$\frac{\sum_{i\in I} z_{ik}}{30}/2 \leq x_k^{\text{ex}} \qquad \forall k \in K \tag{5.17}$$

$$\frac{\sum_{i\in I} z_{ik}}{30}/2+1 \geq x_k^{\text{ex}} \qquad \forall k \in K \tag{5.18}$$

The final constraints prevent the total number of MMTs exceeds the maximal number allowed in the seaport area:

$$x_k^{\text{in}} + x_k^{\text{ex}} \leq N^{\max} \qquad \forall k \in K \tag{5.19}$$

As a point of comparison, we introduce the total time of the base case scenario, where no MMTs are used. It can be expressed as:

$$\Phi^{\text{base}} = \sum_{k\in K}\sum_{r\in R}\left(F_{rk}(t_{rS}+t_{Sr}) + \sum_{i\in I} t_i^{\text{hand}}(D_{rik}+D_{irk}) + F_{rk}\left(\sum_{i\in I} t_{ik}^{\text{wait}} + t_S^{\text{sail}}|I|\right)\right) \tag{5.20}$$

We also define Key Performance Indicators (KPIs) to evaluate the MMT concept's efficiency further. The first one is the total number of vessels N^{port} (IWVs and shuttles) sailing in the seaport during a whole year, which is calculated with:

$$N^{\text{port}} = \sum_{k\in K}\left(\sum_{r\in R}(1-y_{rk}^*)F_{rk} + \sum_{i\in I} z_{ik}^*\right) \tag{5.21}$$

where z_{ik}^* is the optimal value of z for terminal i at month k and y_{rk}^* the optimal value of y for region r at month k (note that for the base case, y_{rk}^* and z_{ik}^* will be set to zero as there are no MMTs involved). This KPI reflects the level of congestion for the IWVs in the port.

The second KPI is the time savings ΔT per inland waterway vessel linked to the MMTs:

$$\Delta T = \frac{\Phi^{\text{base}} - \Phi^*}{\sum_{k \in K} \sum_{r \in R} y^*_{rk} F_{rk}} \tag{5.22}$$

Finally, we report the average occupation rate $\bar{\rho}$ for the MMTs over a whole year. This indicator will show if the MMTs are used efficiently and is expressed as:

$$\bar{\rho} = \frac{1}{12} \sum_{k \in K} \frac{\sum_{r \in R} \sum_{i \in I} y^*_{rk} (D_{rik} + D_{irk})}{(x_k^{\text{in}*} + x_k^{\text{ex}*}) U^{\max}} \tag{5.23}$$

where $x_k^{\text{in}*}$ and $x_k^{\text{ex}*}$ are the optimal numbers of import and export MMTs at month k and $U^{\max}$ the maximal handling capacity of an MMT crane module during a month.

5.5 Case study

The proposed assessment methodology is applied to a case study, where the use of Modular Mobile Terminals is investigated for the ports of Rotterdam and Antwerp. For both seaports, it is assumed that each inland waterway vessel has to visit 4 sea terminals, where the handling capacity is 20 TEUs per hour (thus a handling time of 0.05hr/TEU). The waiting time of an IWV at each sea terminal is estimated at an average of 4 hours during each terminal visit (van Hassel et al., 2021) and sailing time between these sea terminals is set to 1 hour (including maneuverings).

The data concerning hinterland container transport (using waterways) are reported in the research article of Nicolet, Shobayo, van Hassel, & Atasoy (2023). In particular, it contains for each seaport:

- the yearly import and export demand to and from each hinterland region represented at the NUTS-2 level;
- the distance of each region from the seaport;
- the sailing time between each region and the seaport;
- the yearly number of inland waterway transport services between each region and the seaport;
- and the average number of containers per inland waterway service.

The container volume data come from the ASTRA model (Fiorello et al., 2010) for 2021. This demand is assumed to be split evenly between all the visited sea terminals. The distance is estimated by (van Hassel et al., 2019). The sailing times are issued from a cost and time model (Shobayo et al., 2021), whereas the data concerning IWT services come from the NOVIMOVE project (Majoor et al., 2021). Note that the number of monthly services is assumed constant and obtained by dividing the yearly services by twelve. Finally, the average number of containers per service is computed by dividing the volumes by the number of services.

Some seasonality factors are used to derive the monthly transport demand between each seaport and each region. They represent the share of the total demand in a given month and are estimated using historical data from container transport on the Rhine between 1993 and 2020 (Rhineforecast, 2021). Figure 5.5 shows the factors corresponding to a typical year and the ones corresponding to the year 2018, when a major drought occurred on the Rhine, thus disrupting transport via water with capacities of IWVs decreased from a factor 4 to 5 (van Dorsser et al., 2020). For a typical year, those factors remain relatively stable, varying between 7.6% and 9.1%. However, the interval is much broader for 2018 (between 5% and more than 10.5%), with a peak in demand in March but particularly a very low demand in the last quarter of the year due to the low water levels.

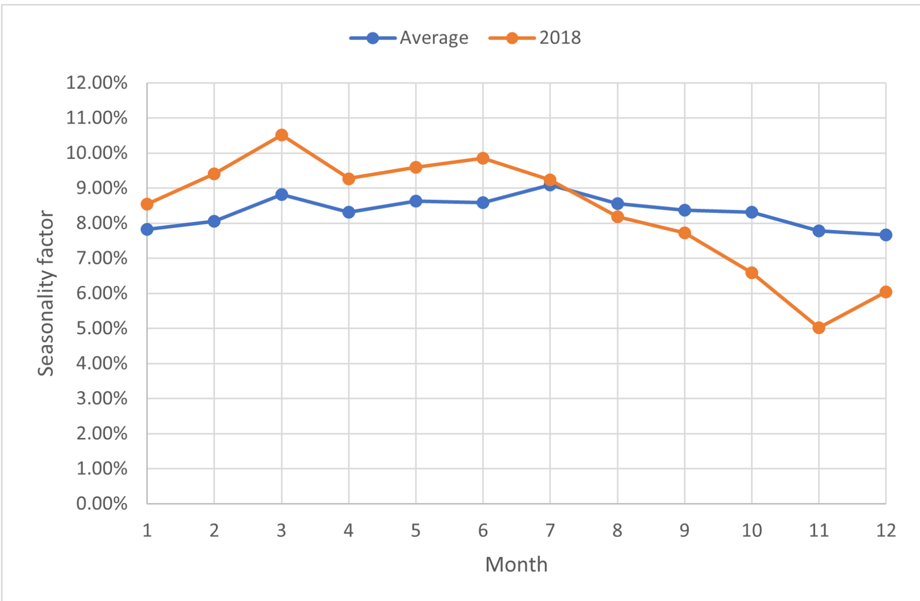

Figure 5.5: Seasonality factors for an average year and year 2018, with a high seasonality pattern (Rhineforecast, 2021).

Regarding the parameters related to the MMTs, each module has a capacity equal to 138 TEUs. The handling time of the crane module is set to 0.05hr/TEU, and its maximal handling capacity during a month to 10,000 TEUs. Each inland vessel is assumed to experience a waiting time of 1 hour before being handled both at the import and export MMTs. Moreover, a maneuvering time of 15 minutes between the import and export MMTs is considered. The maximum number of MMTs allowed in the seaport is 8 for both seaports, and the sailing time of shuttles between their sea terminal and the MMTs is estimated to be 1.65 hours for Rotterdam and 1.05 hours for Antwerp. These last figures are based on a preceding study that evaluated some locations potentially suitable for MMTs in these seaports (Freling et al., 2022).

Using the aforementioned inputs, the optimal configuration of MMTs will be determined for both seaports for a typical year and for a year with high seasonality to highlight the differences. In particular, for each month, the analysis determines the number of import and export terminals, the shuttles' frequency, and regions linked to the MMTs to minimize the total time spent by all vessels in the system. The KPIs corresponding to this optimal solution are also reported.

Notably, the optimal number of MMTs could vary from month to month to match the demand variations. Nevertheless, from a financial point of view, investing in an asset that will be underutilized or only be used for part of the year is not desirable. Hence, further computations are performed, where the number of MMTs is fixed throughout the year. This experience is conducted for 1, 2, 3, and 4 pairs of import-export MMTs to compare the performance of each configuration and evaluate the most favorable one.

In the following subsections, the optimal solution (with a variable number of MMTs through the year) in terms of time savings is first presented with the aforementioned KPIs. Then, the results with a fixed number of MMTs are described.

5.5.1 Optimal solution

The problem is solved with an exact method, using the commercial solver Gurobi. The main results of the dynamic time savings optimization for the ports of Rotterdam and Antwerp are shown in Table 5.2. Three cases are presented: the base case where no MMTs are deployed and two cases with MMTs (one typical year and one year with high seasonality).

In almost all cases, the number of mobile terminals is set to 8 (4 import and 4 export) for each month of the year. Only the case with high seasonality for Antwerp has some variations in the number of MMTs deployed per month, which results in an average number of active import and export MMTs of 3.5 through the year. That is why the average number of shuttles per month between the MMTs and each sea terminal

Table 5.2: Summary of results (value of objective function, average number of MMTs, average frequency to each deep-sea terminal, average number of linked regions).

	Rotterdam				Antwerp			
	Φ [hr]	$\bar{x}^{\text{in}} = \bar{x}^{\text{ex}}$	$\bar{z}$	$\bar{y}$	Φ [hr]	$\bar{x}^{\text{in}} = \bar{x}^{\text{ex}}$	$\bar{z}$	$\bar{y}$
Base case	888424	-	-	-	612959	-	-	-
MMTs	820163 (-7.7%)	4	60	7.7	581614 (-5.1%)	4	58	13.5
MMTs 2018	819227 (-7.8%)	4	56	8.4	579699 (-5.4%)	3.5	50	12.9

is only 50 in that case against around 60 for the other cases. These values represent between 14 and 15 shuttles per pair of modular terminals each month, thus a shuttle departure every two days. The average number of linked regions is noticeably higher for Antwerp than for Rotterdam. This is caused by the latter port having much greater cargo volumes per region.

For time savings, the MMTs significantly reduce the total time spent by all ships in the system: more than 7% for Rotterdam and 5% for Antwerp. This reduction becomes more pronounced if the time in the hinterland is not considered: Figure 5.6 shows how the total time is split between sailing, serving, and waiting in the seaport

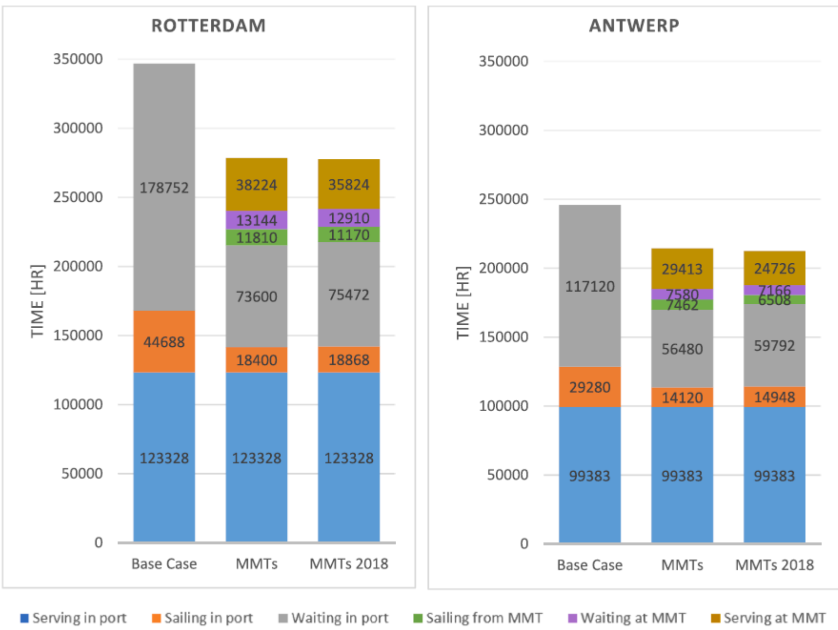

Figure 5.6: Detail of time spent in the seaport and at MMTs.

and at the MMTs. It appears that a considerable reduction in the waiting time at deep-sea terminals and the sailing time between them is achieved through using MMTs. This reduction is around 50% for Antwerp and almost 60% for Rotterdam. This allows for considerable time savings despite the additional time required to handle vessels at the MMTs and to sail to the sea terminals.

To better understand the choice driver of linking a region to the MMTs, Table 5.3 reports the hinterland regions of the port of Rotterdam together with the average number of TEUs per vessel sailing between them and Rotterdam. It also shows the yearly container volume, the yearly number of services, and the number of months each region is linked to the MMTs for the year 2018. When the regions are listed in ascending order of the number of TEUs per IWV, it becomes apparent that this factor influences the decision to link a region to the modular terminals. Regions having vessels with low volumes will be linked in priority to the MMTs, whereas regions with the highest volumes will never be linked. Although Table 5.3 only considers the port of Rotterdam and the year 2018, the same remarks also hold for the other cases.

Table 5.3: Considered regions of Rotterdam's hinterland with the average number of TEUs per vessel, the total container volume and number of services, and the number of months when the region is linked to MMTs for 2018.

Region	Average TEUs on IVWs	Yearly volume [TEUs]	Yearly number of services	Number of months linked to MMTs
DE13	28	4224	75	12
NL41	41	259597	3189	12
NL42	41	82342	1000	12
DE12	49	16213	163	12
NL22	61	80950	654	12
NL34	92	73676	400	9
NL32	108	215667	993	9
DEA2	123	59523	240	4
FRF1	131	38375	146	4
BE22	141	52766	189	4
DE11	146	4648	16	2
NL31	148	92839	312	3
DE71	159	50655	160	2
DEB1	166	19162	58	3
BE25	172	93117	270	1
DEA1	187	586647	1563	0
DEB3	197	221315	562	0
BE23	200	320989	800	0
CH03	243	193827	400	0

Table 5.4: Values of KPIs.

	Rotterdam			Antwerp		
	N^{port}	ΔT	$\bar{\rho}$	N^{port}	ΔT	$\bar{\rho}$
Base case	11172	-	-	7320	-	-
MMTs	7464	10.4 hr	76.9%	6302	8.3 hr	61.3%
MMTs 2018	7409	10.7 hr	74.6%	6125	9.3 hr	58.6%

The values of the KPIs are reported in Table 5.4. The significant time reduction achieved by the MMTs translates into substantial time savings for vessels linked to these terminals. They allow saving from 8 to 11 hours per vessel for each port visit. Moreover, the linked vessels will not visit the seaport anymore, resulting in fewer vessels in the ports despite the addition of shuttle barges between the MMTs and the sea terminals. There would be around 1,000 vessels less in the port of Antwerp and 3,700 in the port of Rotterdam per year, thus a diminution of 15% and 33%, respectively. This great reduction for Rotterdam is explained by the fact that there are a lot of services concerning the regions linked to the MMTs. For example, regions NL41 and NL42, which are always connected, represent 4,189 services: the number of IWVs in the seaport will decrease by the same amount. Finally, the average utilization rate of MMTs is around 60% for Antwerp and 75% for Rotterdam, but a decrease is observed for 2018 with high seasonality. This is because the demand is less stable throughout the year, and the MMTs will have less cargo to handle in the months of lower demand.

5.5.2 Fixed number of MMTs

We now discuss the results when the number of MMTs through the year is fixed: Table 5.5 displays the KPIs for the ports of Rotterdam and Antwerp.

For both seaports, the total time Φ is decreasing with an augmentation of the deployed MMTs. This is due to the waiting and sailing times of IWVs in the seaport diminishing as more vessels are linked to MMTs. However, it is accompanied by the increased time needed at MMTs to handle the vessels and the shuttles' frequency to the seaport. As a result, the marginal time savings become lower as the number of MMTs increases, as depicted in Figure 5.7. It also highlights the differences in magnitude between the two ports, with Rotterdam experiencing much greater time savings. There are also noticeable differences between Rotterdam and Antwerp for the other KPIs: the results will be described separately in the following paragraphs.

Table 5.5: Results with fixed number of MMTs.

	Rotterdam				Antwerp			
MMTs	**2**	**4**	**6**	**8**	**2**	**4**	**6**	**8**
Φ [hr]	870054	833009	823667	820163	587382	583907	582613	581581
ΔT	11.1	12.4	11.4	10.4	12.7	11.0	9.5	8.3
N^{port}	10231	8131	7620	7464	6032	6066	6163	6312
$\bar{\rho}$	70.8%	77.8%	78.4%	79.6%	69.8%	61.0%	59.7%	60.8%

Port of Rotterdam

Figure 5.7 shows that large time savings can still be achieved by installing 4 MMTs instead of 2. The configuration with 4 Modular Terminals also generates the most time reduction per vessel that is visiting MMTs. The time savings reach 12.4 hours per vessel per port visit, whereas they are below 12 hours for all the other configurations. This is because the total time decreases too slowly compared to the growth in the number of vessels linked to MMTs.

Regarding the number of vessels in the seaport, the same trend as for the marginal time savings appears: a great drop when passing from 2 to 4 MMTs, and then only a slight decrease. It indicates that a significant reduction of congestion in the port can be achieved with 4 MMTs instead of 2, with 2100 vessels less in the seaport per year (about 40 per week). The configuration with 4 MMTs also allows for more efficient

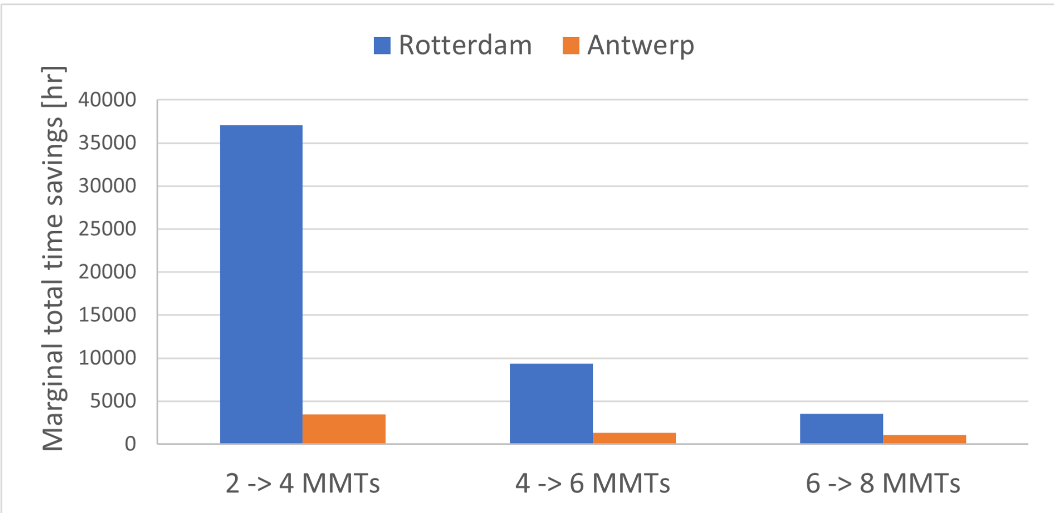

Figure 5.7: Marginal time savings by adding more MMTs for both seaports.

use of the installed capacity as the mean utilization rate rises by 7%. However, this figure grows from a minor amount when more than 4 MMTs are installed.

Overall, the results support that installing 4 Modular Terminals (2 for import and 2 for export) would provide the biggest benefits for the Port of Rotterdam. It would provide maximal time savings for inland vessels while significantly reducing the congestion in the port. Finally, having 4 MMTs installed would ensure that the MMTs are optimally utilized and always deployed at any time of the year.

Port of Antwerp

In the case of Antwerp, the time savings generated by installing more Modular Terminals are limited (see Figure 5.7). Also, the maximal time reduction per vessel happens when 2 MMTs are installed, with 12.7 hours.

For the other KPIs, the case with 2 MMTs is the most advantageous, as it has the lowest number of ships sailing in the seaport and the highest utilization rate. The former occurs because when more MMTs deployed, the number of additional vessels linked to them is lower than the number of additional shuttles needed to serve the sea terminals. Therefore, leading to increased ships in the port despite having fewer IWVs. The decreasing utilization rates are explained by the fact that volumes are less important than in the port of Rotterdam. Therefore the additional cargo passing through the added MMTs does not compensate for the increase in capacity.

For all these reasons, the deployment of 2 Modular Terminals (1 for import and 1 for export) is sufficient for the port of Antwerp. It is indeed the most favorable case for all the considered KPIs.

5.6 Choice-driven methods

The feasibility of the MMTs has now been demonstrated from a time savings perspective. We can then use the choice-driven models developed in the previous three chapters of this thesis to further assess this innovation. The content of this section is a quantitative analysis of the impact of MMTs on shippers and IWT operators, that complements the qualitative analysis proposed by Shobayo (2023). The idea is to use the aforementioned outputs in terms of time savings and the outputs from the economic analysis (Nicolet, Shobayo, van Hassel, & Atasoy, 2023) and input them in the choice-driven models of this thesis.

For this evaluation, we use the same 9-node network as in Chapter 3 (see: Figure 5.8). Therefore, the focus will be solely on the Port of Rotterdam. The results

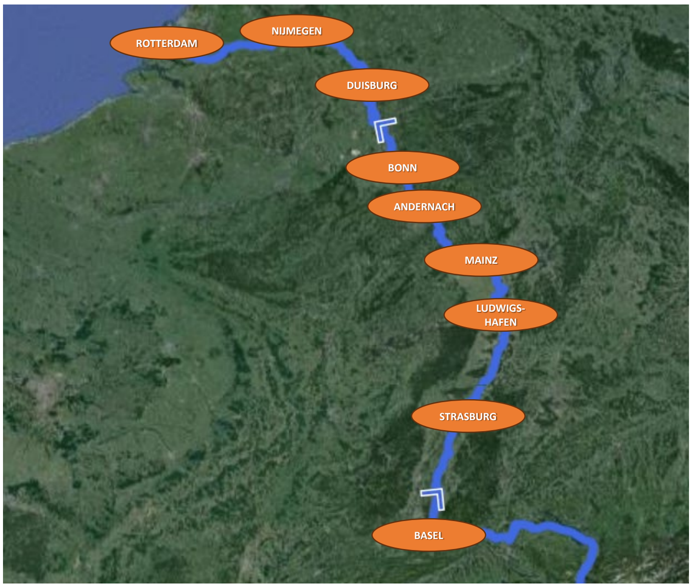

Figure 5.8: Network of the case study: the Rhine part of the RA corridor (Rivermap, 2024).

show that it is most profitable to install 4 MMTs. Moreover, 4 regions of the considered network are linked to the MMTs: they correspond to the terminals of Nijmegen (NIJ), Bonn (BON), Ludwigshafen (LUH) and Strasburg (SXB). The variation in time ($\Delta t^{\mathcal{M}}_{\text{IWT}}$) and costs ($\Delta c^{\mathcal{M}}$) resulting from the MMTs for these terminals are presented in Table 5.6 and will be inputted in the choice-driven models. It should be noted that linking the terminals of NIJ and BON to the MMTs is necessary, even though it ends up in additional costs. Indeed, the transported containers coming from (or going to) these terminals add up to the containers from/to LUH and SXB. This generates some consolidation effect, which allows for some cost savings for the latter two terminals and time savings for vessels from/to the 4 considered terminals.

Table 5.6: Time and cost variations engendered by MMTs for the Port of Rotterdam. The cost variations come directly from the published work of Nicolet, Shobayo, van Hassel, & Atasoy (2023).

RTM $\leftrightarrow$	**NIJ**	**BON**	**LUH**	**SXB**
Time variation $\Delta t^{\mathcal{M}}_{\text{IWT}}$ [hr]	-12.4	-12.4	-12.4	-12.4
Cost variation for IWT operators $\Delta c^{\mathcal{M}}_{\text{op}}$ [€/TEU]	+0	+9	-5	-23
Cost variation for shippers $\Delta c^{\mathcal{M}}_{\text{shipper}}$ [€/TEU]	+5	+13	+0	-18

5.6.1 Demand model

To estimate the impact of MMTs on the attractiveness of IWT for shippers, we make use of the Weighted Logit Model accounting for the Value of Time (VoT) that has been developed in Chapter 2. The deterministic utility functions for each mode on a given OD pair are expressed as follows:

$$V_{\text{IWT}} = \alpha_{\text{IWT}} + \beta_{c,\text{Inter}} \boldsymbol{c}^{\boldsymbol{\mathcal{M}}}_{\textbf{IWT}} + \beta_{a,\text{Inter}} a_{\text{IWT}} + \beta_{f,\text{Inter}} f_{\text{IWT}} + \beta_{p,\text{IWT}} p \tag{5.24}$$

$$V_{\text{Rail}} = \alpha_{\text{Rail}} + \beta_{c,\text{Inter}} (c_{\text{Rail}} + \text{VoT}\, t_{\text{Rail}}) + \beta_{a,\text{Inter}} a_{\text{Rail}} + \beta_{f,\text{Inter}} f_{\text{Rail}} \tag{5.25}$$

$$V_{\text{Road}} = \alpha_{\text{Road}} + \beta_{c,\text{Road}} (c_{\text{Road}} + \text{VoT}\, t_{\text{Road}}) + \beta_{a,\text{Road}} a_{\text{Road}} \tag{5.26}$$

where:

$$\boldsymbol{c}^{\boldsymbol{\mathcal{M}}}_{\textbf{IWT}} = c_{\text{IWT}} + \Delta c^{\mathcal{M}}_{\text{shipper}} + \text{VoT}(t_{\text{IWT}} + \Delta t^{\mathcal{M}}_{\text{IWT}}) \tag{5.27}$$

The values of the coefficients α and β are shown in Table 2.8 and the modal shares are computed following the method described in Chapter 2. We set $\Delta c^{\mathcal{M}}_{\text{shipper}}$ and $\Delta t^{\mathcal{M}}_{\text{IWT}}$ to zero for the case without MMTs, while they take the values displayed in Table 5.6 for the case with MMTs. The resulting shares for IWT in both cases are reported in Table 5.7.

The results show that the impact of MMTs on the demand varies between OD pairs. Logically, the increase in IWT share is the highest between RTM and SXB as both time and cost savings are achieved. On this OD pair, the share increases by more than 4%. Between LUH and RTM, no cost savings are generated: there are only time savings. Therefore, the increase in IWT share remains limited around 2.5%. For the last two OD pairs, the time savings are achieved at the expanse of an increase in costs. The changes in IWT share are thus very limited. Nevertheless, even with the higher costs, the share of IWT is not expected to decrease on the OD pairs linking NIJ and BON to RTM. This is due to the shorter distance between RTM and these two terminals compared to LUH and SXB. The relative importance of the time savings in $c^{\mathcal{M}}_{\text{IWT}}$ is then more important and they thus manage to balance the impact of the cost increase on the modal share.

Table 5.7: Share of IWT estimated with our demand model without and with MMTs.

		NIJ	**BON**	**LUH**	**SXB**	**all**
RTM → ...	without MMTs	26.5%	42.5%	62.7%	78.2%	49.1%
	with MMTs	26.8%	42.5%	65.4%	82.8%	49.4%
... → RTM	without MMTs	20.4%	37.7%	61.7%	79.6%	44.0%
	with MMTs	20.6%	37.7%	64.4%	83.9%	44.2%

Our demand model suggests that the MMT concept has the potential to make IWT more attractive to shippers on two of the four targeted OD pairs, while the share of IWT is predicted to remain stable on the remaining two OD pairs in spite of higher estimated costs. The MMT concept can then be considered as an advantage for the shippers as it allows to decrease IWT travel times with a limited impact on the costs. Finally, the last column of Table 5.7 consider all OD pairs of the network displayed in Figure 5.8: the results show that the impact of MMTs at the network level is limited. Indeed, since the MMTs act as a consolidation platform, the targeted OD pairs are the ones with low container volumes. The share gains at the network level are then limited to 0.25% since the OD pairs with high volumes that are not linked to MMTs attenuate the results.

This model gives some indications on the impact of MMTs on the shippers. However, it considers demand in isolation from supply. In particular, it does not capture the reaction of IWT operators to the new situation caused by the MMTs. Indeed, the operators may use the time savings to re-arrange their services. In the next section, a supply model is applied to estimate the impact of MMTs on an IWT operator.

5.6.2 Supply model

To estimate the impact of MMTs on the design and pricing of services, we make use of the Choice-Driven Service Network Design and Pricing developed in Chapter 3. The only difference compared to the 9-node network case presented in Section 3.4.5 is that the maximum operating time of vessels is set to 168 hours. For the case with MMTs, the travel time between Rotterdam and the terminals NIJ, BON, LUH and SXB is reduced by 12 hours and the value of $\Delta c_{\text{op}}^{\mathcal{M}}$ (shown in Table 5.6) is added to the variable costs of services between Rotterdam and these terminals. The results of the CD-SNDP using a deterministic choice model, without and with the MMTs are presented in Table 5.8.

To understand the impact of the MMTs on the IWT operator, one shall first look at the resulting services and the number of vessels assigned to them. The time savings achieved between RTM and LUH allow the operator to run more services between these two ports when MMTs are installed. With only 2 more vessels assigned, the operator can propose 4 additional services. As a result, the operator re-organizes their other services: they greatly reduce the frequency on the RTM-MAI-LUH service and stop serving RTM-DUI-LUH, as well as the last service in Table 5.8. The latter one is replaced by 3 other services passing through the same terminals. Moreover, the operator can now serve AND and almost double the frequency from RTM all the way towards BSL due to the additional flexibility provided by the MMTs.

Table 5.8: Solutions of CD-SNDP without and with MMTs, with expected values returned by the operator's optimization problem and realized values, which are obtained when the optimal services are proposed to the actual population of shippers through an out-of-sample simulation (see Section 3.4.2).

		Without MMTs	With MMTs
Realized profits (expected) [€]		288k (2551k)	275k (2643k)
Realized revenues (expected) [€]		1236k (3901k)	1252k (4012k)
Realized fixed costs (expected) [€]		678k (678k)	717k (717k)
Realized variable costs (expected) [€]		271k (672k)	260k (653k)
Overall realized market shares (incl. IWT competitor)		12.0% (37.7%)	12.2% (37.8%)
Realized market shares RTM↔LUH (incl. IWT competitor)		30.0% (74.9%)	30.0% (74.9%)
Realized market shares RTM↔SXB (incl. IWT competitor)		43.8% (86.6%)	44.1% (86.6%)
Prices [€/TEU]	RTM↔DUI	126	126
	RTM↔AND	-	86
	RTM↔MAI	162	150
	RTM↔LUH	231	231
	RTM↔SXB	128	124
	RTM↔BSL	141	165
	DUI↔LUH	43	35
	DUI↔BSL	70	78
Weekly frequencies (vessels)	RTM-DUI	18 (10)	20 (11)
	RTM-LUH	6 (5)	10 (7)
	RTM-DUI-LUH	5 (4)	-
	RTM-MAI-LUH	8 (7)	2 (2)
	RTM-LUH-BSL	4 (4)	6 (5)
	RTM-DUI-MAI-LUH	9 (8)	9 (8)
	RTM-LUH-SXB-BSL	-	2 (2)
	RTM-DUI-AND-MAI-LUH	-	1 (1)
	RTM-DUI-MAI-LUH-BSL	-	5 (6)
	RTM-DUI-MAI-LUH-SXB-BSL	3 (4)	-

The substantially higher frequency between RTM and BSL makes the operator's service more attractive to shippers, which allows the operator to increase the price by 24€/TEU. As shown in Table 3.7, the OD pair between RTM and BSL is among the ones with most demand. Therefore, the large price raise leads to increased revenues in spite of prices being lowered on other OD pairs (due to a decrease of the frequency). The expected rise in revenue returned by the optimization model reaches 100k€ (a growth of almost 3%), whereas the realized revenue only increases by 16k€ (approximately +1%)[3]. The 5€ decrease of costs per TEU between RTM and LUH also causes

[3]The large difference between the expected and realized values is caused by the limited information of the operator about their demand's preferences. Indeed, the operator assumes a deterministic choice

a drop in the total expected and realized variable costs for the operator. However, the additional services proposed when MMTs are installed lead to an increase of almost 40k€ in the fixed costs. In the optimization model of the operator, it is expected that the joint increase of revenues and decrease of variable costs would compensate for the higher fixed costs: the MMTs would then allow for more profits for the operator. However, the simulated results show that the increase of revenues due to the MMTs may not be sufficient to cover the higher fixed costs of the operator. That is why a decrease in the profits realized by the operator is observed.

Finally, the results show that the MMTs allow to slightly increase the market share of the operator. The overall increase of 0.2% is in line with the results of the demand model. However, when looking specifically at the OD pairs RTM↔LUH and RTM↔SXB, the realized increase in the operator's shares caused by the MMTs is quite far from what has been estimated by the demand model in the previous section (respectively 2.5% and 4%). This is because the demand model did not consider that IWT operators would modify their prices and services to take advantage of the time savings offered by the MMTs. This shows that the resulting impacts of an innovation can vary greatly depending on the viewpoint from which the analysis is carried. Contrary to the demand model, the supply model applied in this section also considers the shippers' response to the services and prices proposed by the operator. However, as mentioned in Chapter 4, this supply model also comes with its limitations. In the last section, we thus apply a competition model to get a more realistic estimation of the MMTs impact on the IWT system.

5.6.3 Competition model with supply-demand interactions

Using the competition framework developed in Chapter 4 will allow to get some insights on the impact of MMTs on the whole IWT sector. The competition model is applied to the same 9-node network, as in Figure 5.8, with the same parameters as in the previous section. We consider 2 IWT operators, which both have a fleet made of 24 small vessels and 18 big vessels. They also have identical assumptions about the price $\hat{p}_{ij}$ charged by the other operator and their frequency $\hat{f}_{ij}$ on each OD pair (i, j): these are set to realistic market values. It is finally assumed that both operators have limited information available and use Equation (4.1) to estimate their competitor's utility. The results of the competition model with supply-demand interactions without and with the MMTs are presented in Table 5.9.

model, whereas the shippers perform their mode choice according to a stochastic model. For more details, the reader is referred to Chapter 3.

Table 5.9: Solutions of competition model (IWT operator 1 | IWT operator 2) without and with MMTs.

		Without MMTs	With MMTs
Realized profits [€]		299k|308k	338k|347k
Realized revenues [€]		1086k|1096k	1086k|1095k
Realized fixed costs [€]		594k|594k	567k|567k
Realized variable costs [€]		194k|194k	181k|181k
Realized shares		11.0%|11.0%	10.9%|10.9%
Prices [€/TEU]	RTM↔DUI	122|123	122|123
	RTM↔MAI	214|212	173|171
	RTM↔LUH	200|202	220|222
	DUI↔MAI	6|9	0|5
	DUI↔LUH	58|56	25|28
	MAI↔LUH	-|-	-|-
Weekly frequencies	RTM-DUI	16|16	16|16
	RTM-LUH	-|-	10|10
	RTM-MAI-LUH	12|12	2|2
	RTM-DUI-MAI-LUH	19|19	19|19

With or without MMTs, the IWT operators concentrate their services between RTM and the terminals of DUI, MAI, and LUH. Nevertheless, the setting with MMTs makes the service RTM-LUH faster and thus more appealing to operators compared to the service RTM-MAI-LUH: they then decrease the weekly frequency of the latter by 10 to operate 10 times per week the former. Moreover, removing the intermediate stop in MAI generates a decrease in the fixed costs of both operators. Overall, the frequency between RTM and LUH remains unchanged but IWT services become more attractive to the shippers because the intermediate stop is removed, making the service quicker and more reliable. Knowing this, the IWT operators can then increase the price charged between RTM and LUH by 20€. On the other hand, there are only 2 services per week left between RTM and MAI (compared to 12 without MMTs). This forces the operators to decrease their price by 40€ to remain competitive.

In the end, the losses in revenue caused by the price drop on the RTM↔MAI pair are compensated by the price rise on the RTM↔LUH: the revenues realized by the operators remain similar with and without MMTs. However, the re-arrangement of services causes a decrease of the fixed costs and the MMTs allow to decrease the variable costs between RTM and LUH. As a result, both operators achieve higher profits when the MMTs are installed.

Finally, because the changes in frequency are compensated by changes in price, the market shares of the operators do not evolve. The conclusion is then similar to the previous sections: the MMTs barely have an impact on the attractiveness of the IWT sector as a whole. Nevertheless, this competition model with supply-demand interactions show that the MMTs have the potential to increase the profits of IWT operators. Therefore, some additional measures can be taken so that shippers also benefit from the MMTs. For example, limiting the price rise that can be performed by the operators between RTM and LUH to 10€ would still allow them to increase their profits while making the IWT alternative more appealing to shippers.

5.7 Conclusions

This chapter has demonstrated the potential of using the Modular Mobile Terminal as a floating consolidation and a dedicated handling space for container barges. We address RQ4 by applying the choice-driven models developed in the previous 3 chapters and analyzing the potential effects of the innovation on the stakeholders of the freight transport system. The obtained results lay the groundwork for a business case with important insights that help to narrow down the research scope for follow-up studies. These insights are related to the suitable number of MMTs to operate, the cargo flows that are relevant to target, and the potential response of transport operators to this innovation.

The proposed time savings optimization model is applied to two ports (Rotterdam and Antwerp) and two cases (moderate seasonality and high seasonality scenarios). The results of the analysis suggest that the MMTs are most suitable for regions and vessels with small cargo volumes and can deal with the effects of a high seasonality pattern (caused, for example, by a disruption). Regarding the specific ports, the study indicates that 4 MMTs would be optimal for the port of Rotterdam, while 2 MMTs would optimally be installed in Antwerp. The average time savings of inland vessels in the seaport achieved with this innovation can reach up to 12 hours. Thus from the assumptions and available data, the concept can be seen as a viable solution for consolidating and handling low container volumes.

We then analyze the potential of MMTs further by applying the choice-driven models developed in the previous chapters of this thesis. Looking purely at the demand side, it seems that this innovation has the potential to increase the share of IWT on the OD pairs that are linked to the MMTs. But when considering also the supply side, the results suggest that the IWT operators would take advantage of the innovation to re-arrange their services and modify their prices. In particular, the competition model shows that the time savings on the OD pair linked to MMTs allow operators to redesign their services and to increase their prices. In the end, the share of IWT does not increase, as the shippers do not benefit from the advantages of this innovation. Therefore, additional measures accompanying the installation of MMTs are required so that all actors of the IWT system benefit from this innovation.

Chapter 6

Conclusions & research directions

This thesis presents choice-driven methods focusing on demand, supply and competition aspects of the freight transport system. These methods aim at improving the decision-making in terms of innovation development, policy implementation, or infrastructure investment to make freight transport more sustainable, efficient and resilient.

In this chapter, we conclude the thesis by answering the research questions in Section 6.1 and recommending directions for future research in Section 6.2, while practical insights for decision-makers are provided in Section 6.3.

6.1 Conclusions

This thesis provides answers to the following main research question: "How to improve decision-making in freight transport by considering the heterogeneous actors and their interactions?". To tackle it more conveniently, this main question has been decomposed into 4 research questions, which have been addressed in Chapters 2-5. The following paragraphs recall the 4 questions and summarize the answers provided in the previous chapters.

RQ1: How can the transport demand be accurately modeled taking heterogeneity into consideration?

In Chapter 2, a Weighted Logit Mixture model is developed to estimate heterogeneous preferences of shippers in terms of mode choice directly from aggregate data. Contrarily to segmentation, our methodology allows to capture the underlying heterogeneity in the population, which cannot be explained by deterministic factors. We then use the developed method to estimate the variability of cost sensitivity among the shippers by applying it to the European Rhine-Alpine corridor. The mode choice predictions of our method are then compared to the ones of a benchmark, which considers an homogeneous cost sensitivity among shippers. On top of providing more information on the preferences of shippers, our model returns more accurate mode choice predictions at the disaggregate level.

RQ2: What is the impact of including mode choice decisions of shippers in the decision-making of intermodal carriers?

In Chapter 3, we tackle a Choice-Driven Service Network Design and Pricing problem taking into account the shippers' heterogeneity and the influence of unobserved attributes on the mode choice. These features make it a stochastic optimization problem, for which a "predetermination heuristic" is developed to reduce the solution time. The developed approach is applied to design the services of an Inland Waterway Transport (IWT) operator between various terminals on the Rhine-Alpine corridor and set the prices proposed to shippers. To assess the performance of our method, it is compared to existing models, which assume that shippers are purely cost-minimizers. Depending on the network size and the behavioral assumptions, our method enables the transport operator to get profits that are 2 to 5 times higher than with the models using "cost-minimizing" assumptions.

RQ3: How shall the supply-demand interactions be modeled to accurately represent the freight transport market?

In Chapter 4, a competitive Service Network Design and Pricing model including supply-demand interactions is developed. The proposed model represents the intermodal transport market more accurately by considering imperfect information of the transport operators and their competitive relationship. The functioning of this competition model is verified on the IWT stretch between Rotterdam and Duisburg. All outcomes can be realistically explained and situations causing a monopoly can be identified. It is shown that situations of asymmetric information and monopoly have a detrimental effect on the attractiveness of IWT and shoulde, therefore, be avoided.

RQ4: What insights does the consideration of actors and their behavior bring in the evaluation of an improvement measure?

In Chapter 5, a Modular Mobile Terminal (MMT) concept is proposed to improve the container handling for IWT in seaports. The time savings are quantified through an optimization model, which also determines how many MMTs to include and which cargo flows to serve. The outputs, as well as estimates of cost variations, are used to apply the choice-driven methods developed in Chapters 2-4 and further evaluate the MMT concept. Using only the demand model of Chapter 2 or the supply model of Chapter 3 to assess MMTs already gives informative insights on the innovation's impacts, but the picture is incomplete. The supply-demand model of Chapter 4 shows that IWT operators may use the time savings to re-arrange their services and increase their prices, which means that the innovation's advantages would not be passed on to the shippers. This evaluation with choice-driven methods thus highlights the need for accompanying measures along with the installation of MMTs to make all actors benefit from the innovation.

To sum up, this thesis answers the main research question by proposing three choice-driven methods based on a market representation of the freight transport system. Such methods can serve several purposes. Firstly, they can support the policy-makers in their decisions by providing them more insights about the stakeholders' responses to a policy and about the resulting changes in the system. They can also be used by transport companies to optimize their services and make more informed decisions. Finally, transport planners can use these methods to foresee the potential impacts of an innovation on the involved actors, as well as the possible modified market dynamics.

6.2 Future research directions

Along with their advantages, the methods proposed in this thesis also come with their limitations: thus suggesting potential avenues for future research.

6.2.1 Collect more reliable data

With the rise of machine learning techniques and artificial intelligence, the need for reliable data is greater than ever. The choice-driven methods proposed in this thesis are no exception. The performance of the mode choice model presented in Chapter 2 greatly depends on the amount of input data and their accuracy. For example, reliability is not included in the specification of the utility functions although it has a major influence on mode choice. It would then be beneficial to collect data and/or come up with new metrics quantifying this attribute to obtain a more comprehensive description of the underlying behavior of shippers and achieve a better predictive power.

Regarding the pricing and service design decisions, more reliable data would also improve the outcomes of the optimization model developed in Chapter 3. A more detailed estimation of the costs faced by a transport operator, such as the idling costs of not using all vehicles that are available (Bilegan et al., 2022), will lead to decisions that are more in line with the operational reality. Moreover, precise data on the competing entities regarding their fleet compositions, the services they offer or the terminals with whom they have contractual relationships will help getting more realistic insights and improve the decision-making. All these remarks also hold for the competition model described in Chapter 4.

Finally, detailed inputs are also needed to estimate more accurately the time savings that can be achieved with MMTs using the optimization model of Chapter 5. In particular, more accurate sailing and waiting times of vessels between and at terminals are needed, as well as data about the spread of containers among the terminals.

6.2.2 Challenge some modeling assumptions

Making assumptions is part of the process of designing any model. Nevertheless, several assumptions made in this thesis deserve to be challenged, such as the following ones:

- In the three choice-driven models, each transport mode is considered independent from the others. However, IWT and Rail have in common that they are scheduled intermodal services. Moreover, in the models of Chapters 3 and 4, the utilities of the IWT operator and the competing IWT carrier are considered independent from each other. But these alternatives are definitely correlated since they both propose IWT services. This correlation then needs to be taken into account in the proposed models.

- For the Mixture formulation of the mode choice model in Chapter 2, it is assumed that the random cost coefficient follows a Lognormal distribution. But the long tail of this distribution can cause an overestimation of the coefficient (Hess et al., 2005). That is why further experiments should be conducted with different assumptions on the probability distribution to capture the cost sensitivity variation in greater details.

- In the time savings optimization model of Chapter 5, it is assumed that the inland vessels are homogeneous, that they are calling at terminals following regular time intervals, and that containers are evenly split between terminals. However, the real situation is certainly not as simple. Assessing the MMTs by considering heterogeneous vessels, irregular vessel arrivals and uneven cargo splits is thus needed to get a more detailed estimation of the time savings.

6.2.3 Develop more detailed modeling representations

The last point of the previous list leads to this other research direction. The assessment of the MMT concept in Chapter 5 would benefit from a study at the vessel level instead of regional level. Indeed, the operations of the MMT could be simulated with a higher level of detail: for example, a queuing model could be introduced to accurately calculate the waiting times of the inland vessels. The shuttles and sea terminals could also be explicitly represented to model shuttle assignments to sea terminals.

Regarding the mode choice model of Chapter 2, it estimates the variation of preferences in the whole population but does not give any indication about the causes of this variation. A segmentation based on deterministic features, such as the shipping distance, would help to (partially) translate the probability distribution into more tangible characteristics. A latent class formulation can also be used to reveal the various behavioral patterns leading to the observed probability distribution. Then, a similar Mixture methodology can be applied to the resulting segments or classes to reveal the remaining heterogeneity of preferences.

A segmentation of the population can also be performed regarding the pricing decisions of operators in Chapters 3 and 4. The current formulation implies that a single price per OD pair is set for all shippers. However, some revenue management strategies can be used in order to propose different prices to different customers: thus optimizing the generated revenues. It would also to develop the full potential of the formulation with Mixed Logit, as the prices can be adapted to the different cost sensitivities of shippers.

6.2.4 Consider dynamic effects

Beside the aforementioned revenue management, dynamic pricing can be included in the choice-driven methods of Chapters 3 and 4, particularly in the context of IWT. Indeed, due to climate change, rivers often undergo periods of low water levels, which limits the capacity of container carrying vessels and increases the transportation costs per container. Therefore, IWT operators apply surcharges (Jonkeren et al., 2007) to cover their costs during the low water periods: this aspect should therefore be included in pricing models.

Regarding the mode choice model of Chapter 2, a proper re-estimation procedure should be developed to facilitate the update of the estimates when new data (such as shipment data or more accurate estimates) become available.

In Chapter 5, the monthly variations of transport demand have been considered for the assessment of MMTs. Further dynamics, such as the variation in the daily traffic of inland vessels or the operating time of terminals, can be considered. In this thesis, the focus has mainly been on the tactical time horizon: a shift towards more operational models is then required to capture more dynamic effects.

6.2.5 Transition to integrated models

Instead of shifting from a tactical point of view to an operational one, the different time horizons can also be combined in a single model. Integrated methods can be developed to cover more time dimensions of the decision-making. In the case of the MMTs, the optimization model proposed in Chapter 5 can be supplemented with a simulation module to execute the movements resulting from a given configuration.

Integrated models are not limited to time dimensions. They can also consider the influence of systems that are adjacent to the freight transport system, such as the financial, energy, or climate systems. The behavior of the involved actors can also be integrated: this thesis lays the foundations for the evaluation of measures through choice-driven methods. But instead of using them a posteriori as in Chapter 5, future research should move to more holistic methods. They could integrate the choice-driven elements directly into the decision-making regarding the design of a policy or an innovation.

6.3 Managerial insights

Beside the theoretical conclusions and future research avenues described above, this thesis also provides some practical insights that can help policy-makers and managers to improve their decision-making. They are listed as follows:

- The mode choice model of Chapter 2 reveals that there exists a significant variation of the cost sensitivity among the shippers. This heterogeneity then needs to be considered into the pricing of transport services or in the impact analysis of a new transport measure. More generally, this thesis shows that including more information (such as additional features, heterogeneity, and uncertain parameters) leads to better decisions. Indeed, the estimations of modal shares are more accurate when heterogeneity and Value of Time are considered. Regarding transport supply, Chapter 3 shows that including insights about shippers' preferences allows to substantially increase an operator's profits.

- Still on the supply side, it is recommended that transport operators use a cycle-based formulation when designing their services. As presented in Chapter 3, this formulation allows for an explicit representation of asset usage, since vehicles have to start and end a service at the same location. Moreover, results show that it leads to reduced costs and increased demand because it accounts for the cargo consolidation effect.

- Multiple indicators should be used to validate and assess the performance of a model. In particular, the validation of the mode choice model in Chapter 2 shows that analyzing the outputs of a model only at aggregated level can lead to incorrect conclusions about the model's performance. Moreover, results of the competition model proposed in Chapter 4 highlight the importance of the model's assumptions on the outputs. Therefore, every model requires a careful validation.

- The Modular Mobile Terminal innovation presented in Chapter 5 represents a viable solution for the handling of inland vessels carrying low container volumes by serving as a consolidation platform in the seaport environment. The time savings of inland vessels in the seaport can reach up to 12 hours thanks to this innovation. Nevertheless, the choice-driven methods show that vessel operators can take advantage from the situation so that shippers ultimately do not benefit from the gains. That is why accompanying measures are needed to complement this innovation.

Finally, this thesis emphasizes the key importance of considering the behaviors and reactions of actors that are concerned by any policy, innovation, or investment. This will ensure decision-makers that their measures have the desired effects. Quantitative models, such as the ones developed in this thesis, already give valuable insights. Nevertheless, they should be completed by a qualitative analysis to get a more thorough understanding of the involved stakeholders: consulting practitioners should thus be an integral part of the decision-making process to reach viable business cases.

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Glossary

List of abbreviations

The following abbreviations are used in this thesis:

Generic terms

IWT	Inland Waterway Transport
IWV	Inland Waterway Vessel
KPI	Key Performance Indicator
MMT	Modular Mobile Terminal
NUTS	Nomenclature of Territorial Units for Statistics
OD	Origin-Destination (pair)
RC	Research Challenge
RQ	Research Question
TEU	Twenty-foot Equivalent Unit

Demand-side specific

ADA	Aggregate-Disaggregate-Aggregate
ASC	Alternative Specific Constant
LoS	Level of Service
MNL	MultiNomial Logit (model)
RUM	Random Utility Maximization
VoR	Value of Reliability
VoT	Value of Time
WLM	Weighted Logit Model

Supply-side specific

AP	Auxiliary (optimization) Problem
BLP	BiLevel Problem
CD-SNDP	Choice-Driven Service Network Design and Pricing

iid	independent and identically distributed
JDP	Joint Design and Pricing
MILP	Mixed-Integer Linear Programming
SAA	Sample Average Approximation
SND	Service Network Design

Freight corridor and terminals (in the upstream direction)

RA	Rhine-Alpine (corridor)
RTM	Rotterdam
NIJ	Nijmegen
DUI	Duisburg
BON	Bonn
AND	Andernach
MAI	Mainz
LUH	Ludwigshafen
SXB	Strasbourg
BSL	Basel

Summary

Container transport plays a crucial role in the global economy. However, it is facing many challenges including: climate change, supply chain disruptions, and a cost-of-living crisis. Constant improvement measures are needed to face these challenges, so that the container transport system becomes more sustainable, more adaptive, and more efficient. These measures can take the form of investments, policies, or innovations. In order for these to be efficient, decision-makers need a thorough understanding of the container transport system, together with the involved stakeholders. Therefore, realistic and accurate models considering the behaviors and relationships of the different actors in the system are needed.

This thesis adopts a market perspective to model the container transport system. On the supply side, transport operators propose transport services and, on the demand side, shippers purchase the services to send their goods. Moreover, the supply and demand sides are constantly interacting regarding long-, medium-, or short-term decisions.

Based on this market representation, we develop choice-driven methods to support decision-making in container transport by focusing on demand, supply, and competition aspects considering heterogeneous behaviors and interactions of the actors. The developed methods are then used to assess the impact of a logistics innovation on the actors of the container transport system. In particular, the following topics have been studied:

- Mode choice of shippers considering heterogeneous preferences (Chapter 2)

  A demand model has been developed to estimate the heterogeneous preferences of shippers regarding their mode choice decision. In particular, the proposed model uses aggregate transport data of the Rhine-Alpine corridor to estimate the variability of cost sensitivity among shippers. The obtained results show that the proposed approach not only estimates the preferences of shippers better, but also gives more accurate prediction than a model with homogeneous preferences. The proposed approach thus provides a better estimation of the potential impacts of an innovation or policy on the modal share.

- Choice-driven design and pricing of transport services (Chapter 3)

  A supply model has been developed to support transport operators in the design and pricing of their services by considering information about the preferences of shippers. Compared to the existing methods (that consider the shippers to be purely cost minimizers), the proposed approach considers shippers' heterogeneity and the unobserved attributes playing a role in shippers' choices. The approach is applied to a stretch of the Rhine-Alpine corridor: the results show that the transport operator can achieve substantially higher profits with our approach compared to the existing methods.

- Supply-demand interactions and competition in container transport (Chapter 4)

  The proposed approach overcomes some limitations of the aforementioned choice-driven model. In particular, it considers the reactions of competing transport operators and it assumes that the decision-makers do not have full information about their competitors and the demand. These features contribute to making the model more realistic. This approach is applied on the Rotterdam-Duisburg stretch to spotlight the underlying mechanisms and verify the model. The results show that the equilibrium solution highly depends on the assumptions of the model. For this reason, the assumptions need to be carefully validated.

- Impact assessment of a modular terminal concept (Chapter 5)

  The aim of this innovation is to achieve time savings for barge operators in seaports. First, an optimization model is proposed to quantify the savings that can be achieved and is applied to the ports of Rotterdam and Antwerp. The results suggest that the modular terminals are most suitable for small cargo volumes. The obtained time savings, along with estimates of cost variations, are then used as inputs for the three aforementioned models to evaluate further the impacts on the stakeholders of the container transport system. Regarding the demand side, this innovation has the potential to increase the share of inland waterway transport. However, when the supply side is also considered, the results suggest that the barge operators would take advantage of the modular terminals to redesign their services and increase their prices. This would prevent shippers from enjoying the benefits of this innovation. Therefore, additional measures are required so that all actors of the system benefit from this innovation.

In short, this thesis presents choice-driven methods focusing on demand, supply and competition aspects of the container transport system. These methods aim at improving the decision-making concerning any policy, innovation, or investment by considering the behaviors and reactions of the concerned actors. This will ensure that the decision-makers consider the various interactions and trade-offs inherent to transport systems when looking for the desired measures.

Samenvatting

Containertransport speelt een cruciale rol in de wereldeconomie. Het staat echter voor grote uitdagingen, waaronder klimaatverandering, verstoringen in de toeleveringsketen en toenemende kosten voor levensonderhoud.. Er zijn voortdurend verbeteringsmaatregelen nodig om deze uitdagingen het hoofd te bieden, zodat het containertransportsysteem duurzamer, flexibeler en efficiënter wordt. Voorbeelden hiervan zijn investeringen, beleidsmaatregelen of innovaties. Om deze maatregelen effectief te laten zijn, hebben besluitvormers grondig inzicht nodig in het containertransportsysteem. Hiervoor zijn realistische en nauwkeurige modellen nodig die rekening houden met het gedrag en relaties van de verschillende actoren in het systeem.

Dit proefschrift gebruikt een marktgerichte benadering om het containertransportsysteem te modelleren. Aan de aanbodzijde bieden transportbedrijven diensten aan, en aan de vraagzijde kopen vervoerders de diensten om hun goederen te verzenden. Bovendien zijn de vraag en aanbodzijde voortdurend in interactie met elkaar, met betrekking tot lange-, middellange- of kortetermijnbeslissingen.

Op basis van deze marktweergave, ontwikkelen we keuzegedreven methoden om besluitvorming in containertransport te ondersteunen, waarbij we ons richten op vraag, aanbod en concurrentieaspecten, rekening houdend met heterogeen gedrag en interacties van de actoren. De ontwikkelde methoden worden vervolgens gebruikt om de impact van een innovatie op de actoren van het containertransportsysteem te beoordelen. In het bijzonder zijn de volgende onderwerpen bestudeerd:

- Keuze van transportmodus door vervoerders met inachtneming van heterogene voorkeuren (Hoofdstuk 2)

  Er is een vraagmodel ontwikkeld om de heterogene voorkeuren van vervoerders met betrekking tot hun keuze van transportmodus te schatten. Het voorgestelde model maakt specifiek gebruik van geaggregeerde transportgegevens van de Rijn-Alpen corridor om de variabiliteit van kostengevoeligheid onder vervoerders te schatten. De verkregen resultaten laten zien dat de voorgestelde aanpak niet alleen de voorkeuren van vervoerders beter inschat, maar ook nauw-

keurigere voorspellingen geeft dan een model met homogene voorkeuren. De voorgestelde aanpak biedt dus een betere schatting van de potentiële effecten van een innovatie of beleidsverandering op het marktaandeel van de verschillende transportmodi.

- Keuzegedreven ontwerp en prijsstelling van transportdiensten (Hoofdstuk 3)

  Een aanbod model is ontwikkeld om transportbedrijven te ondersteunen bij het ontwerpen en beprijzen van hun diensten, door rekening te houden met informatie over de voorkeuren van vervoerders. In vergelijking met de bestaande methoden (die ervan uitgaan dat vervoerders puur focussen op kosten minimalisatie), houdt de voorgestelde aanpak rekening met de heterogeniteit van vervoerders en de niet-waargenomen kenmerken die een rol spelen in hun keuzes. De aanpak is toegepast op een traject van de Rijn-Alpen corridor: de resultaten laten zien dat de transporteur met onze aanpak aanzienlijk hogere winsten kan behalen in vergelijking met bestaande methoden.

- Interactie tussen vraag en aanbod en concurrentie in containertransport (Hoofdstuk 4)

  De voorgestelde aanpak overkomt enkele beperkingen van het eerder genoemde keuzegedreven model. In het bijzonder houdt het rekening met de reacties van concurrerende transportbedrijven en gaat het ervan uit dat de besluitvormers niet over volledige informatie beschikken over hun concurrenten en de vraag. Deze kenmerken dragen bij aan een realistischer model. Deze aanpak is toegepast op het traject Rotterdam-Duisburg om de onderliggende mechanismen te belichten en het model te verifiëren. De resultaten laten zien dat de evenwichtsoplossing sterk afhankelijk is van de aannames van het model. Daarom moeten de aannames zorgvuldig worden gevalideerd.

- Effectbeoordeling van een modulair terminalconcept (Hoofdstuk 5)

  Het doel van deze innovatie is om tijdsbesparing te realiseren voor binnenvaart vervoerders in zeehavens. Eerst wordt een optimalisatiemodel voorgesteld om de besparingen die kunnen worden bereikt te kwantificeren, en dit wordt toegepast op de havens van Rotterdam en Antwerpen. De resultaten suggereren dat de modulaire terminals het meest geschikt zijn voor kleine vrachtvolumes. De verkregen tijdsbesparingen, samen met schattingen van kostenvariaties, worden vervolgens gebruikt als input voor de drie eerder genoemde modellen om de impact op de belanghebbenden van het containertransportsysteem verder te evalueren. Wat de vraagzijde betreft, heeft deze innovatie het potentieel om het aandeel van het binnenvaartvervoer te vergroten. Echter, wanneer ook de aanbodzijde wordt meegenomen, suggereren de resultaten dat binnenvaart vervoerders de modulaire terminals zouden gebruiken om hun diensten te herontwerpen en hun prijzen te verhogen. Dit zou voorkomen dat vervoerders profiteren van de voordelen van deze innovatie. Daarom zijn aanvullende maatregelen nodig om ervoor te zorgen dat alle actoren binnen het systeem profiteren van deze innovatie.

Kortom, dit proefschrift presenteert keuzegedreven methoden die zich richten op vraag-, aanbod- en concurrentieaspecten van het containertransportsysteem. Deze methoden zijn gericht op het verbeteren van de besluitvorming met betrekking tot beleid, innovatie of investeringen, door rekening te houden met het gedrag en de reacties van de betrokken actoren. Dit zal besluitvormers ervan verzekeren dat hun maatregelen de gewenste effecten zullen hebben.

Sommaire

Le transport par container joue un rôle crucial dans l'économie mondialisée. Mais le secteur rencontre de nombreux défis, parmi lesquels figurent le changement climatique, des perturbations dans les chaînes d'approvisionnement, ou encore une crise du pouvoir d'achat. Le transport de container doit donc être constamment amélioré pour que le système devienne plus durable, plus efficace et meilleur marché. Différentes mesures d'amélioration peuvent être envisagées: investissements, régulations, innovations, etc. Pour s'assurer de l'efficacité des mesures mises en œuvre, les décideurs doivent avoir une compréhension détaillée du système de transport. C'est pourquoi des modèles réalistes, fiables, et considérant les comportements et réactions des différents acteurs du système, sont nécessaires.

Dans cette thèse, le système de transport par container est représenté comme un marché: les *opérateurs de transport* proposent des services de transport, consituant l'offre; tandis que les *expéditeurs* souscrivent à des services pour transporter leurs marchandises, constituant la demande. De plus, les acteurs de l'offre et de la demande interagissent constamment concernant les décisions à court, moyen, et long terme.

En nous basant sur cette représentation de marché, des méthodes sont élaborées pour assister la prise de décision dans le domaine du transport par container. Ces méthodes mettent l'accent sur l'offre, la demande et la concurrence tout en considérant les différents comportments des acteurs et leurs interactions. Une fois développées, ells sont utilisées pour évaluer l'impact d'une innovation logistique sur les acteurs du système de transport. En particulier, les sujets suivants ont été étudiés:

- Choix du moyen de transport par les expéditeurs en considérant leurs préférences (Chapitre 2)

  Un modèle de demande est développé afin d'estimer les variations de préférences des expéditeurs lorsqu'ils choisissent le moyen de transport pour leur marchandise. En particulier, le modèle estime les différentes sensibilités au prix parmi les expéditeurs. Pour ce faire, des données de transport agrégées pour le corridor Rhin-Alpes sont utilisées. Les résultats obtenus montrent que notre approche

fournit non seulement une meilleure estimation des préférences des expéditeurs, mais aussi une prédiction plus précise du choix du moyen de transport comparé à un modèle considérant que les préférences sont uniformes. L'approche proposée permet donc une meilleure estimation des impacts potentiels d'une innovation ou régulation sur le choix fait par les expéditeurs.

- Planification et tarification des services de transport par les opérateurs considérant les choix des expéditeurs (Chapitre 3)

  Un modèle d'offre est développé afin d'assister les opérateurs de transport dans la planification et tarification de leurs services en tenant compte des informations relatives aux préférences des expéditeurs. Contrairement aux méthodes existantes qui considèrent que les expéditeurs cherchent uniquement à minimiser leur coûts, notre approche tient compte à la fois des facteurs non observés mais qui influencent le choix des expéditeurs, ainsi que de la diversité de leurs préférences. Le modèle est appliqué à un tronçon du corridor Rhin-Alpes et les résultats démontrent que l'approche proposée est capable de générer des profits plus importants que lorsque les méthodes existantes sont utilisées.

- Interactions entre offre et demande, et concurrence dans le domaine du transport par container (Chapitre 4)

  Une approche est proposée afin de surmonter certaines restrictions du modèle d'offre mentionné ci-dessus. En particulier, cette approche tient compte des réactions des concurrents et du fait que les opérateurs de transport ne disposent que d'informations incomplètes au sujet de leurs concurrents et de la demande. Ces considérations améliorent le réalisme du modèle proposé. Celui-ci est appliqué au tronçon Rotterdam-Duisburg afin de mettre en évidence les dynamiques du modèle et de vérifier son fonctionnement. Les résultats montrent que les hypothèses de départ influencent fortement l'état d'équilibre du système retourné par le modèle. C'est pourquoi une validation minutieuse de ces hypothèses est nécesssaire.

- Évaluation d'impacts d'un concept de terminal modulaire (Chapitre 5)

  Cette innovation vise à faire gagner du temps aux opérateurs de barges dans les ports maritimes. Premièrement, un modèle d'optimisation est développé afin de quantifier les gains de temps potentiels. Le modèle est appliqué aux ports de Rotterdam et Anvers et les résultats montrent que le terminal modulaire est plus avantageux pour les barges à faibles volumes de containers. Ensuite, les résultats numériques en termes de gain de temps ainsi que les estimations des coûts engendrés sont insérés dans les trois modèles décrits ci-dessus. Cela permet d'évaluer plus en profondeur les impacts du terminal modulaire sur les acteurs du système de transport. Le modèle de demande indique que cette innovation a le potentiel d'augmenter la part modale du transport fluvial. Mais lorsque les modèles d'offre sont aussi pris en compte, les résultats suggèrent que les opérateurs de barges utiliseraient l'innovation à leur avantage afin de restructurer leurs services et augmenter leurs tarifs. Cela implique que les expéditeurs ne bénéficieraient d'aucune retombée positive. C'est pourquoi des mesures additionnelles sont nécessaires afin que tous les acteurs du système profitent de cette innovation.

Pour résumer, cette thèse présente des méthodes axées sur la demande, l'offre et la concurrence dans le domaine du transport par container. Ces méthodes visent à améliorer la prise de décision concernant une régulation, un investissement, ou une innovation en considérant les comportements et réactions des acteurs concernés. Les décideurs peuvent ainsi s'assurer que leurs mesures ont bien les effets escomptés.

About the author

Adrien Nicolet was born on the 13th of November 1994, in Châtel-Saint-Denis (Fribourg) Switzerland. At an early age, he developed a passion for transportation. This drive made him later pursue a Bachelor degree in Civil Engineering, followed by a Master degree with a specialization in Transport and Mobility at EPFL (Switzerland). His results earned him a prize for the best Master average of Civil Engineering.

Driven by the will to deepen his knowledge about logistics, he joined the Section of Transport Engineering and Logistics (TEL) in the Department of Maritime & Transport Technology at the Delft University of Technology (The Netherlands) to pursue a PhD degree in October 2020. The results of his research are presented in this dissertation. During his time at the TEL section, he also co-organized the PhD meetings of the section and took part in a European research project in collaboration with academics and practitioners. His research interests revolve around transport planning, behavioral analysis, optimization, and multi-agent simulation.

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2. **Adrien Nicolet**, Bilge Atasoy. Choice-driven service network Design and pricing in intermodal transport. *11th Symposium of the European Association for Research in Transportation (hEART)*, Zürich (Switzerland), 2023.

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