Flexible, Dynamic, and Collaborative Synchromodal Transport Planning Considering Preferences

Zhang, Y.

DOI
10.4233/uuid:ab712847-e788-4e13-8680-6049ac234c4c

Publication date
2023

Document Version
Final published version

Citation (APA)
Zhang, Y. (2023). *Flexible, Dynamic, and Collaborative Synchromodal Transport Planning Considering Preferences*. [Dissertation (TU Delft), Delft University of Technology]. https://doi.org/10.4233/uuid:ab712847-e788-4e13-8680-6049ac234c4c

Flexible, Dynamic, and Collaborative Synchromodal Transport Planning Considering Preferences

Yimeng Zhang

Flexible, Dynamic, and Collaborative Synchromodal Transport Planning Considering Preferences

Dissertation

for the purpose of obtaining the degree of doctor
at Delft University of Technology
by the authority of the Rector Magnificus prof.dr.ir. T.H.J.J. van der Hagen
chair of the Board for Doctorates
to be defended publicly on Monday 26 June 2023 at 10:00 o'clock

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The research described in this thesis was supported by the China Scholarship Council under grant 201906950085.

TRAIL Thesis Series no. T2023/7, The Netherlands Research School TRAIL
P.O. Box 5017, 2600 GA Delft, The Netherlands
E-mail: info@rsTRAIL.nl

Published and distributed by: Yimeng Zhang
Cover design: Yimeng Zhang
E-mail: yimengzhang94@gmail.com

ISBN 978-90-5584-326-8

Printed in The Netherlands

"Mind and Hand."

The motto of the Massachusetts Institute of Technology aligns with the core idea of Wang Yangming (1472-1529) philosophy.

Preface

During my Ph.D. journey, I am filled with a range of emotions - excitement, peace, struggle, frustration, happiness, achievement, and satisfaction. Looking back, there is one memory that stands out above the rest - the feeling of picking myself up after every setback. Whether it was debugging code, rethinking faulty logic, rewriting inaccurate sentences, or resubmitting after a journal rejection, every challenge taught me the importance of persistence and resilience in research. Indeed, the very word "research" embodies the idea of constantly revisiting and refining our ideas until they are ready for the world.

For me, the motivations behind this perseverance are many - curiosity, stress, and the desire to see an idea through to its completion. And the rewards have been manifold as well - I have become more logical, practical, and creative as a researcher and engineer. Most importantly, I am proud of the small contribution I have made in my research direction.

My research topic, optimization, is all around us, much like the journey of life itself. While some may not see life as an optimization problem, I believe that both life and research can inspire and inform each other in profound ways. Life, with its multiple objectives, dynamic nature, and need for collaboration, especially when it comes to human behavior, has many parallels with the research I am engaged in. I am grateful to my supervisors, Prof. Rudy R. Negenborn and Dr. Bilge Atasoy, for guiding me on this exciting journey. Their wealth of knowledge and experience in optimization and transportation is remarkable and has been invaluable to my development as a researcher. They are critical, inspiring, and supportive in equal measure, with Rudy offering a logical perspective and Bilge displaying remarkable responsibility (even scheduling meetings just a week after giving birth). I have learned so much from them and have been inspired by their creativity and kindness.

I would also like to express my gratitude to Prof. Lori Tavasszy, Dr. Frederik Schulte, Prof. Edwin van Hassel, Prof. Frank Meisel, Dr. Arne Heinold, Dr. Breno Alves Beirigo, Dr. Rie Larsen, for their valuable insights and discussions that have shaped my research. Dr. Johan Los, my officemate, has offered invaluable assistance with collaborative planning. Dr. Wenjing Guo is my collaborator and her expertise in intermodal transport was helpful in building my first model. My fellow Ph.D., Dr. Zhe Du, Dr. Yaming Huang, Dr. Linying Chen, Dr. Pengfei Chen, and Dr. Changyuan Chen, have also been wonderful lunch companions.

I would be remiss if I did not mention my colleagues who have made my time here so enjoyable. My officemates Jake Walker, Esma Ozdemir, Annabel Broer, and Dr. Congbiao Sui, have been helpful with both English and Dutch, and have created a warm and welcoming environment. My friends and colleagues Adrien Nicolet, Cigdem Karademir, Abhishek Dhyani, Ahmed Hadi, Nikolaos Kougiatsos, Konstantinos Zoumpourlos, Wei Jun Wong, Xiaohuan Lyu, Rongxin Song, Xin Xiong, Pan Fang, Mingxin Li, Yitao Huang, Xiuhan

Chen, Qianyi Chen, and Ping He, have been great companions in both works and play.

I am also grateful to the China Scholarship Council (CSC), which funded my Ph.D. project. My master's supervisors, Prof. Yuanqiao Wen and Prof. Chunhui Zhou, also deserve thanks for opening the door to research for me and supporting my application to the CSC.

I want to thank my girlfriend, Ruixue Ai, for her incredible support. She has been an amazing partner, always there to offer words of encouragement and comfort when I need them most. Her love and kindness have made a huge difference of my life.

Last but not least, I am deeply indebted to my parents, Qinglong Zhang and Yuqiao Zhang, whose unwavering support has been my constant source of strength and inspiration.

Yimeng Zhang,
Delft, February 2023

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Chapter 1

Introduction

This thesis focuses on flexible, dynamic, and collaborative planning for synchromodal transport, taking into consideration the preferences of carriers and shippers. This chapter introduces the challenges tackled in this thesis and describes the methodologies to address those challenges. The chapter is organized as follows: Section 1.1 provides an introduction to synchromodal transport planning and the challenges it faces. Section 1.2 outlines the research questions that the thesis seeks to address. The research approaches adopted in this thesis are detailed in Section 1.3. Finally, the contributions of this thesis are presented in Section 1.4, and the overall structure of the thesis is presented in Section 1.5.

1.1 Synchromodal transport planning & challenges

The needs of human society for efficient, cost-effective, and sustainable freight transport have led to the development of intermodal transport (Agamez-Arias and Moyano-Fuentes 2017). Intermodal transport refers to freight transported by at least two modes, e.g., ship, train, and truck, without handling the freight themselves in changing modes (UNECE 2001). Compared to unimodal road transport, intermodal transport utilizes the advantages of different modes and has a positive impact on economics and environment by reducing the need for long-haul trucking (Agamez-Arias and Moyano-Fuentes 2017). In order to mitigate climate change, different countries and regions have put forward initiatives to use intermodal transport. The ambition of the European Commission is to shift 30% of road freight transport by 2030 to more environmentally friendly modes, such as rail and inland waterways. This shift should reach 50% by 2050 (European Commission 2011). China has announced its "Carbon Peak and Carbon Neutrality" policy, which aims at achieving a peak in carbon emissions by 2030 and carbon neutrality by 2060, for which the volume of rail–ship container transportation should increase by 15% each year between 2021 and 2025 (State Council of China 2021a,b).

The stakeholders in intermodal transport include shippers, freight forwarders, carriers, terminal operators, and government entities, all of whom have objectives such as minimizing costs, time, and emissions, and maximizing efficiency, profit, and reliability with different priorities. To achieve these objectives, research in intermodal transport has gained attention from various domains, including transportation, logistics, real-time control, and operations research. The scope of research encompasses all aspects of the planning problem, including strategic, tactical, and operational decision-making (Agamez-Arias and Moyano-Fuentes 2017, Mathisen and Hanssen 2014, SteadieSeifi et al. 2014). Despite these efforts, the current state of intermodal transport is still challenged by various barriers to its utilization, such as a lack of flexibility, delays caused by uncertainty in travel time, and a lack of cooperation among transport actors (Vural et al. 2020).

In order to achieve the operational and sustainability objectives of stakeholders, the concept of synchromodal transport is proposed as an extension of intermodal transport. Synchromodal transport has been studied in the context of transport networks in different regions and countries, including Europe (Hrušovskỳ et al. 2021, Qu et al. 2019), China-Europe (Guo et al. 2021b), and the United States (Farahani et al. 2023). Through synchronization between different transport modes and collaboration among transport operators, synchromodal transport decides and adapts routes/modes in real time and optimally uses resources to provide efficient, reliable, and sustainable services that meet the preferences of stakeholders (Ambra et al. 2019, Giusti et al. 2019, SteadieSeifi et al. 2014). The main differences between intermodal transport and synchromodal transport include mode-free booking, real-time planning, and collaborative planning (Giusti et al. 2019, Guo et al. 2021b).

Mode-free booking means that shippers leave mode and route choices to transport operators (Tavasszy et al. 2017). It allows carriers to make adjustments to the routes and schedules of different modes of transportation like truck and barge depending on the demand and specific situation (e.g., unexpected events or disruptions) without being tied to a predefined mode of transportation. This flexibility enables the carrier to choose the most efficient and cost-effective mode of transportation for a particular shipment, which is crucial for mode-free booking to be successful. In other words, without the flexibility to adjust routes and schedules, mode-free booking would not be able to fully realize its potential for cost savings and efficiency improvements. Service flexibility is an emerging core component of logistics services (Khakdaman et al. 2022). The use of multiple modes and flexible services with different characteristics and constraints such as capacity, route, and schedule, adds to the complexity of the planning process. Previous studies, such as Demir et al. (2016), Guo et al. (2020), Qu et al. (2019), typically assume that the routes and schedules of services are predetermined and the assignment to those services is optimized with the developed models. This results in a lack of flexibility in synchromodal transport planning, as the services cannot be updated during optimization.

Real-time planning is critical for ensuring the efficient operation of the supply chain and reducing costs associated with disruptions and delays (Qu et al. 2019). By providing the ability to dynamically update transport plans in response to disturbances and disruptions, real-time planning enables synchromodal transportation to consistently and effectively deliver goods to their destination in a timely manner. Real-time planning also takes into account demand, travel time, and service time uncertainty, which can have a significant impact on the reliability of synchromodal transport, and allows for updates under uncertainty to ensure reliable transportation (Van Riessen et al. 2015a). Several studies have addressed the issue of travel time and demand uncertainty in real-time synchromodal transport planning, as demonstrated by literature such as Guo et al. (2021a), Hrušovskỳ et al. (2018), SteadieSeifi et al. (2021), and Guo et al. (2022). However, there is a gap in the literature regarding the service time uncertainty, which is crucial for the reliability of synchromodal transport.

Synchromodal transport that involves trains, barges, and trucks requires considerable coordination and cooperation (UNCTD 2022). Collaborative planning in synchromodal transport involves carriers working together and sharing resources and information in order to optimize the delivery of goods. Collaborative planning includes both vertical collaboration among carriers with interconnected networks and horizontal collaboration among carriers with overlapping networks to improve the utilization of resources and increase service frequency (Lee and Song 2017, Li et al. 2017). Collaborative planning can enable carriers to respond more effectively to changing demand and disruptions, as they can rely on each other for backup resources. It can also help to increase the range of services and improve service quality, as carriers can offer a wider variety of services by working together. Vertical collaborative planning has been explored in the literature, as demonstrated by studies such as Guo (2020), Li et al. (2017), and Larsen (2022). Conversely, horizontal collaborative planning has not yet received an adequate level of attention in the existing literature for intermodal and synchromodal transportation.

Although synchromodal transport uses the above approaches to improve the performance of the transportation system and provide better services, it is still hard to satisfy all objectives of stakeholders because some objectives may conflict with each other. Therefore, the preferences of stakeholders need to be taken into account in synchromodal transport planning to determine which modes and routes meet the specific needs and goals of stakeholders. This thesis focuses on two important stakeholders in synchromodal transport, i.e., the shipper and carrier (or freight forwarder). Shippers are the parties sending the goods and carriers organize and coordinate the transportation of goods for shippers.

In synchromodal transport planning, both carriers and shippers have objectives such as minimizing cost, time, and emissions, but their preferences may differ, as shown in Figure 1.1. Carriers may have different preferences on objectives due to factors like business models, operational strategies, capacity and resources, customer base, geographical location, and routes. Shippers also have various preferences due to factors such as business models, type of goods transported, geographical location, and inventory management. A shipper or carrier may prioritize speed and timeliness over cost savings if the goods being shipped are perishable or time-sensitive. They may also prioritize environmental sustainability and may choose modes of transportation that have a lower carbon footprint. In Figure 1.1, Carrier C is more concerned about emissions compared to Carriers A and B. Shipper E regards minimizing emissions as the most important thing, whereas Shipper F wants to transport shipments in a faster way. Apparently, Carrier B and Shipper E have non-aligned objectives. If Carriers B and C serve a request together, they also have conflicts on decisions affecting emissions and time.

While many studies have focused on optimizing the use of resources and reducing costs, few studies have considered the preferences of stakeholders, such as carriers and shippers, in the planning process. The consideration of preferences in synchromodal transport planning is crucial for the selection of appropriate modes and routes, as it aligns the transport solution with the specific goals and needs of carriers and shippers. In synchromodal transport, shippers may cede control to freight forwarders, determining only price and quality requirements (Khakdaman et al. 2020). Carriers need to consider shipper preferences to match services with demands considering requests with various preferences and trade-offs. Neglecting stakeholders' preferences may result in mismatches, high logistics costs, and/or low satisfaction of shippers. However, considering preferences is a complex task as preferences can be heterogeneous and vague. Heterogeneous preferences require trade-offs not

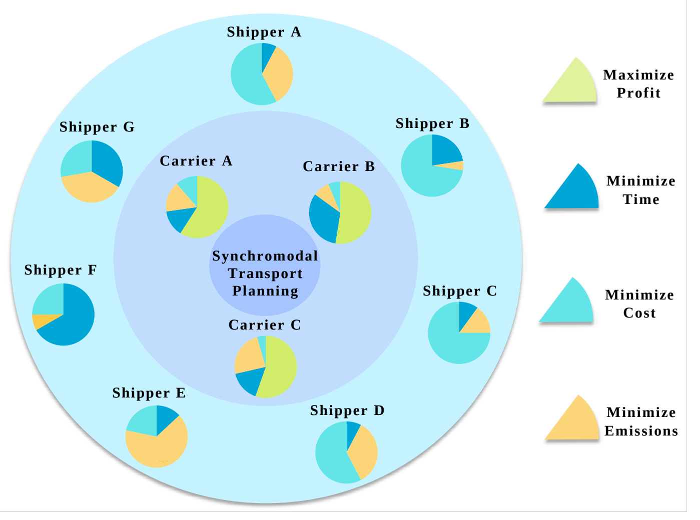


Figure 1.1: Carriers and shippers with different preferences in synchromodal transport

only between objectives but also between different shippers. Each shipper may have unique preferences, such as different priorities for cost, time, and environmental impact, which can make it difficult to find a solution that satisfies all parties. Vague preferences may be expressed as a linguistic term or a label, which are difficult to model and incorporate into the planning process, as they require specific techniques for handling vagueness. The consideration of preferences in collaborative planning is also a difficult task. For example, in the context of collaboration among carriers for serving shippers' requests with preferences, it is necessary to design suitable collaborative planning mechanisms to ensure that unsatisfied requests are forwarded to the appropriate carriers efficiently according to their available resources.

In summary, the successful implementation of synchromodal transport requires a transport planning approach that includes flexible planning, real-time adjustments to service time uncertainty, horizontal collaboration among carriers, and the integration of preferences from both carriers and shippers into the transport planning process. This will ensure that the needs and preferences of all parties involved are met in a timely and efficient manner.

1.2 Research questions

This thesis aims to propose optimization models and methodologies for the purpose of flexible, dynamic, and collaborative synchromodal transport planning, taking into consideration the preferences of both carriers and shippers, with the ultimate aim of enhancing efficiency and sustainability in transportation operations. In light of the challenges outlined in Section 1.1 and the research gaps identified in Chapter 2, the main research question of this thesis is:

Q: How can flexible, real-time, and collaborative synchromodal transport planning ap-

proaches be developed considering the heterogeneous and vague preferences of carriers and shippers?

The key questions are listed as follows:

1. Q1: How can routes be optimized for the carrier to provide flexible services?

   In synchromodal transport, carriers typically receive requests from shippers and optimize routes using available services. However, existing literature often assumes that routes and schedules of services in synchromodal transport are fixed. In reality, the ability to adapt to changing demands and disruptions requires the use of flexible services in synchromodal transport. Flexibility in routes and schedules can help to avoid idle capacity and ensure that vehicles are utilized according to actual demand. By providing the ability to adapt to changing circumstances and meet the specific requirements of shippers, flexible services enable the carrier to provide transport plans that are in line with the preferences of shippers. Therefore, it is necessary to develop an optimization model that takes into account flexible services in synchromodal transport planning. To address research question Q1, Chapter 3 develops the mathematical model and solution algorithm for synchromodal transport planning with flexible services.

2. Q2: How can a real-time planning approach be developed for carriers to provide reliable services while taking into account uncertainties in service time?

   The ability to respond to uncertainty in real-time has emerged as a vital capability in synchromodal transport. The uncertainty in the transport network includes travel time, service time, and demand uncertainties. Travel time and demand uncertainties have been relatively well studied in the literature (Demir et al. 2016, Guo et al. 2021b, Van Riessen et al. 2015c). However, few scholars research the service time uncertainty in synchromodal transport, although it is common in practice. The service time uncertainty needs to be taken into account in the transport planning model to improve the reliability of synchromodal transport. To address research question Q2, Chapter 4 develops a re-planning method and uses a model-assisted Reinforcement Learning approach to deal with service time uncertainty. The following sub-questions will be answered: (1) Should the affected requests be served by the current vehicle? (2) If not, which vehicles can be used for serving them?

3. Q3: How can heterogeneous and vague preferences of carriers and shippers be incorporated into the planning approach?

   In order to ensure the long-term profitability of the overall system, synchromodal transport planning needs to consider shipper and carrier preferences that are by nature heterogeneous and vague. Heterogeneous preferences refer to the fact that different carriers and shippers may have different needs and preferences, which can be difficult to capture and represent. Vague preferences refer to the fact that carriers and shippers may have imprecise preferences, which can be difficult to quantify and incorporate into transport planning. Considering preferences refers to the ability of the transport service to meet the specific needs, wishes, and expectations of the shipper or carrier, such as cost, time, reliability, and environmental impact. This can involve trade-offs between competing objectives and balancing heterogeneous preferences of the shipper and carrier. As different shippers may have different preferences, what may be considered satisfactory for one shipper may not be for another. Therefore, it requires a good understanding of the shipper's preferences and needs. To address research question Q3, Chapters 5 and 6 develop synchromodal transport planning models considering preferences of carriers and shippers, respectively.

4. Q4: What types of collaborative planning should be adopted and what is their effect on the consideration of preferences?

   There are different collaborative planning types with advantages and disadvantages, including centralized, distributed, and decentralized approaches. Based on the characteristics of synchromodal transport, the most suitable approach needs to be selected. In centralized approaches, carriers are required to fully disclose information and resources, with control centralized to a single agent. However, in practice, carriers may be hesitant to share private information and prefer self-automation. In contrast, decentralized approaches empower carriers to make autonomous decisions, but may lack coordination and thus prove less efficient and sustainable than centralized approaches. Distributed approaches offer a compromise, balancing the benefits of centralization and decentralization. In these approaches, carriers share limited information on requests and services, with an agent coordinating transport planning. The specific type of collaborative planning implemented can have a significant impact on performance in terms of efficiency, sustainability, and satisfaction in synchromodal transport. Therefore, the performances of different types of collaborative planning and the effect on the consideration of preferences need to be evaluated. To address research question Q4, Chapter 7 develops a collaborative planning model considering preferences.

1.3 Research approach

The approach of this research is shown in Figure 1.2.

Firstly, the optimization model for carriers is established to achieve flexibility in synchromodal transport planning (Q1). The carrier receives requests from shippers, and then the optimization model generates routing and scheduling plans for vehicles, including barges, trains, and trucks. A mathematical model and a customized heuristic algorithm are proposed for transport planning with fixed and flexible services.

Secondly, research on real-time synchromodal transport planning is conducted to address service time uncertainty and provide more reliable planning for carriers (Q2). Building upon the static transport planning approach for Q1, a re-planning approach that accounts for dynamic unexpected events at terminals is proposed. When such events occur, they can cause service time uncertainty and have varying effects on requests and vehicles. The proposed approach employs a decision-making process to determine which requests should be reassigned to different vehicles, and which vehicles should be utilized, based on information related to requests, vehicle routing and scheduling, and the unexpected event. Additionally, the proposed approach learns online from historical experience to improve its ability to handle service time uncertainty.

Thirdly, based on the established optimization model, the preferences of carriers and shippers are considered in a multi-objective/attribute setting to get the preferred solutions (Q3). Different from the approach for Q1, the proposed approaches consider that shippers specify preferences for the requests and that the carriers have preferences for transport plans while serving the demand for the shippers. To account for the heterogeneity of preferences, multi-objective optimization and multi-attribute decision making techniques are developed for preferences of carriers and shippers, respectively. Additionally, the vagueness of preferences is addressed through the application of the weight interval method and fuzzy set theory.

Finally, collaborative planning is studied, and carriers and shippers with their objectives/preferences will be involved in the collaborative planning (Q4). Carriers receive requests from shippers that include specified preferences and develop corresponding transport plans. In the proposed distributed approach, if a carrier is unable to fulfill the preferences of a request, the request is then forwarded to a coordinator and shared with other carriers. Using an auction-based method, the proposed approach determines the most suitable carrier to fulfill the request based on bids submitted by participating carriers.

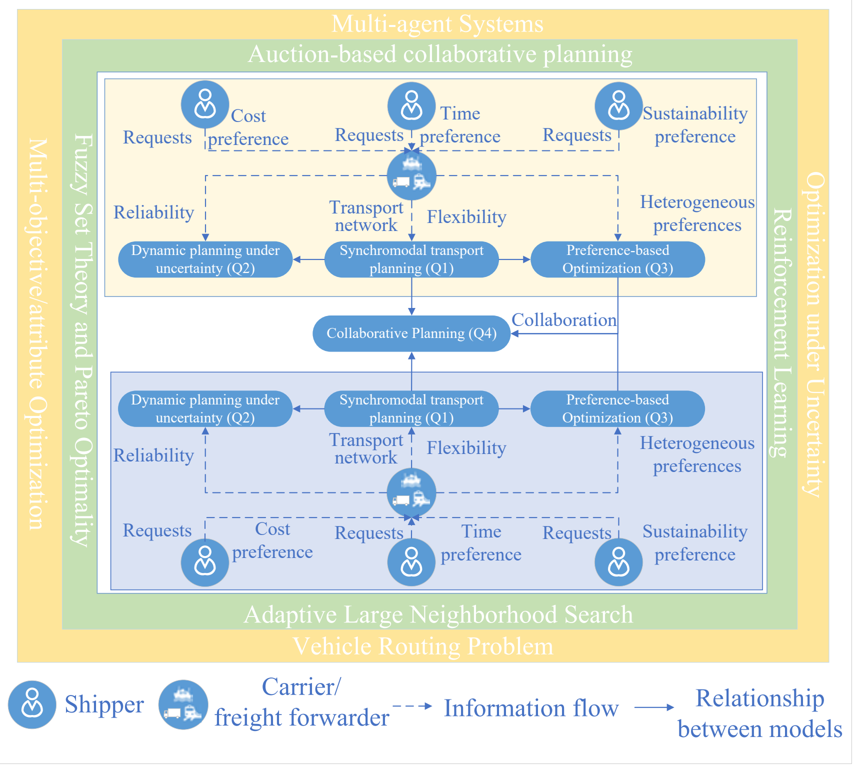


Figure 1.2: The approach of this research

The approaches and techniques used in this research include Adaptive Large Neighborhood Search (ALNS) (research question Q1 and Chapter 3), Reinforcement Learning (research question Q2 and Chapter 4), Pareto Optimality (research question Q3 and Chapter

5), Fuzzy Set Theory (research question Q3 and Chapter 6), and Auction-based collaborative planning (research question Q4 and Chapter 7). This research uses knowledge from various domains, such as Vehicle Routing Problems, Multi-objective/attribute Optimization, Multi-agent Systems, and Optimization under Uncertainty.

1.4 Thesis contributions

This thesis contributes to the Operations Research and Transportation&Logistics Science disciplines by developing a series of transport planning approaches in the synchromodal transport field. The main contributions of this research are:

1. Development of a mathematical model and an efficient solution algorithm for optimizing routes and schedules of fixed and flexible vehicles in synchromodal transport (Chapter 3, Zhang et al. (2020b, 2022b)).
2. Introduction of a synchromodal transport re-planning problem under service time uncertainty and development of a model-assisted Reinforcement Learning approach to handling this uncertainty (Chapter 4).
3. Multi-objective optimization model for synchromodal transport planning that considers vague preferences of carriers (Chapter 5, Zhang et al. (2022a)).
4. Development of methodologies for synchromodal transport planning that considers heterogeneous and vague preferences of shippers using multiple attributes decision making and fuzzy set theory (Chapter 6, Zhang et al. (2022d)).
5. Designing of a conceptual framework for horizontal collaboration that considers preferences of shippers in the context of sustainability (Chapter 7, Zhang et al. (2022c)).
6. Evaluation and analysis of the proposed approaches through computational experiments and case studies using real-world data (Chapters 3-7, Zhang et al. (2020b) and Zhang et al. (2022a,b,c,d)).

1.5 Thesis outline

The outline of this thesis is shown in Figure 1.3. A literature review is conducted in Chapter 2. This chapter also identifies the main research gaps. In Chapter 3, a mathematical model is developed for synchromodal transport planning with flexible services (STPP-FS). This model considers both fixed and flexible services, as well as transshipment and synchronization between them. To solve the medium- or large-sized problem instances of the STPP-FS model, an ALNS heuristic algorithm with customized operators and performance improvement approaches is proposed. In Chapter 4, building upon the research problem in Chapter 3, the synchromodal transport re-planning problem under service time uncertainty is introduced and a model-assisted reinforcement learning approach is proposed to address this problem in real-time. Extending from the STPP-FS model in Chapter 3, Chapters 5 and 6 consider preferences of carriers and shippers through the use of multi-objective optimization and multiple attribute decision-making techniques, respectively. Chapter 6 considers the transport planning for one carrier. Chapter 7 considers collaborative planning among carriers to provide more alternative services and consider preferences through a conceptual framework for horizontal collaboration. Chapter 8 concludes the thesis and provides directions for future research.

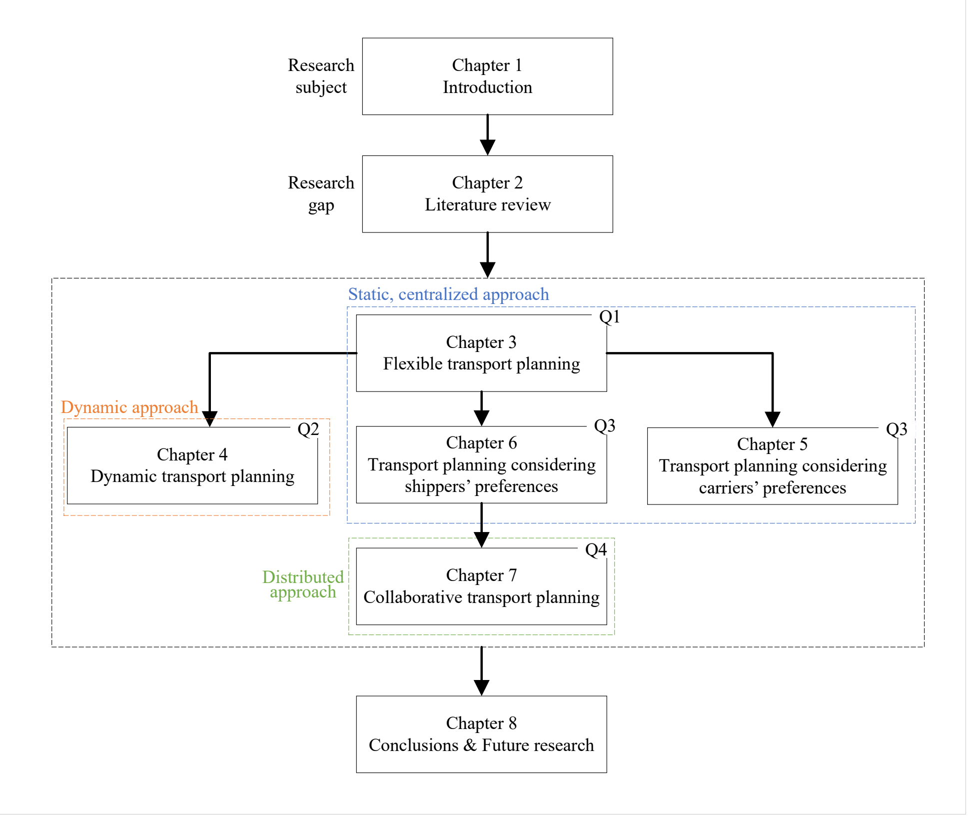


Figure 1.3: The outline of this thesis.

Chapter 2

Literature review

The research topic of this thesis is synchromodal transport planning, including flexible, dynamic, preference-based, and collaborative transport planning. Both synchromodal, multimodal, and intermodal transport studies are reviewed, as the limited studies in synchromodal transport are complemented by the relevant studies in multimodal and intermodal transport.

This chapter is organized as follows: Section 2.1 introduces synchromodal transport planning and reviews the critical success factors to achieve synchromodal transport planning. Section 2.2 reviews the challenges in static planning. Section 2.3 identifies the different types of uncertainties and the need for dynamic planning. Section 2.4 investigates the multi-objective optimization and preference-based optimization in synchromodal transport planning. Section 2.5 reviews collaborative planning approaches in synchromodal transport. Section 2.6 concludes the chapter and provides motivations for the following chapters highlighting the contributions to the literature.

2.1 Synchromodal transport planning

Multimodal transport is the original concept of combining the use of several transport modes, as described in UNCTAD (2020). Intermodal transport is the next concept in line, characterized by integration, the use of one and the same load unit, and the door-to-door concept as described in the definition proposed by the EC (1997) and the joint definition by UNECE (2001). Combined transport and co-modal transport are other concepts that are similar to intermodal transport but with slightly different characteristics as discussed in literature review articles of Reis (2015), SteadieSeifi et al. (2014), Van Riessen et al. (2015a). Synchromodal transport is the newest concept, characterized by the ability to switch freely between transport modes at particular times while the cargoes are in transit as described in the works of Behdani et al. (2014), Tavasszy et al. (2017), Verweij (2011).

Synchromodal transport offers multiple benefits such as improved resource utilization, increased reliability, cost savings, improved flexibility, and environmental benefits. These benefits are achieved by combining different modes of transport, reducing empty runs and providing alternative routes, allowing carriers to quickly respond to changes in demand or disruptions in the supply chain, and using more sustainable modes of transport. To achieve synchromodal transport, scholars have studied it from different perspectives, such as business, legal barriers, physical infrastructure, digital planning tools, awareness, and implementation (Rentschler et al. 2022). Synchromodal transport planning consists of planning at strategic, tactical, and operational levels (SteadieSeifi et al. 2014). Strategic level planning deals with long-term decisions related to investments in transportation infrastructure, such as building or expanding networks. Tactical level planning concerns optimization by utilizing the existing infrastructure, such as choosing services and transportation modes, allocating capacities, and planning itineraries and frequency. Operational level planning focuses on the real-time management of transportation services, considering the dynamic and uncertain nature of transportation demand and addressing any issues that arise in real-time. It involves making quick decisions on transportation modes, routes, and resource allocation to meet the actual demand. It is considered to be the most complex among the three levels as it involves dealing with real-time requirements of multiple parties and requires the use of advanced algorithms to make accurate and efficient decisions. This thesis focuses on synchromodal transport planning at tactical and operational levels.

The stakeholders in synchromodal transport planning include port authorities, terminal operators, carriers, freight forwarders, and shippers (Agbo et al. 2017). A shipper is an individual or company that sends goods to a recipient or another location by hiring a carrier or using a freight forwarder. Carriers are companies that physically transport goods, while freight forwarders are companies that act as intermediaries between shippers and carriers. This thesis focuses on shippers, carriers, and freight forwarders. Between carriers and freight forwarders, the focus is mainly on carriers as they are responsible for transport planning and execution. Note that, in some cases freight forwarders also own resources to transport goods, i.e., they can act also as carriers.

Table 2.1 reviews explanatory research on synchromodal transport and summarizes the critical success factors of synchromodal transport planning, including mode-free booking, integrated planning, flexible planning, real-time planning, collaborative planning, and preference-based planning. Other critical success factors not in operational transport planning, including trust among stakeholders, information and communication technologies (ICT) and intelligent transportation system (ITS) technologies, physical infrastructure, legal and political framework, mental shift, service cost, and pricing (Agbo et al. 2017, Giusti et al. 2019), are not considered in the review. It is worth noting that the review papers and explanatory research on synchromodal transport listed in Table 2.1 do not propose any transport planning models, but rather identify success factors for synchromodal transport planning.

Synchromodal transport involves shippers leaving mode selection to the carrier, allowing for flexibility in mode choice based on shipper needs and real-time availability. This is referred to as mode-free booking and is necessary for synchromodal transport (Behdani et al. 2014). Integrated planning is the process of optimizing transportation by considering all modes and resources in the entire network, it is more efficient than only scheduling specific routes and modes for each individual connection (Pfoser et al. 2021). Mode-free booking and integrated planning are prerequisites of other critical success factors. Without mode-free booking, shippers would be restricted to a specific mode of transportation, limiting the ability of the service provider to make adjustments based on real-time availability and customer requirements. This would make it difficult to achieve flexibility in transportation planning. Without integrated planning, the transportation plan would be limited to individual connections and specific routes, resulting in suboptimal utilization of resources and fewer alternative routes. This would make it difficult to achieve an optimal and efficient plan. Therefore, without mode-free booking and integrated planning, it is hard to achieve other critical success factors. Literature reviews on other critical success factors are provided in the following sections. Based on the literature review on critical success factors, this thesis addresses flexible, real-time, preference-based, and collaborative planning in Chapters 3, 4, 5&6, and 7, respectively. This thesis covers all of these success factors, and the proposed methodologies can be helpful in achieving synchromodal transport.

Table 2.1: Critical success factors of synchromodal transport planning in the literature

Article	Mode-free booking	Integrated planning	Flexible planning	Real-time planning	Collaborative planning	Preference-based planning
Behdani et al. (2014)	✓	✓	✓	✓	✓	
Van Riessen et al. (2015a)		✓	✓	✓		
Pfoser et al. (2016)	✓	✓		✓	✓	✓
Tavasszy et al. (2017)	✓	✓	✓	✓	✓	✓
Agbo et al. (2017)	✓	✓		✓	✓	✓
Guo et al. (2017)	✓	✓	✓	✓	✓	
Giusti et al. (2019)	✓	✓	✓	✓	✓	✓
Pfoser et al. (2021)	✓	✓		✓	✓	
Acero et al. (2022)	✓	✓	✓			
This thesis	✓	✓	✓	✓	✓	✓

2.2 Static planning

Static planning in synchromodal transport planning refers to the process of creating a transportation plan based on requests and available services. This type of planning typically takes place in advance and does not account for real-time changes in the transportation system. It forms the basis for dynamic and collaborative planning by providing a foundation for adjusting the transportation plan as needed. In the literature, static transport planning has primarily focused on the use of mathematical models and heuristic algorithms to optimize the routing and scheduling of vehicles and the flow of goods between different modes of transportation.

In synchromodal transport planning, both Minimum Cost Network Flow (MCNF) and Path-based Network Design (PBND) models are used to optimize the transport of containers over various links in the network, where each link has capacity constraints (Farahani et al. 2023, Van Riessen et al. 2013). MCNF models, such as the shipment matching problem, define links as services and match these services with requests (Demir et al. 2016, Guo et al. 2020). PBND models, on the other hand, have predetermined paths (subsequent links) for the transport of containers, which reduces the number of decision variables and can be more efficient compared to MCNF. However, PBND models may also lose some potential solutions and have a higher cost than MCNF models. Both MCNF and PBND models assume that the services (links or paths) are predefined and adhere to fixed time schedules. Some researchers allow for some flexibility in these models, but only in the form of flexible due or departure times (Demir et al. 2016, Van Riessen et al. 2013). These models, known as Service Network Design Problems (SNDP), use either MCNF, PBND, or a combination of both to model the transport of containers. Some papers allow for flexible due times and charge delay penalties (Ghane-Ezabadi and Vergara 2016, Guo et al. 2020, Van Riessen et al. 2013), while others allow for flexible departure times within a defined time window (Demir et al. 2016, Hrušovskỳ et al. 2018, Moccia et al. 2011). Qu et al. (2019) propose a re-planning model for synchromodal transport that integrates shipment rerouting and service rescheduling. This model benefits from two types of flexibility: the ability to split shipments and the inclusion of buffer times on the departure of services (Qu et al. 2019). However, this model does not consider changing pre-planned service routes.

Shipment routing is considered while vehicle routing is ignored when the service is a link or path. Vehicle routing is crucial for achieving synchromodal transport as it is necessary for flexible routing and scheduling (Larsen et al. 2021). Ignoring vehicle routing limits the potential for flexibility in transport operations. Some studies consider the routing of trucks. In the studies of Pérez Rivera and Mes (2019), Wolfinger et al. (2019), the routes of trucks are flexible, but only in the first- and last-mile of transport. Additionally, they limit each request to using at most one long-haul vehicle (ship or train). Larsen et al. (2021) consider simultaneous planning of container and truck routes, and the barge and train's routing is not considered.

Table 2.2 summarizes the studies in static planning and highlights that flexibility has not received enough attention to date. Flexibility in synchromodal transport planning is important because it allows for the adaptability of the transport plan to changing circumstances and demands. This can include changes in the availability of certain modes of transport, changes in customer requirements or preferences, and disruptions or unexpected events. Flexibility allows for the creation of transport plans that are more resilient to these changes, leading to more efficient and cost-effective transport operations. Additionally, flexibility can help to reduce the amount of unused or underutilized capacity in the transport system, leading to more sustainable transport operations.

One way to incorporate flexibility into synchromodal transport planning is through the use of flexible vehicles, such as trucks or barges, that are able to change routes and schedules and adapt to changes in demand and specific situations. However, there are also challenges to achieving flexibility in synchromodal transport planning. One of the main challenges is the need to develop effective optimization algorithms and decision-making frameworks that can handle the large solution space and complex constraints associated with flexible transport operations. This includes the coordination and synchronization between different transport modes, involving both fixed and flexible vehicles, as well as the routing and scheduling for requests and vehicles. This thesis proposes a synchromodal transport planning approach for integrated shipment and vehicle routing and considers both fixed and flexible vehicles in Chapter 3.

2.3 Dynamic planning

In synchromodal transportation, the utilization of multiple modes of transportation to transport goods from one location to another may result in various uncertainties. These uncertainties include, but are not limited to:

1. travel time uncertainty, which can be caused by factors such as traffic and weather conditions (Demir et al. 2016, Guo et al. 2022, 2021a, Yee et al. 2021);

Table 2.2: Summary of the literature review on static planning

Article	integrated vehicle and shipment routing	vehicle routing	flexible routing	flexible scheduling
Moccia et al. (2011)				dep
Van Riessen et al. (2013)				due and dep
Mes and Iacob (2016)				tw
Ghane-Ezabadi and Vergara (2016)				due
Demir et al. (2016)				dep
Hrušovskỳ et al. (2018)				dep
Wolfinger et al. (2019)	✓	truck	first- and last-mile trucks	wait and dep
Qu et al. (2019)				dep
Resat and Turkay (2019)				wait, due
Pérez Rivera and Mes (2019)	✓	truck	first- and last-mile trucks	N/A
Guo et al. (2020)				due and sto
Larsen et al. (2021)	✓	truck	trucks	wait, dep, due
Farahani et al. (2023)				wait and due
This thesis	✓	truck, barge, and train	trucks, barges	dep, due, wait, sto

dep: departure time, tw: time window, due: due time, wait: waiting time, sto: storage time

2. service time uncertainty, which can be caused by factors such as cargo loading and unloading, maintenance of equipment, weather-related issues, and congestion at terminals (Demir et al. 2016);

3. and demand uncertainty, which can be caused by factors such as market fluctuations, seasonal variability, and disruptions in supply chains (Demir et al. 2016, Guo et al. 2021b, Yee et al. 2021).

Such uncertainties can cause delays and disrupt the transportation schedule, leading to unhappy customers and financial losses for the transport company. It is therefore imperative that these uncertainties be taken into consideration when planning and executing synchromodal transport.

To mitigate these uncertainties in synchromodal transport, dynamic planning is essential. Dynamic planning is a process that enables real-time adjustments to transportation plans, taking into account the current and expected uncertainties. These adjustments can be made periodically (such as in the case of the rolling horizon approach) (Guo et al. 2021a,b, Li et al. 2015b, Pérez Rivera and Mes 2019, Rivera and Mes 2022, Van Riessen et al. 2016, Zhang and Pel 2016) or in real-time (such as in the case of the event-triggered approach) (Qu et al. 2019, Zhang and Pel 2016). A variety of methods can be employed to handle uncertainty within the framework of dynamic planning, including stochastic programming (Demir et al. 2016, Guo et al. 2021a,b), robust optimization (Li and Chung 2020), and machine learning (Guo et al. 2022, Pérez Rivera and Mes 2019, Rivera and Mes 2022, Van Riessen et al. 2016). Stochastic programming utilizes probability distributions to represent uncertainty in the model. Robust optimization is specifically designed to be robust against potential disruptions or changes in uncertain parameters. Meanwhile, machine learning techniques learn from experience, either online or offline and update the learned policy to make it more efficient in handling uncertainty. There are also studies that do not explicitly model uncertainty, but rather employ dynamic planning to adjust plans in response to unexpected events as they occur (Qu et al. 2019).

It is worth noting that stochastic programming and robust optimization typically assume the availability of distribution information on uncertainty and modeling uncertainty through these distributions (Guo et al. 2021a). Similarly, offline machine learning also assumes the availability of such distribution or historic information (Van Riessen et al. 2016). However, in real-world situations, such distribution information may not be available due to various reasons, such as a lack of historical records, difficulty in capturing uncertainty patterns through a specific distribution, or complexity in modeling uncertainty caused by multiple factors. In such cases, online learning may be a suitable solution, because it allows updating the model based on the current observations and it can also adapt to changing conditions, which can reduce the risk of poor performance due to inaccurate assumptions about the uncertainty distribution.

Table 2.3 summarizes the literature on dynamic synchromodal transport planning. In the literature, travel time and demand uncertainties have been extensively investigated, however, the service time uncertainty has not been fully addressed. Neglecting service time uncertainty in planning and decision-making can lead to delays and increased costs, negatively impacting the overall performance of synchromodal transport. Service time uncertainty can be influenced by multiple factors and the distribution of service time uncertainty is usually not available. Online learning methods are therefore needed. This thesis proposes an online Reinforcement Learning approach for synchromodal transport re-planning under service time uncertainty in Chapter 4.

2.4 Multi-objective and preference-based planning

The diverse objectives and preferences of shippers and carriers can make synchromodal transport planning a complex and challenging task, as it requires the integration of multiple (possibly conflicting) objectives and preferences into a single optimization model. To address this complexity, some studies have focused on the use of multi-objective optimization and preference-based optimization approaches in synchromodal transport planning.

Multi-objective optimization (MOO) is a method used to solve problems with multiple conflicting objectives. MOO includes different approaches. In the weighted sum method, weights are assigned to objectives and used to create a scalar objective function by linearly combining the multiple objectives with these weights. Another approach is the ε-constraint method, which involves restricting other objectives while minimizing or maximizing one objective (Zhang et al. 2020a). Pareto-optimality is also popular for solving MOO problems in synchromodal transport (Sun and Lang 2015a). Pareto-optimality is a concept used to describe a set of solutions that are not dominated by any other solution, which means that it is better in at least one objective and not worse in any other objectives. The multi-criteria decision making (MCDM) approach is also used, which allows for the explicit consideration

Table 2.3: Summary of the literature review on dynamic planning

Article	uncertainty	re-planning	learning	required prior information
Xu et al. (2015b)	demand	?	N/A	distribution
Li et al. (2015b)	?	periodical	N/A	N/A
Van Riessen et al. (2016)	demand	real-time	DT, offline	historical requests
Zhang and Pel (2016)	N/A	real-time	N/A	N/A
Demir et al. (2016)	travel and service time, demand	?	N/A	distribution
Qu et al. (2019)	N/A	real-time	N/A	N/A
Pérez Rivera and Mes (2019)	demand	periodical	ADP, ?	N/A
Guo et al. (2020)	demand	periodical	N/A	N/A
Guo et al. (2021a)	demand	periodical	N/A	distribution
Yee et al. (2021)	travel time	periodical	?	N/A
Guo et al. (2021b)	demand and travel time	periodical	N/A	distribution
Rivera and Mes (2022)	demand	periodical	ADP, offline	distribution
Guo et al. (2022)	travel time	periodical	RL, offline	distribution
Xu et al. (2023)	travel time		N/A	N/A
Akyüz et al. (2023)	N/A	real-time	N/A	N/A
This thesis	service time	real-time	DRL, online	none

DT: Decision tree; ADP: Approximate dynamic programming; RL: Reinforcement learning; DRL: Deep RL
"?" means that the relevant item is not mentioned in the article.

of multiple conflicting objectives in the decision-making process (Zhang et al. 2020c).

In recent years, there has been a growing interest in incorporating preferences into synchromodal transport planning (Shao et al. 2022, Zhang et al. 2020c). This is because preferences can play a significant role in determining the efficiency and effectiveness of synchromodal transport systems. Efficient synchromodal transport can move goods from one location to another with minimal resources, while effective synchromodal transport meets the needs and goals of the shippers and carriers. Carriers can design more targeted and efficient transport solutions by considering preferences, resulting in reduced waste and better alignment with actual needs. This can also lead to more sustainable solutions, as preferences may include criteria such as emissions. Additionally, considering preferences can improve satisfaction and trust among carriers and shippers, resulting in stronger relationships and greater cooperation among stakeholders, ultimately facilitating the successful implementation of synchromodal transport.

The integration of preferences into transport planning poses a significant challenge, as preferences can be highly heterogeneous and vague. They may be subjective and vary among different shippers and carriers, making it difficult to accurately capture and mathematically model them. In the context of synchromodal transport, shippers may hold conflicting preferences, requiring the carrier to navigate trade-offs among these preferences. There are several approaches to modeling preferences in transport planning. For example, in the weighted sum method, the preferences of the stakeholder are represented as weights for each objective. To handle the heterogeneity, multi-attribute decision making (MADM) is a method used to evaluate and compare different options or alternatives based on multiple criteria or attributes (Zanakis et al. 1998). To handle the vagueness, the fuzzy set theory is often used to represent preferences in a mathematical way, which can be compared and aggregated by the use of mathematical techniques to find the best solution (Koohathongsumrit and Meethom 2022).

Table 2.4 shows the summary of studies on multi-objective optimization and preferences in synchromodal transport. Some studies model preferences but do not consider them for transport planning (Koohathongsumrit and Meethom 2022, Oudani 2023, Pamucar et al. 2022). The vagueness of preferences is ignored in the synchromodal transport planning (Shao et al. 2022, Zhang et al. 2020c). In road transport, incorporating preferences in transport planning is also studied. For example, Dumez et al. (2021), Los et al. (2018) consider the delivery location preferences of recipients, Afshar-Bakeshloo et al. (2016), Baniamerian et al. (2018), Ghannadpour et al. (2014) consider fuzzy or soft time window preferences of recipients in the objective, and Zhang et al. (2013) use customer service level constraints to ensure the on-time shipment delivery preferences of recipients. In order to incorporate preferences of shippers and carriers into the transport planning, this thesis proposes approaches for synchromodal transport planning considering heterogeneous and vague preferences in Chapters 5 and 6.

Table 2.4: Summary of the literature review on multi-objective optimization and preferences in synchromodal transport

Article	planning	preferences	approach	heterogeneity	vagueness
Verma and Verter (2010)	✓		WS		
Resat and Turkay (2019)	✓		ε and PO		
Zhang et al. (2020c)	✓	shipper	MCDM	✓	
Shao et al. (2022)	✓	shipper	PO	✓	
Koohathongsumrit and Meethom (2022)		carrier	MCDM, FS	✓	✓
Pamucar et al. (2022)		expert	OPA-P		✓
Oudani (2023)			PO and MCDM		
This thesis	✓	shipper and carrier	PO, MADM, and FS	✓	✓

WS: weighted-sum method; ε: ε-constraint method; PO: Pareto-optimality; MCDM: Multi-criteria decision making; MADM: Multi-attribute decision making; OPA-P: Ordinal Priority Approach under picture fuzzy sets; FS: Fuzzy set theory

2.5 Collaborative planning

Collaborative planning can be divided into three types: centralized planning, decentralized planning, and distributed planning (Negenborn and Maestre 2014). If a controller has full power on all carriers, it is called centralized planning. When carriers are in charge of the local transport planning and require no communication among them, it is decentralized planning. When the carriers communicate in order to find a cooperative solution for the overall planning, it is distributed planning. Further divided by the means of exchanging requests, distributed planning can be non-auction or auction-based (Gansterer and Hartl 2018). There are various levels of cooperation between carriers, depending on the level of sharing information and resources and the establishment of joint partnerships.

Current research on collaborative planning mainly focuses on vertical collaboration for carriers with interconnecting transport networks. Puettmann and Stadtler (2010) study decentralized planning of carriers through iterative proposal exchange, analyzing stochastic demand on coordinated plans. Li et al. (2017) investigate a coordinated model predictive container flow control problem among multiple hinterland carriers in interconnected service areas. The Lagrangian relaxation method is used for the coordination among carriers. Guo (2020), Huang et al. (2021) and Zhou et al. (2023) use a similar coordination method as Li et al. (2017). Guo (2020) consider shipment requests that have specific time windows instead of container flows in Li et al. (2017). Larsen et al. (2020) propose a departure learning method for co-planning between barge and truck carriers. Studies have shown that collaboration can lead to significant performance improvements in synchromodal transport, such as cost savings (Guo 2020). Collaborative planning can enable carriers to share resources and information, such as equipment, routes, and demand forecasts, and to reduce empty runs and duplication of services. Collaborative planning can also facilitate the integration of multiple transport modes and the coordination of transshipment operations, which can improve the utilization of resources and the flexibility of the transport system.

There is more research on collaborative planning in road transport, compared to synchromodal transport (Gumuskaya et al. 2020). In the field of road transportation, researchers frequently investigate the concept of horizontal collaboration. Within this area of study, the auction-based approach is a commonly utilized methodology (Los et al. 2022). Auction-based collaborative planning refers to the use of auctions as a means to exchange requests among carriers. Auctions can provide a transparent and fair platform for carriers to negotiate and agree on terms for the provision of transport services. By allowing carriers to bid for requests from shippers and to offer their available capacity, auctions can facilitate the matching of demand and supply, leading to increased efficiency and improved utilization of resources. Furthermore, auctions can enable carriers to diversify their portfolio of services by making use of shared services from other carriers.

Table 2.5 summarizes the literature review on collaborative planning in synchromodal transport. Horizontal collaborative planning and auction-based distributed planning need to be investigated in synchromodal transport. The studies on collaborative planning do not consider preferences, although collaborative planning can also better satisfy the preferences of stakeholders. It can help carriers offer a wider range of services to shippers and meet their heterogeneous preferences. This can increase the attractiveness of synchromodal transport to shippers, as it provides them with more options and the possibility of finding a service that better fits their needs. This thesis proposes an auction-based approach for horizontal collaborative planning in synchromodal transport considering the preferences of shippers in Chapter 7.

Table 2.5: Summary of the literature review on collaborative planning in synchromodal transport

Article	participants	category	approach	preferences
Puettmann and Stadtler (2010)	drayage and intermodal carriers	VC	DP	
Li et al. (2017)	intermodal carriers	VC	DIP	
Guo (2020)	intermodal carriers	VC	DIP	
Larsen et al. (2020)	barge and truck carriers	VC	DIP	
Huang et al. (2021)	intermodal carriers	VC	DIP	
Zhou et al. (2023)	intermodal carriers	VC	DIP	
This thesis	intermodal/unimodal carriers	HC	ADP	✓

VC: Vertical collaborative planning; HC: Horizontal collaborative planning; CP: Centralized planning; DP: Decentralized planning; DIP: Distributed planning; ADP: Auction-based distributed planning; P: Preference.

2.6 Conclusions

In this literature review, we have discussed the concept of synchromodal transport and its potential advantages for improving efficiency, flexibility, and reliability. In terms of static planning, we have discussed different types of planning models and emphasized the importance of flexibility in enabling synchromodal transport to adapt to changing demands and disruptions. In terms of dynamic planning, we have discussed the importance of handling uncertainty in order to achieve reliable synchromodal transport. We have also reviewed the methods that can be used to handle travel time, service time, and demand uncertainties. In terms of preferences, we have discussed how they can be difficult to incorporate into transportation planning due to their heterogeneous and vague nature. We have also reviewed the existing studies on how preferences are modeled and considered in synchromodal transport, and the benefits of taking preferences into account in transport planning. Finally, in terms of collaborative planning, we have discussed the importance of collaboration in enabling synchromodal transport to provide a wider range of services and satisfy the preferences of stakeholders. We have also reviewed the different approaches to collaborative planning, including centralized, decentralized, and distributed approaches, and the benefits that can be obtained through collaboration.

We have also highlighted the challenges in synchromodal transport planning, including the importance of flexibility in static planning, the learning ability under service time uncertainty in dynamic planning, the consideration of heterogeneous and vague preferences in transport planning, and the need for horizontal collaborative planning among carriers. This thesis fills the research gap by proposing optimization models and solution algorithms that consider these factors in the context of synchromodal transport planning through domain knowledge-based methodologies and data-driven techniques. The approaches for static planning considering flexibility, dynamic planning, transport planning considering carriers' preferences, transport planning considering shippers' preferences, and horizontal collaborative planning are proposed in Chapters 3, 4, 5, 6, and 7, respectively. We have also highlighted the challenges in synchromodal transport planning, including the importance of flexibility, the learning ability under service time uncertainty, the consideration of heterogeneous and vague preferences, and the need for horizontal collaborative planning among carriers. This thesis fills the research gap by proposing optimization models and solution algorithms that consider these factors in the context of synchromodal transport planning through domain knowledge-based methodologies and data-driven techniques. The approaches for static planning considering flexibility, dynamic planning, transport planning considering carriers' preferences, transport planning considering shippers' preferences, and horizontal collaborative planning are proposed in Chapters 3, 4, 5, 6, and 7, respectively.

Chapter 3

Flexible services: Mathematical model and heuristic algorithm

As discussed in Chapters 1 and 2, service flexibility plays an important role in improving the utilization of resources to reduce costs, emissions, congestions, and delays. Despite its significance, there remains a gap in the consideration of flexible services within the context of synchromodality. In order to fill this gap, this chapter addresses research question Q1: How can routes be optimized for the carrier to provide flexible services?

This chapter is organized as below: Section 3.1 introduces the background of considering flexibility in synchromodal transport planning. Section 3.2 presents a brief literature review of articles related to synchromodal transport planning. Section 3.3 defines the problem in detail. The optimization problem is formulated by Mixed-integer Linear Programming in Section 3.4. Section 3.5 presents the solution methodology, i.e., a customized ALNS with a series of operators and performance improvement methods. In Section 3.6, experimental settings and results are provided. Section 3.7 concludes this chapter.

Parts of this chapter have been published in Zhang et al. (2020b) [1] and Zhang et al. (2022b)[2].

3.1 Introduction

As a distinct feature of synchromodality, service flexibility plays a key role in improving the utilization of resources (Behdani et al. 2014, Delbart et al. 2021, Giusti et al. 2019, Van Riessen et al. 2015a, Zhang and Pel 2016). The service flexibility means that the decision-maker can change vehicles' routes and schedules based on demand and available resources. In other words, flexible services enable the decision-maker to achieve the objective better by exploiting the benefits of each modal choice in synchromodal transport (ST).

[1]Zhang, Y., Atasoy, B., Souravlias, D., & Negenborn, R. R. (2020). Pickup and delivery problem with transshipment for inland waterway transport. In *Proceedings of 11th International Conference on Computational Logistics (ICCL 2020)*, Enschede, The Netherlands, pp. 18-35, September 28–30, 2020.

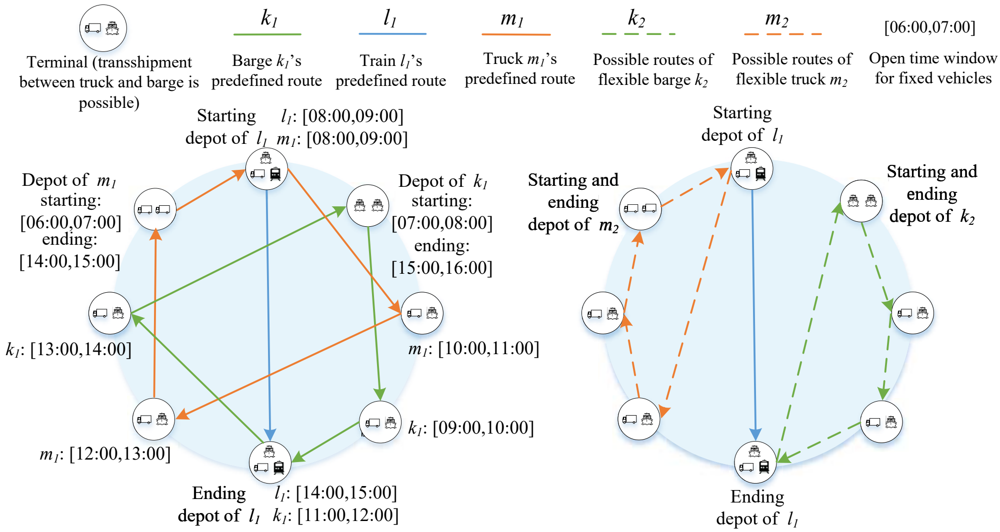
[2]Zhang, Y., Guo, W., Negenborn, R. R., & Atasoy, B. (2022). Synchromodal transport planning with flexible services: Mathematical model and heuristic algorithm. Transportation Research Part C: Emerging Technologies, 140, 103711.

Flexibility has different functions under different scenarios. Specifically, when the objective is to minimize cost, flexible services can reduce more costs than predefined services by avoiding empty miles, improving loading factors of low-cost vehicles, minimizing storage time, etc. Besides, flexible services can provide more alternatives to alleviate the impacts of congestion or other unexpected events than fixed services. Flexibility is also vital to handle transport demand in the most efficient and sustainable way by using different modes and routes in an integrated network (Delbart et al. 2021, Giusti et al. 2019).

However, the majority of the existing models in ST, e.g., Demir et al. (2016) and Guo et al. (2020), only consider services with fixed routes and schedules. The flexible services are not considered mainly due to the following reasons: (a) providing flexible services needs the development of various technologies, such as digital platform, information and communication technologies, and physical internet (Ambra et al. 2019, Giusti et al. 2019); (b) achieving flexible services needs to consider transshipment and synchronization of operations (Giusti et al. 2019); (c) tackling the optimization problem with flexible services needs customized, sophisticated and efficient algorithms due to computational complexity (Wolfinger 2021). Therefore, existing studies usually assume that the routes and schedules of services are predefined, which loses the flexibility of trucks and ships. In reality, routes of trucks and ships can be changed according to demands and weather, and transport operators and shippers are flexible in their negotiations depending on the circumstances, such as transportation volume and disturbances (Van Riessen et al. 2013). The requirement of flexibility and the development of modern technologies are driving the transformation from fixed to flexible services in ST.

Figure 3.1 illustrates the routing of vehicles with fixed versus flexible services. In the following, vehicles with fixed services and vehicles with flexible services are abbreviated as fixed vehicles and flexible vehicles, respectively. In Figure 3.1, the nodes are ST terminals, which could be ports or truck/train stations, and these nodes are connected by roads, railways, or inland waterways. When the vehicle is fixed, it can only run between predefined terminals. In contrast, when it's a flexible vehicle, its transport network is expanded, and it can go to any terminal if there are suitable routes for it. Assuming the routes are fixed may cause empty miles and low load factors, which increases the transport cost. Fixed vehicles' departure and arrival times need to fit in the predefined open time windows at terminals. Besides, the schedules of different requests are the same when using the same fixed vehicles. In contrast, the schedules are adjustable when using flexible vehicles because the transport operator can customize schedules for different requests to avoid unnecessary storage and delay. Although flexible vehicles could bring benefits for ST, fixed vehicles are still necessary in the current ST. For instance, the schedules of freight trains are usually predefined due to the higher priority accorded to passenger trains (Wolfinger et al. 2019). Therefore, the mix of fixed and flexible vehicles needs to be considered in synchromodal transport panning.

Flexible routing and scheduling need a vehicle routing component, which is often addressed by coarse approximations in the existing models that cannot be applied to ST with flexible services (Drexl 2012). For example, the links or paths are used to "transport" containers in the literature (Demir et al. 2016, Guo et al. 2020, Van Riessen et al. 2013). When considering flexible routing and scheduling at the operational level, the transport operator needs to take the capacity and speed of each vehicle into account and decide which vehicle will be used to serve requests. Moreover, the schedules of flexible vehicles, such as arrival/departure time and waiting time, need to be decided by the model. It is more con-



(a) Routing of vehicles with fixed services (b) Routing of vehicles with flexible services

Figure 3.1: Routing of vehicles with fixed and flexible services in synchromodal transport.

venient to calculate these times by adding a vehicle routing component as in the case of Vehicle Routing Problems (VRPs). The request routing is also required due to the possible transshipment between vehicles. Therefore, request routing and vehicle routing need to be modeled simultaneously. Furthermore, the transshipments of requests and interdependency between vehicles complicate both routing and scheduling in synchromodal transport planning (Drexl 2014, Rais et al. 2014, Zhang and Pel 2016).

In order to address the above-mentioned modeling requirements for synchromodality, we define the optimization problem as Synchromodal Transport Planning Problem with Flexible Services (STPP-FS). In STPP-FS, vehicles and requests are planned simultaneously, which allows the model to keep flexible during operations. The objective is to minimize the total cost, including transit cost, transfer cost, storage cost, carbon tax, waiting cost, and delay penalty. Besides typical constraints in routing optimization, such as time windows and capacity constraints, the special constraints for ST are considered in STPP-FS, including constraints on transshipments, different modes, fixed and flexible vehicles, and complex schedules. An ALNS heuristic is developed to solve the proposed problem efficiently. The proposed model allows flexible planning based on transport demands, which improves the utilization of available resources and reduces costs and emissions. To the best of our knowledge, this is the first study that formulates the STPP-FS and develops a customized ALNS to solve it.

3.2 Literature Review

This section presents a review of the literature on the optimization models in synchromodal transport planning and the studies in the freight transportation domain that considers flexible vehicles and transshipments.

3.2.1 Optimization models in synchromodal transport planning

In the literature, containers in ST are moved by vehicles with fixed schedules (Agamez-Arias and Moyano-Fuentes 2017, Guo et al. 2020, SteadieSeifi et al. 2014). These models can be divided into two groups: Minimum Cost Network Flow model (MCNF) and Path-based Network Design model (PBND) (Van Riessen et al. 2013). Both MCNF and PBND assume that the services (links or paths) are predefined and obey fixed time schedules, which loses flexibility due to the following reasons:

1. These service routes (links or paths) are predefined depending on historical information, such as transport volume and decision makers' experience. Because it is not practical to keep all possible service options, some potential routes are neglected due to historical low demand when designing services, although they can serve current requests in a better way. Therefore, research on synchromodal routing is mostly limited to commodity flow formulations based on predefined services, and vehicle routing is usually ignored (Wolfinger et al. 2019).

2. The time schedules are fixed and vehicles' departure/arrival time may not fit the pickup/delivery time windows of requests, which may cause unnecessary waiting cost, transshipment cost, storage cost, and delay penalties. Moreover, strictly complying with predefined time schedules is not realistic because there are uncertainties and disturbances (Van Riessen et al. 2013).

Some scholars allow some flexibility in the model but only allow the flexible due/departure times (Demir et al. 2016, Ghane-Ezabadi and Vergara 2016, Guo et al. 2020, Moccia et al. 2011, Qu et al. 2019, Van Riessen et al. 2013, Wolfinger et al. 2019). They regard the problem as a Service Network Design Problem (SNDP) and uses MCNF, PBND, or a combination of MCNF and PBND to model it. In practice, transport operators do not strictly follow the schedules because there are always new requests and delays, which makes some vehicles unavailable and needs other unplanned vehicles to serve the requests (Zhang and Pel 2016). Moreover, there are not always enough requests that make full use of the capacities of vehicles. Therefore, an optimization model with flexible services for ST is needed. To achieve flexible services, this study adds a vehicle routing component and these vehicles are highly dependent on each other due to flexibility, which leads to phenomena such as chain reactions that do not occur in MCNF and PBND. Furthermore, flexibility brings in computational complexity as the number of feasible services increases, and then a powerful and customized heuristic is needed. Therefore, the distinctions of our study compared with MCNF/PBND lie in having a mixed fleet of fixed and flexible vehicles in the research problem, a vehicle routing component in modeling, and a customized heuristic in the solution methodology.

3.2.2 Optimization models with flexible vehicles and transshipments in freight transport

Optimization models that consider flexible vehicles and transshipments in freight transportation are usually regarded as Pickup and Delivery Problem with Transshipment (PDPT). The PDPT is a variant of the Pickup and Delivery Problem (PDP), where requests can change vehicles at transshipment points during their trips (Masson et al. 2013, Mitrović-Minić and Laporte 2006, Shang and Cuff 1996). Qu and Bard (2012) use a Greedy Randomized Adaptive Search Procedure (GRASP) to generate the initial solution of PDPT for transport of aircraft and then use ALNS to improve the initial solution. Rais et al. (2014) propose several variants for PDPT, including cases with and without time windows, a heterogeneous fleet of vehicles, variable size fleet, split loads, and a limited number of transfer nodes visited by a vehicle. A small instance with seven requests is solved using Gurobi optimization software in their paper. Ghilas et al. (2016) integrate freight flows with scheduled public transportation services in short-haul transport, and the packages can be transferred between trucks and scheduled lines. Danloup et al. (2018) use both Large Neighborhood Search (LNS) and Genetic Algorithm (GA) to solve PDPT, where transport duration limitation is considered for requests and pickup/delivery time windows are ignored, therefore there is no time synchronization in their paper. Moreover, a request can be transshipped at most once, i.e., it cannot be served by more than two vehicles in their model.

Wolfinger and Salazar-González (2021) propose a branch-and-cut algorithm for solving PDP with split loads and transshipments (PDPSLT), however, the time window is not considered and the time synchronization method is not proposed. In another paper of Wolfinger (2021), the time window is considered and LNS is used to solve PDPSLT, and some insights regarding the benefits of combining split loads and transshipments are provided. In Wolfinger (2021)'s model, transshipment is allowed at dedicated transshipment locations and not allowed at customer locations.

The key feature of PDPT is the synchronization of activities among different vehicles. These synchronization requirements make routes interdependent (Drexl 2013, Hojabri et al. 2018). For example, if a special request is inserted into a route of vehicle k and delayed request r served by vehicles k and l, all later requests in the route of vehicle l will also be delayed. Then these already scheduled requests need to be re-planned due to interconnections between routes.

3.2.3 Summary and contributions

This section compares the model developed in this study with the existing studies in the literature in Table 3.1.

In Table 3.1, all models are divided into three groups, i.e., models in ST (upper part), models in freight transport (lower part), and the proposed model (the last row). Almost all models consider transshipment but only part of them considers synchronizations among vehicles. The models in ST include multiple modes and fixed vehicles, while models in freight transport consider more flexibilities. In comparison, the model developed in this study has synchronization requirements, flexible routes, and flexible schedules, which include flexible due time, flexible waiting time, flexible storage time, and flexible departure time.

Regarding the studies in freight transport, Ghilas et al. (2016)'s study seems similar to

Table 3.1: Comparison between the proposed model and existing models in the literature

Article	Problem	Mode	Service	Objective	Heuristic	T	S	F	FR	FDue	FW	FS	FDep
Synchromodal transport													
Moccia et al. (2011)	SNDP	railway, road	link &path	c	BC	✓	✓	✓					✓
Van Riessen et al. (2013)	SNDP	waterway, railway, road	link &path	c, t, d	–	✓		✓	✓	✓			
Ghane-Ezabadi and Vergara (2016)	SNDP	–	path	c	DS	✓		✓		✓			
Demir et al. (2016)	STPP	waterway, railway, road	link	c, t, e, w, d	–	✓	✓	✓					✓
Hrušovskỳ et al. (2018)	SNDP	waterway, railway, road	link	c, t, e, w, d	–	✓	✓	✓					✓
Wolfinger et al. (2019)	MMLHRP	waterway, railway, road	vehicle	c	ILS	✓	✓	✓	✓		✓		✓
Qu et al. (2019)	SNDP	waterway, railway, road	link	c, t, s, d	–	✓	✓	✓					✓
Resat and Turkay (2019)	STTP	waterway, railway, road	link	c, t, e	–	✓	✓	✓		✓	✓		
Pérez Rivera and Mes (2019)	SMDP and PDP	waterway, railway, road	vehicle and link	c	–	✓	–	✓	✓				
Guo et al. (2020)	STPP	waterway, railway, road	link	c, t, s, e, w, d	PGFM	✓	✓	✓		✓		✓	
Larsen et al. (2021)	STPP	waterway, railway, road	link and vehi-cle	c, t, s, d	–	✓	✓	✓	✓	✓	✓		✓
Farahani et al. (2023)	SNDP	waterway, railway, road	link	c, t, d	GA	✓	✓	✓		✓	✓		
Freight transport													
Qu and Bard (2012)	PDPT	road	vehicle	c	GRASP& ALNS	✓	✓		✓		✓		✓
Rais et al. (2014)	PDPT	road	vehicle	c	–	✓	✓		✓	✓	✓		✓
Ghilas et al. (2016)	PDPTWSL	metro, road	vehicle	c, t	ALNS	✓	✓	✓	✓		✓	✓	✓
Danloup et al. (2018)	PDPT	road	vehicle	n, dis	LNS&GA	✓			✓				✓
Wolfinger and Salazar-González (2021)	PDPSLT	road	vehicle	c, t	–	✓			✓				
Wolfinger (2021)	PDPSLT	road	vehicle	c, t	LNS	✓	✓		✓		✓		✓
This study	STPP-FS	waterway, railway, road	vehicle	c, t, s, e, w, d	ALNS	✓	✓	✓	✓	✓✓✓	✓	✓	✓

–: not considered in the related paper.
T: Transshipment operations; S: Synchronization of operations; F: Fixed vehicles; FR: Flexible routing; FDue: Flexible due time; FW: Flexible waiting time; FS: Flexible storage time; FDep: Flexible departure time; c, t, s, e, w, d, n, dis: transit cost, transfer cost, storage cost, carbon tax, waiting cost, delay penalty, number of used vehicles, distance; SNDP: Service Network Design Problem; MMLHRP: Multimodal Long Haul Routing Problem; PDPT: PDP with Transshipment; PDPTWSL: PDP with Time Windows and Scheduled Lines; PDPSLT: PDP with Split Load and Transshipment; STPP: Synchromodal Transport Planning Problem; STPP-FS: STPP with Flexible Services; BC: Branch-and-cut algorithm; DS: Decomposition-based Search; ILS: Iterated Local Search; PGFM: preprocessing heuristics of Path Generation and Feasible Matches; GRASP: Greedy Randomized Adaptive Search Procedure; LNS: Large Neighborhood Search; ALNS: Adaptive LNS; GA: Genetic Algorithm

us. However, we establish models for different fields, and the sizes of transport networks are also different. They consider trucks and scheduled lines in urban transport. However, in this study, services with different modes, including barges, trucks, and trains, are allowed to be used to transport containers in hinterland transport. Besides, the objectives of our mathematical models are different, which will influence the solutions significantly. While Ghilas et al. (2016) design more origin and destination nodes but a few transshipment nodes, all the nodes in our model can be transshipment nodes. These differences make the routes of vehicles in synchromodal transport more dependent on each other and it also makes the problem in ST more difficult to solve because it causes complicated chain reactions and heavy burdens on the computation time (see detailed explanations in Section 3.5.4). Compared with PDPT in the literature (Danloup et al. 2018, Wolfinger 2021), there are some new characteristics in STPP-FS, such as more than two modes, a mix of fixed and flexible vehicles, and complex schedules. Moreover, these characteristics influence each other, which makes the transshipment and synchronization in STPP-FS more complex than PDPT.

In contrast, both Guo et al. (2020) and Demir et al. (2016) solve Synchromodal Transport Planning Problem (STPP) and consider the same modes with our study, including waterway, railway, and road. Guo et al. (2020) design the same objective function and Demir et al. (2016) only do not consider the storage cost compared with ours. In their studies, some links between two terminals are defined as services, and each service has a specific capacity, travel and service times, costs, and CO_2 emissions. The requests need to be picked up/delivered within specific time windows and can be transferred between services. Therefore, the most related articles are the studies of Guo et al. (2020) and Demir et al. (2016). However, there are still significant differences between the studies. The services in Guo et al. (2020) and Demir et al. (2016) are fixed and vehicle routing is not considered. In this study, the possibility of using transshipments increases a lot due to flexible services, therefore the complexity of STPP-FS grows exponentially. Moreover, the vehicle routing and request routing need to be considered simultaneously in STPP-FS, which makes the modeling more complicated. Therefore, the modeling approach for STPP-FS is different from both models in synchromodal and freight transport.

The main contributions of this study are briefly summarized as follows. Firstly, we propose a mathematical model to provide a formulation of the STPP-FS. Fixed vehicles are restricted by predefined routes and time windows at terminals. On the contrary, flexible vehicles have flexible routes and schedules. Transshipment and synchronization of both fixed and flexible vehicles are considered. Only fixed, only flexible, or hybrid fleets can be handled by the proposed model. The proposed model with flexibilities necessitates an efficient solution algorithm as the solution space is large. To address this need, we develop a customized Adaptive Large Neighborhood Search (ALNS) heuristic algorithm according to the characteristics of STPP-FS. Therefore, the second contribution is the ALNS with specific adaptations and improvements, which include customized operators (e.g., a swap operator) for ST, feasibility checking methods, and performance improvement approaches. Finally, we provide insights about the added value of flexibility in ST through computational experiments that compare the proposed approach to different benchmarks. In a nutshell, we design and validate a model that optimizes routes and schedules for fixed and flexible vehicles simultaneously in ST and can be used by freight forwarders and carriers for more economic and sustainable transport operations.

3.3 Problem Description

We consider a setting with multiple shippers and a transport operator. The transport operator can be the freight forwarder, carrier, or transport platform in reality, and makes decisions on the routing and scheduling of vehicles (Li et al. 2015b). The shippers provide the request information, including pickup and delivery terminals, number of containers, and time windows; and the transport operator provides transport network information, including terminal information, distances among terminals, vehicle information, and cost. The transport operator wants to optimize the transport operations and provide low-cost services to shippers (Di Febbraro et al. 2016). Moreover, the transport operator is assumed to be able to keep flexible schedules by collaborating with terminal operators. All travel times between terminals are known beforehand, except trucks' travel times which are influenced by traffic congestion. All costs are in Euros and the unit of containers is Twenty-foot Equivalent Unit (TEU).

The characteristics of the proposed STPP-FS include multiple modes, transshipment, the mix of fixed and flexible vehicles, complex schedules, and synchronization, as shown in Figure 3.2.

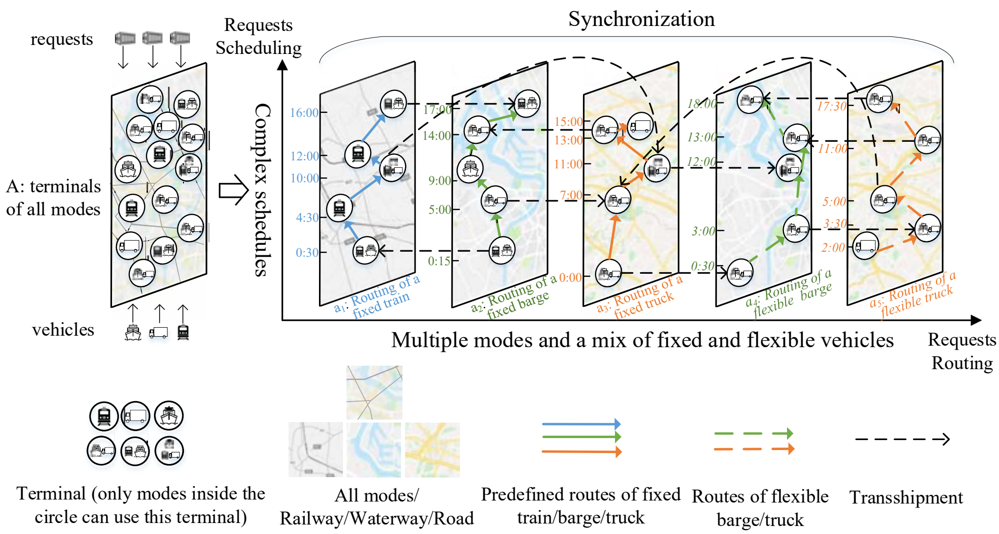


Figure 3.2: Characteristics of the STPP-FS. To illustrate the problem clearly, the real-life transport network (layer A) is decomposed into five layers (a_1, a_2, a_3, a_4, a_5), which are routing and scheduling of five types of vehicles. The main horizontal and vertical axes are the routing and scheduling of requests, respectively. The vehicles and requests are planned simultaneously in this study.

1. Multiple modes. In ST, trucks, barges, and trains are used to serve requests, and one request can be served using any combination of these modes. Different modes have different parameters on capacity, speed, costs, and emissions. Barges usually have the lowest emissions and costs but have the slowest travel speed. Trains have a moderate speed and cost. We assume that a truck service is a truck fleet and each truck can serve requests in the fastest way when containers arrive. Trucks are the fastest vehicles but the transportation cost is higher than trains and barges.

2. Transshipment. A request can be transferred between vehicles at transshipment terminals, which can provide transshipment equipment and a yard for the temporary storage of containers. Typically a transshipment terminal has functions of regular terminals, therefore it can also be pickup/delivery terminals. Different transshipment terminals provide different types of services, such as transshipments between barges and trucks. Transshipments between vehicles with the same mode but different time

schedules are also possible. Compared with ST with only fixed vehicles, the flexible services increase the possibility of transshipments significantly. In Figure 3.3, request r is transported by a barge firstly and then transferred to a truck fleet. At the transshipment terminal, the barge should arrive earlier than trucks. When trucks arrive at the transshipment terminal before the barge completes the unloading, trucks will wait for the barge.

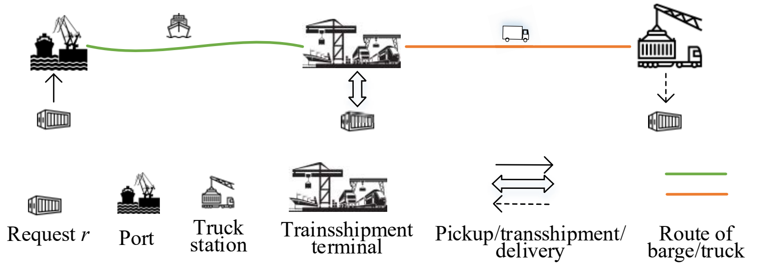


Figure 3.3: Transshipment

3. The mix of fixed and flexible vehicles. In ST, trucks and barges may be flexible while trains are fixed. Fixed vehicles can only run between predefined terminals, and the departure time and arrival time are also predefined. Flexible vehicles can go to any terminal (on available routes, such as waterways for barges) and have no predefined schedules. Therefore, there are five types of vehicles, i.e., fixed barges, trains, and trucks, and flexible barges and trucks, as shown in Figure 3.4. In Figure 3.4, there are three terminals, i.e., terminal A, B, and C, and two requests, i.e., requests r_1 and r_2, which are transported in different ways by five types of vehicles. Request r_1's pickup terminal and transshipment terminal are terminals A and B. Request r_2's transshipment terminal and delivery terminal are terminals B and C. When requests are transported by the fixed barge, two barges are needed, i.e. barge k_1 from terminal A to B for request r_1 and barge k_2 from terminal B to C for request r_2. When the barge is flexible, only one barge k_1 is needed and k_1 starts at A and goes through B to C. Another flexible barge k_2 could go to other terminals and transport other requests. The case with fixed trains l_1 and l_2 is similar to fixed barges. Regarding truck fleet, one request is usually served by multiple trucks, and each truck transports one container. The difference between fixed and flexible truck fleets is similar to barges.

4. Complex schedules. In the scheduling of ST, the waiting time, storage and delay need to be considered. If a vehicle arrives before containers at the pickup terminal or transshipment terminal, it can wait until containers arrive. If containers arrive before vehicles, they can be temporarily stored in the terminal with a storage fee until the vehicle arrives. If a vehicle is delayed at the delivery terminal, it will be charged with a delay penalty. The transshipment makes the waiting time and delay of one vehicle influenced by another vehicle, and the waiting and storage time could be changed to synchronize vehicles. Moreover, the mix of fixed and flexible vehicles and transshipments between different modes also make the scheduling more complicated. Figure 3.5 shows the schedules of fixed barges k_1 and k_2 in Figure 3.4. Containers

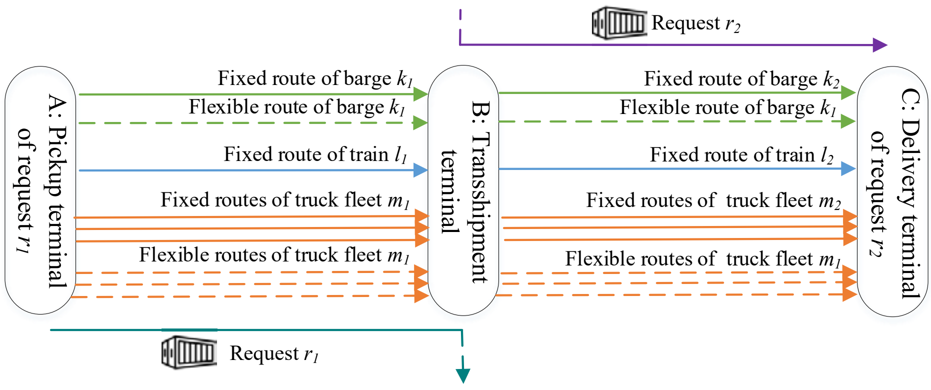


Figure 3.4: Five types of vehicles

must be loaded/unloaded in the open time windows for vehicles at each terminal. At terminal A, the open time window for vehicle k_1 is $[1,3]$, and request r_1's pickup time window is $[2,4]$. Therefore, request r_1 will be picked up at time 2. Request r_2 arrives at terminal B at time 5. However, vehicle k_1 has not arrived and request r_2 needs to wait for vehicle k_1 at terminal B. Therefore, request r_2 is stored at terminal B until time 7. During the open time window ($[7,8]$) at terminal B, k_1 unloads r_1 and k_2 loads r_2. At terminal C, k_2 arrives later than the delivery time window of request r_2, which causes one hour's delay. If requests are transported by flexible vehicles, these unnecessary storage and delay could be avoided, but the overall schedule will be more complex because the schedule of one vehicle will influence the schedule of another vehicle.

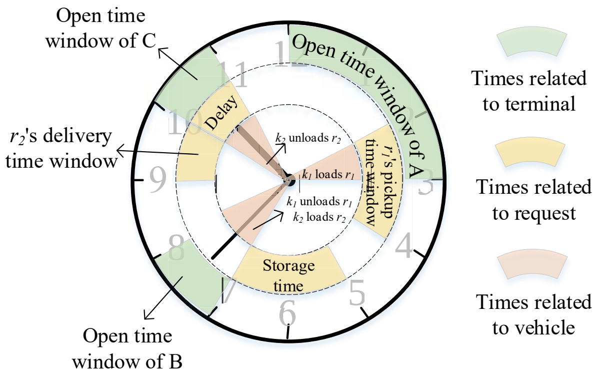


Figure 3.5: Complex schedules

5. Synchronization. Because of the transshipment, changes in a vehicle's route may affect another vehicle's route. Such influences might trigger a chain reaction in all routes, which may make the original plan infeasible. When vehicles influence each other, synchronization between vehicles is required in ST. Specifically, the synchro-

nization coordinates vehicles and minimizes the changes to the original plan. The complex schedules also complicate the time synchronization between vehicles. As shown in Figure 3.6, there are three requests (r_2, r_3, and r_4) that are served by a flexible barge, a flexible truck fleet, and a train with fixed services. The requests are transferred between these three services at two transshipment terminals and a vehicle may transport more than one request at the same time. Request r_2 is transferred twice, i.e., from barge to truck and then to train. When a new request r_1 is inserted into the barge's route, not only the barge's schedule is influenced, but also the train's schedule is influenced due to the transshipment of request r_2. Moreover, the barge and train's schedules are also influenced by the changes in the truck's schedule due to the transshipment of requests r_2 and r_4 at another transshipment terminal.

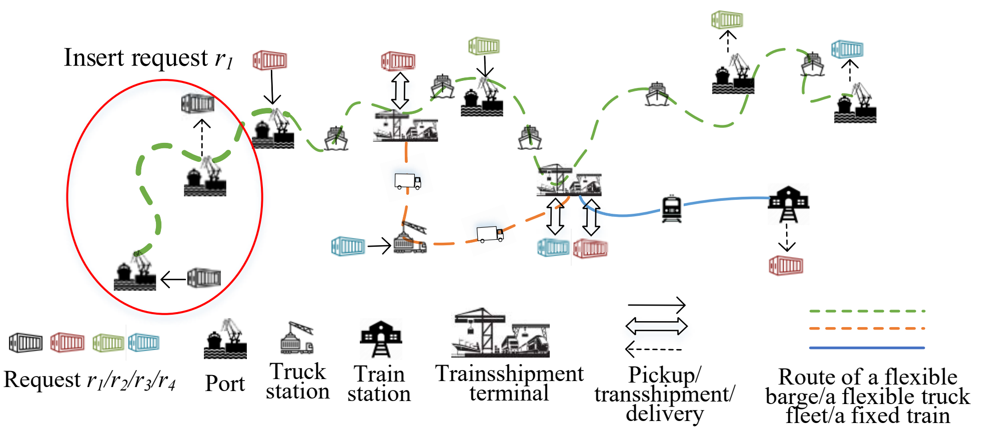


Figure 3.6: Synchronization

3.4 Mathematical Model

This section presents the Mixed-integer Linear Programming model to formulate the STPP-FS. There are multiple modes $w \in W$ in a transport network. The transport network is defined as a directed graph $G = (N, A)$, where N represents the set of terminals (ports and train/truck stations) and $A = \{(i, j)|i, j \in N, i \neq j\}$ represents the set of arcs (roads, railways, and inland waterways). $P, D, T, O \subseteq N$ are sets of pickup terminals, delivery terminals, transshipment terminals, and depots of vehicles. In ST, the same terminal could belong to all P, D, T, O sets and be accessed by all transport modes. The nonnegative travel time τ_{ij}^{k} equals the distance between i and j divided by speed v_k of vehicle k. Note that distances are different for different modes because different modes use different routes between i and j. Moreover, the travel time $\tau_{ij}^{\prime kr}$ of trucks is considered time-dependent, which means travel time at peak periods will be longer than non-peak periods due to traffic congestion (Guo et al. 2020).

The unit of capacity of vehicles is TEU. Barges and trains have fixed capacities and a truck's capacity is 1 TEU. We assume that each truck fleet has an unlimited number of trucks. The pickup and delivery terminals of request $r \in R$ are designated by $p(r)$ and $d(r)$.

Let $o(k)$ and $o'(k)$ represent the starting and the ending depot of vehicle $k \in K$. Some depots may be the same terminals with pickup/delivery terminals, which makes some constraints of pickup/delivery terminals, such as time window constraints, will also work on these depots when the related vehicle does not serve the request. Dummy depots $\overline{o}(k)$ and $\overline{o'}(k)$ are therefore created. Fixed vehicles can only go to terminals in predefined routes, and there is an open time window at each terminal $[a_i^k, b_i^k]$, in which fixed vehicles can load/unload containers.

A solution of the STPP-FS is a set of $|K|$ routes that serve all requests and route k starts and ends at (dummy) depots. At any moment, the number of containers carried simultaneously by vehicle k cannot exceed capacity u_k. For every request r, terminals $p(r)$ and $d(r)$ can be served by the same vehicle k, which means $d(r)$ being served after $p(r)$. Terminals $p(r)$ and $d(r)$ can also be served by distinct vehicles $k_1 \in K$ and $k_2 \in K$, and r is transferred from k_1 to k_2, which means vehicle k_2 must start its service at the transshipment terminal after vehicle k_1 which unloads the containers. Request r needs to be picked up in time window $[a_{p(r)}, b_{p(r)}]$ and delivered in time window $[a_{d(r)}, b_{d(r)}]$, but the delivery time can exceed $b_{d(r)}$ with a delay penalty. Vehicle k is allowed to wait for containers at terminal i and request r is allowed to be stored at terminal i when the vehicle has not arrived.

The objective of the proposed STPP-FS is minimizing cost (Euros), which consists of transit cost (F_1), transfer cost (F_2), storage cost (F_3), carbon tax (F_4), waiting cost (F_5), and delay penalty (F_6), as shown in Equations (3.1)-(3.7) (Guo et al. 2020). The emissions are calculated using an activity-based method by Demir et al. (2016) and the amount of emissions is related to vehicle type, distance, and amount of containers. The decision variables are shown in Table 3.2. The binary variables x_{ij}^k and y_{ij}^{kr} decide whether vehicle k uses arc (i,j) or not and whether vehicle k carries request r on arc (i,j) or not, respectively. The binary variable z_{ij}^k is used for subtour elimination. We also have the binary variable s_{ir}^{kl}, which decides whether request r is transferred from vehicle k to vehicle l at terminal i or not. For barge and train services, constraints for both vehicle flow (constraints related to variables x_{ij}^k) and request flow (constraints related to variables y_{ij}^{kr}) are considered. Some constraints for vehicle flows do not apply to truck services, because truck services in this study are truck fleets and trucks in a truck fleet may serve different requests with different schedules.

Table 3.2: Decision variables

x_{ij}^k	Binary variable; 1 if vehicle k uses the arc (i,j), 0 otherwise.
y_{ij}^{kr}	Binary variable; 1 if request r transported by vehicle k uses arc (i,j), 0 otherwise.
z_{ij}^k	Binary variable; 1 if terminal i precedes (not necessarily immediately) terminal j in the route of vehicle k, 0 otherwise.
s_{ir}^{kl}	Binary variable; 1 if request r is transferred from vehicle k to vehicle $l \neq k$ at transshipment terminal i, 0 otherwise.

$$\min\ F = F_1 + F_2 + F_3 + F_4 + F_5 + F_6 \tag{3.1}$$

$$F_1 = \sum_{k \in K} \sum_{(i,j) \in A} \sum_{r \in R} (c_k^1 \tau_{ij}^k + c_k^{1'} d_{ij}^k) q_r y_{ij}^{kr} \tag{3.2}$$

$$F_2 = \sum_{k,l \in K, k \neq l} \sum_{r \in R} \sum_{i \in T} (c_k^2 + c_l^2) q_r s_{ir}^{kl} + \sum_{k \in K} \sum_{(i,j) \in A_p} \sum_{r \in R} c_k^2 q_r y_{ij}^{kr} + \sum_{k \in K} \sum_{(i,j) \in A_d} \sum_{r \in R} c_k^2 q_r y_{ij}^{kr} \tag{3.3}$$

$$F_3 = \sum_{k,l \in K, k \neq l} \sum_{r \in R} \sum_{i \in T} c_k^3 q_r s_{ir}^{kl} ({t'}_i^{lr} - \bar{t}_i^{kr}) + \sum_{k \in K} \sum_{(i,j) \in A_p} \sum_{r \in R} c_k^3 q_r y_{ij}^{kr} ({t'}_i^{kr} - a_{p(r)}) \tag{3.4}$$

$$F_4 = \sum_{k \in K} \sum_{(i,j) \in A} \sum_{r \in R} c_k^4 e_k q_r d_{ij}^k y_{ij}^{kr} \tag{3.5}$$

$$F_5 = \sum_{k \in K_{\text{b\&t}}} \sum_{i \in N} c_k^5 t_{ki}^{\text{wait}} \tag{3.6}$$

$$F_6 = \sum_{r \in R} c_r^{\text{delay}} q_r t_r^{\text{delay}} \tag{3.7}$$

Constraints (3.8)-(3.26) are the spatial constraints and Constraints (3.27)-(3.49) are the time-related constraints.

Constraints (3.8)-(3.15) are typical constraints in PDP. Constraints (3.8) and (3.9) ensure that a vehicle begins and ends at its begin and end depot, respectively. Constraints (3.8)-(3.9) are modified from Rais et al. (2014), and these constraints only limit the routes of barges and trains because each truck service is considered as a fleet of trucks which might have different routes. Constraints (3.10)-(3.12) are the subtour elimination constraints and provide tight bounds among several polynomial-size versions of subtour elimination constraints (Öncan et al. 2009). Constraints (3.13) and (3.14) ensure that containers for each request must be picked and delivered at its pickup and delivery terminal, respectively. Constraints (3.15) are the capacity constraints.

$$\sum_{j \in N} x_{\overline{o}(k)j}^k \leqslant 1 \quad \forall k \in K_{\text{b\&t}} \tag{3.8}$$

$$\sum_{j \in N} x_{\overline{o}(k)j}^k = \sum_{j \in N} x_{j\overline{o'}(k)}^k \quad \forall k \in K_{\text{b\&t}} \tag{3.9}$$

$$x_{ij}^k \leqslant z_{ij}^k \quad \forall i,j \in N, \ \forall k \in K_{\text{b\&t}} \tag{3.10}$$

$$z_{ij}^k + z_{ji}^k = 1 \quad \forall i,j \in N, \ \forall k \in K_{\text{b\&t}} \tag{3.11}$$

$$z_{ij}^k + z_{jp}^k + z_{pi}^k \leqslant 2 \quad \forall i,j,p \in N, \ \forall k \in K_{\text{b\&t}} \tag{3.12}$$

$$\sum_{k \in K} \sum_{j \in N} y_{p(r)j}^{kr} = 1 \quad \forall r \in R \tag{3.13}$$

$$\sum_{k \in K} \sum_{i \in N} y_{id(r)}^{kr} = 1 \quad \forall r \in R \tag{3.14}$$

$$\sum_{r \in R} q_r y_{ij}^{kr} \leqslant u_k x_{ij}^k \quad \forall (i,j) \in A, \ \forall k \in K \tag{3.15}$$

Constraints (3.16) and (3.17) facilitate transshipment. Constraints (3.16) ensure that the transshipment occurs only once per transshipment terminal. Constraints (3.17) forbid transshipment between the same vehicle k.

$$\sum_{j\in N} y_{ji}^{kr} + \sum_{j\in N} y_{ij}^{lr} \leqslant s_{ir}^{kl} + 1 \quad \forall r \in R,\ \forall i \in T,\ \forall k,l \in K \tag{3.16}$$

$$s_{ir}^{kk} = 0 \quad \forall r \in R,\ \forall i \in T,\ \forall k \in K \tag{3.17}$$

Flow conservation constraints of both vehicles and requests are handled by Constraints (3.18)-(3.23). Constraints (3.18) represent flow conservation for vehicle flow and (3.19)-(3.22) represent flow conservation for request flow. Constraints (3.19) are for regular terminals and Constraints (3.20) are for transshipment terminals. Constraints (3.21) and (3.22) ensure the flow conservation of requests when vehicle k passes the transshipment terminal but no transfer happens. Constraints (3.21) and (3.22) consider a special case in STPP-FS, where request r is not transferred at terminal $i \in T$ but vehicle k passes terminal i due to operations for other requests. Constraints (3.23) link y_{ij}^{kr} and x_{ij}^{k} variables to guarantee that for a request to be transported by a vehicle, that vehicle needs to traverse the associated arc.

$$\sum_{j\in N} x_{ij}^{k} - \sum_{j\in N} x_{ji}^{k} = 0 \quad \forall k \in K_{\text{b\&t}},\ \forall i \in N \setminus \overline{o}(k), \overline{o'}(k) \tag{3.18}$$

$$\sum_{j\in N} y_{ij}^{kr} - \sum_{j\in N} y_{ji}^{kr} = 0 \quad \forall k \in K,\ \forall r \in R,\ \forall i \in N \setminus T, p(r), d(r) \tag{3.19}$$

$$\sum_{k\in K}\sum_{j\in N} y_{ij}^{kr} - \sum_{k\in K}\sum_{j\in N} y_{ji}^{kr} = 0 \quad \forall r \in R,\ \forall i \in T \setminus p(r), d(r) \tag{3.20}$$

$$\sum_{j\in N} y_{ij}^{kr} - \sum_{j\in N} y_{ji}^{kr} \leqslant \sum_{l\in K} s_{ir}^{lk} \quad \forall k \in K,\ \forall r \in R,\ \forall i \in T \setminus p(r), d(r) \tag{3.21}$$

$$\sum_{j\in N} y_{ji}^{kr} - \sum_{j\in N} y_{ij}^{kr} \leqslant \sum_{l\in K} s_{ir}^{kl} \quad \forall k \in K,\ \forall r \in R,\ \forall i \in T \setminus p(r), d(r) \tag{3.22}$$

$$y_{ij}^{kr} \leqslant x_{ij}^{k} \quad \forall (i,j) \in A,\ \forall k \in K,\ \forall r \in R \tag{3.23}$$

Characteristics of ST are considered in Constraints (3.24)-(3.26). Constraints (3.24) avoid vehicles running on unsuitable routes, for example, the truck cannot run on inland waterways. Constraints (3.25) take care of predefined routes for certain vehicles. Constraints (3.26) ensure the transshipment occurs in the right transshipment terminal because some transshipment terminals only allow the transshipment between two specific modes. When the containers need to be transferred from barges to trucks, terminals that only allow transshipment between barges and trains will not be considered. Constraints (3.24)-(3.26) are unique to this model because they consider the characteristics of vehicle routing in ST.

$$x_{ij}^{k} = 0 \quad \forall k \in K_w,\ \forall (i,j) \in A \setminus A_w,\ \forall w \in W \tag{3.24}$$

$$x_{ij}^{k} = 0 \quad \forall k \in K_{\text{fix}},\ \forall (i,j) \in A \setminus A_{\text{fix}}^{k} \tag{3.25}$$

$$s_{ir}^{kl} = 0 \quad \forall k \in K_{w_1},\ \forall l \in K_{w_2},\ \forall i \in T \setminus T_{w_1}^{w_2},\ \forall r \in R,\ \forall w_1, w_2 \in W \tag{3.26}$$

Constraints (3.27)-(3.31) are time constraints related to services, which are necessary for both fixed and flexible services. Constraints (3.27) guarantee that service start time is later than the arrival time of containers. Constraints (3.28) ensure that the service finish time equals service start time plus service time. Constraints (3.29) maintain that the departures happen only after all services are completed. Constraints (3.30) ensure that the request's arrival time cannot be earlier than the vehicle's arrival time. Constraints (3.31) define the vehicle's last service start time.

$$t_i^{kr} \leqslant t'^{kr}_i \quad \forall i \in N,\ \forall k \in K,\ \forall r \in R \tag{3.27}$$

$$t'^{kr}_i + t''^{kr}_i \sum_{j \in N} y_{ij}^{kr} \leqslant \bar{t}_i^{kr} \quad \forall i \in N,\ \forall k \in K_{\text{b\&t}},\ \forall r \in R \tag{3.28}$$

$$\bar{t}_i^{k} \geqslant \bar{t}_i^{kr} \quad \forall i \in N,\ \forall k \in K_{\text{b\&t}},\ \forall r \in R \tag{3.29}$$

$$t_i^{k} \leqslant t_i^{kr} \quad \forall i \in N,\ \forall k \in K_{\text{b\&t}},\ \forall r \in R \tag{3.30}$$

$$t'^{k}_i \geqslant t'^{kr}_i \quad \forall i \in N,\ \forall k \in K_{\text{b\&t}},\ \forall r \in R \tag{3.31}$$

Constraints (3.32) and (3.33) ensure that the time on the route of barges or trains is consistent with the distance travelled and speed, and Constraints (3.34) and (3.35) ensure the time on the route of trucks. When waiting time is not considered, Constraints (3.32) are enough to take care of arrival time t_j^k. Since vehicles should wait at terminals in this study, Constraints (3.33) need to be added to restrict travel time tightly and avoid wrongly adding waiting times to t_j^k ($t_j^k > \bar{t}_i^k + \tau_{ij}^k$). Constraints (3.36) and (3.37) take care of the time windows for pickup terminals and fixed terminals, respectively.

$$\bar{t}_i^k + \tau_{ij}^k - t_j^k \leqslant M(1 - x_{ij}^k) \quad \forall (i,j) \in A,\ \forall k \in K_{\text{b\&t}} \tag{3.32}$$

$$\bar{t}_i^k + \tau_{ij}^k - t_j^k \geqslant -M(1 - x_{ij}^k) \quad \forall (i,j) \in A,\ \forall k \in K_{\text{b\&t}} \tag{3.33}$$

$$\bar{t}_i^{kr} + \tau_{ij}^k - t_j^{kr} \leqslant M(1 - y_{ij}^{kr}) \quad \forall (i,j) \in A,\ \forall k \in K_{\text{truck}} \tag{3.34}$$

$$\bar{t}_i^{kr} + \tau_{ij}^k - t_j^{kr} \geqslant -M(1 - y_{ij}^{kr}) \quad \forall (i,j) \in A,\ \forall k \in K_{\text{truck}} \tag{3.35}$$

$$t'^{kr}_{p(r)} \geqslant a_{p(r)} y_{ij}^{kr},\ \bar{t}_{p(r)}^{kr} \leqslant b_{p(r)} + M(1 - y_{ij}^{kr}) \quad \forall (i,j) \in A, \forall r \in R,\ \forall k \in K \tag{3.36}$$

$$t_i^{kr} \geqslant a_i^k y_{ij}^{kr},\ \bar{t}_i^{kr} \leqslant b_i^k (y_{ij}^{kr} + M(1 - y_{ij}^{kr})) \quad \forall (i,j) \in A,\ \forall r \in R,\ \forall k \in K_{\text{fix}} \tag{3.37}$$

Constraints (3.38) are time constraints for transshipment. If there is a transshipment from vehicle k to vehicle l, but vehicle l arrives before vehicle k departs, vehicle l can wait until vehicle k completes its unloading. Constraints (3.39) and (3.40) calculate waiting time and delay time, respectively, and these constraints are used to reduce waiting times and delay costs.

$$\bar{t}_i^{kr} - t'^{lr}_i \leqslant M(1 - s_{ir}^{kl}) \quad \forall r \in R,\ \forall i \in T,\ \forall k,l \in K,\ k \neq l \tag{3.38}$$

$$t_{ki}^{\text{wait}} \geqslant t'^{k}_i - t_i^k \quad \forall i \in N,\ \forall k \in K_{\text{b\&t}} \tag{3.39}$$

$$t_r^{\text{delay}} \geqslant (\bar{t}_{d(r)}^{kr} - b_{d(r)}) \sum_{i \in N} y_{id(r)}^{kr} \quad \forall r \in R,\ \forall k \in K \tag{3.40}$$

Constraints (3.41) to (3.48) are imposed to linearize the time-dependent travel time functions of trucks and Constraints (3.49) take care of the arrival time of trucks (Guo et al. 2020, Lin et al. 2013).

$$\tilde{t}_i^{kr} = \bar{t}_i^{kr} - 24n_i^{kr} \quad \forall k \in K_{\text{truck}},\ \forall i \in N,\ \forall r \in R \tag{3.41}$$

$$\tilde{t}_i^{kr} = \sum_{b\in\{1,2...,B\}} \zeta_{irk}^{b} t_b \quad \forall k \in K_{\text{truck}},\ \forall i \in N,\ \forall r \in R \tag{3.42}$$

$$\sum_{b\in\{1,2...,B\}} \zeta_{irk}^{b} = 1 \quad \forall k \in K_{\text{truck}},\ \forall i \in N,\ \forall r \in R \tag{3.43}$$

$$\sum_{m\in\{1,2...,B-1\}} \xi_{irk}^{m} = 1 \quad \forall k \in K_{\text{truck}},\ \forall i \in N,\ \forall r \in R \tag{3.44}$$

$$\zeta_{irk}^{1} \leqslant \xi_{irk}^{1} \quad \forall k \in K_{\text{truck}},\ \forall i \in N,\ \forall r \in R \tag{3.45}$$

$$\zeta_{irk}^{B} \leqslant \xi_{irk}^{B-1} \quad \forall k \in K_{\text{truck}},\ \forall i \in N,\ \forall r \in R \tag{3.46}$$

$$\zeta_{irk}^{b} \leqslant \xi_{irk}^{b-1} + \xi_{irk}^{b} \quad \forall k \in K_{\text{truck}},\ \forall i \in N,\ \forall r \in R,\ \forall b \in \{2,3...,B-1\} \tag{3.47}$$

$$\tau'^{kr}_{ij} = \zeta_{irk}^{1}(\theta_1 t_1 + \eta_1) + \sum_{b\in\{2...,B\}} \zeta_{irk}^{b}(\theta_{b-1} t_b + \eta_{b-1}) \quad \forall k \in K_{\text{truck}},\ \forall r \in R,\ \forall (i,j) \in A \tag{3.48}$$

$$(t_j^{kr} - \bar{t}_i^{kr}) y_{ij}^{kr} = \tau'^{kr}_{ij} \quad \forall (i,j) \in A,\ \forall k \in K_{\text{truck}},\ \forall r \in R \tag{3.49}$$

Constraints (3.50) and (3.51) set variables x and y as binary variables.

$$x_{ij}^{k} \in \{0,1\} \quad \forall (i,j) \in A,\ \forall k \in K \tag{3.50}$$

$$y_{ij}^{kr} \in \{0,1\} \quad \forall (i,j) \in A,\ \forall k \in K,\ \forall r \in R \tag{3.51}$$

Compared with studies that model services as links and paths and ignore vehicle routing (Demir et al. 2016, Ghane-Ezabadi and Vergara 2016, Guo et al. 2020, Hrušovskỳ et al. 2018, Moccia et al. 2011, Van Riessen et al. 2013), the vehicles and requests in this study are planned simultaneously by the vehicle routing component (constraints related to x_{ij}^{k} variable), requests routing component (constraints related to y_{ij}^{kr} variable), and the relations between these two components (such as constraints related to the transshipment variable s_{ir}^{kl}). These components enable the proposed model to explore routes that are not defined in advance.

As Constraints (3.25) and (3.37) do not work on flexible vehicles, the number of alternatives is significantly larger than the case of MCNF/PDND models in the literature (Demir et al. 2016, Guo et al. 2020, Van Riessen et al. 2013). It makes the feasible region of the proposed STPP-FS very large and the problem hard to solve. However, some parts of the feasible region can be cut without losing any feasible solutions by using so-called valid inequalities (Cornuéjols 2008). We propose a novel set of valid inequalities (see Appendix A.1), which are divided into three categories, i.e., valid inequalities related to requests, vehicles, and transshipments.

3.5 Adaptive Large Neighborhood Search

Due to the computational complexity, we develop an ALNS heuristic to solve the proposed problem. In the literature, ALNS was proposed to solve PDP based on an extension of the LNS heuristic, which obtains the best solution by using removal and insertion operators to destroy and repair routes iteratively (Ropke and Pisinger 2006). To solve the STPP-FS in this research, we adapt the traditional operators and design new ones in ALNS considering characteristics of ST. Compared with ALNS for PDPT in the literature (Masson et al. 2013, Qu and Bard 2012, Wolfinger 2021), the innovations of the proposed ALNS are (a) getting the initial solutions by multiple methods (Section 3.5.1), (b) customizing operators considering the characteristics of ST (Section 3.5.2), (c) providing feasibility check methods for fixed and flexible vehicles and synchronization methods for interdependent vehicles (Section 3.5.3), and (d) using several performance improvement methods (Appendix A.3).

The pseudocode of the designed ALNS is shown in Algorithm 1. The input of the algorithm is the sets of vehicles K, requests R, terminals N, and arcs A. The output is the optimal solution found, denoted as X_{best}. R_{pool} is a set of active requests that need to be inserted to routes. ALNS finds (near) optimal solutions by using removal and insertion operators. In the beginning, an initial solution $X_{initial}$ is found by the simple removal operator and insertion operator, such as random removal and greedy insertion. Then, the ALNS algorithm searches for solutions within a specified number of iterations, guided by objectives. These iterations are divided into segments. At the beginning of each segment, the weights, i.e., scores of past performance, of operators are refreshed and operators used in the next segment are chosen based on the weights. In each iteration, routes will be destroyed and repaired alternately until all requests are served, i.e., a feasible solution is found.

At the end of the iteration, a decision is made whether to accept current solution $X_{current}$ obtained in this iteration by comparing it with the last solution X_{last} obtained in the last iteration. If the current solution is worse than the last solution, it will be accepted with a probability p in order to avoid local optima easier. Simulated annealing idea is used and probability p gradually declines in order to avoid local optima Ropke and Pisinger (2006), as the following equation shows:

$$p = e^{\frac{-(F(X_{\text{current}})-F(X_{\text{last}}))}{T_{\text{temp}}}} \tag{3.52}$$

where $T_{\text{temp}} > 0$ is the temperature which starts from an initial temperature and gradually decreases in every iteration by cooling rate, c, where $0 < c < 1$.

3.5.1 Initial solution

In the literature, the initial solution is usually obtained from insertion operators from scratch (Qu and Bard 2012, Ropke and Pisinger 2006, Wolfinger 2021). However, in ST, planning from scratch may cause significant changes in the predefined schedules. The transport operator may not be able to make significant changes due to external factors, such as port schedules and reliable services required by shippers. Moreover, the more flexibility the optimization problem has, the harder it is to solve. Optimization based on fixed schedules may reduce the complexities brought by flexibility. Therefore, the predefined fixed schedules could be taken into account when designing the initial solution. We designed different

Algorithm 1: ALNS algorithm

```
Input: K, R, N, A; Output: X_best ;            // X_best means the best solution.
[K, R, N, A] = Preprocessing(K,R,N,A);
define the set of unserved requests as R_pool ;   // R_pool represents the request pool.
obtain initial solution X_initial; set T_temp > 0 depending on X_initial;
X_current ← X_initial; X_last ← X_initial; X_best ← X_last;      // X_current/X_last means the
 current/last solution.
repeat
    refresh weights and choose operators depending on weights at the beginning of each
     segment;
    X_current ← X_last; [X_current, R_pool] = RemovalOperator(X_current, R_pool); flag = False;
until the predefined number of iterations is reached;
while R_pool is not empty do
    if flag == True then
        [X_current, R_pool] = RemovalOperator(X_current, R_pool)
    else
        flag = True
    end
    [X_current, R_pool] = InsertionOperator(X_current, R_pool);
    if insertion operator is a greedy type then
        [X_current, R_pool] = BundleInsertion(X_current, R_pool)
    end
end
[X_current, R_pool] = SwapOperator(X_current, R_pool);
if F(X_current) < F(X_last) then
    X_last ← X_current;
else
    X_last ← X_current with probability p = e^(-(F(X_current)-F(X_last))/T_temp) ;   // Update X_last based on
     the simulated annealing idea (Ropke and Pisinger 2006).
end
if F(X_last) < F(X_best) then
    X_best ← X_last;
end
T_temp ← T_temp · c;                                 // c is the cooling rate.
```

methods to obtain the initial solution:

1. Method R: By the Regret Insertion operator from scratch. This method does not consider predefined fixed schedules.

2. Method S: Using the best solution of the problem with fewer flexibilities, e.g., the best solution when all vehicles are fixed is used as an initial solution for the problem with flexible trucks. This method obtains the solution of full flexibility step by step and the complexity of the problem with flexible vehicles is reduced.

3. Method M: Using the optimal solution of a predefined fixed schedule and the optimal solution is obtained by the matching model proposed by Guo et al. (2020).

There are two differences between method M and method S: (a) method M always uses the solution without flexible vehicles as the initial solution for different flexibility levels, while method S uses the solution with fewer flexibilities which may have some flexible vehicles; (b) method S's initial solution is obtained by ALNS itself and it may be sub-optimal, while method M uses the optimal solution of a predefined fixed schedule.

3.5.2 Operators in ALNS

There are many different operators in the literature (Grangier et al. 2016, Liu et al. 2019, Qu and Bard 2012, Sarasola and Doerner 2020, Wolfinger 2021). Choosing the insertion and removal operators not only needs to consider features of the studied problem but also the balance between exploitation and exploration. How to use the historical experience and predict the future reward also need to be considered. In this work, Transshipment Insertion and Node Removal operators consider the transshipments and specific modes (waterway and railway) in ST. The Greedy Insertion, Most Constrained First insertion, and Worst Removal operators are used for exploiting. Random Insertion, Random Removal, Route Removal, and Related Removal (also called Shaw Removal) operators are responsible for exploring. History Removal and Regret Insertion operators use the historical experience and predict future situations, respectively. Besides insertion and removal operators, a novel Swap operator is proposed to make up for the disadvantages of using an insertion operator or a removal operator alone.

Some operators have been reported in the literature (Danloup et al. 2018, Ropke and Pisinger 2006). The following sections introduce customized operators in detail and the others are introduced briefly.

Insertion operators

All insertion operators have two basic operations, i.e., inserting one request to one route and multiple routes. When a request is inserted into one route of vehicle k, k will finish both pickup and delivery and there is no transshipment. When a request is inserted into multiple routes, firstly the request is segmented into multiple by potential transshipment terminals and then each will be served by one vehicle, and containers are transferred between vehicles.

Greedy Insertion operator tries all possible solutions using one vehicle and more than one vehicle and inserts the request into the best route(s) (Ghilas et al. 2016, Wolfinger 2021).

Transshipment Insertion operator also inserts requests greedily, but it only tries solutions using more than one vehicle and transshipment (Masson et al. 2013, Wolfinger 2021).

Random Insertion operator chooses vehicles and positions randomly and inserts the request once the solution is feasible (Danloup et al. 2018, Qu and Bard 2012).

Regret Insertion operator inserts a request into the route based on regret values. This operator first tries all possibilities of inserting request r into all routes, then determines the regret value for every alternative:

$$c_r = \triangle F_r^{k_{th}} - \triangle F_r^{\text{lowest}} \tag{3.53}$$

where c_r is the regret value; $\triangle F_r$ is the insertion cost of r; $\triangle F_r^{k_{th}}$ is the k_{th} lowest insertion cost and $\triangle F_r^{\text{lowest}}$ is the lowest insertion cost. If now the alternative with $\triangle F_r^{\text{lowest}}$ not be chosen, then it may use a higher cost to insert r in future iterations, therefore c_r can represent a kind of look-ahead information.

In the literature, the r with the highest c_r is usually inserted in one construction step (Qu and Bard 2012, Ropke and Pisinger 2006), therefore n (the number of requests in the request pool) steps are needed to insert all requests. In each step, this operator tries all possible routes and positions for all requests in the requests pool. However, it will cause unnecessary computation when trying to insert requests into the other unchanged routes in the next step (experiments are provided in Section 3.6.5). To avoid such repetitive computation, multiple requests will be tried to be inserted into routes in one construction step. When only inserting one request in one step, at the next step the requests can choose new alternatives based on changed route(s) in this step. When inserting multiple requests, we may lose such alternatives. But these alternatives may be found using other operators and many vehicles have fixed schedules that will not be changed in ST. Therefore, we choose to insert multiple requests in each step to save the computation time.

Because these requests may use the same vehicle in the alternatives, they cannot be inserted into routes one by one depending on the sort of regret values. The possible inserted requests are divided into two groups, (a) requests which have no conflict with other requests, and (b) requests which have conflicts with other requests. Two requests have conflicts when both requests use the same vehicle(s). Notice that if the vehicle is fixed, there is no conflict because the route and schedule of the fixed vehicle will not be changed. The requests in group (a) are inserted into routes directly. For requests in group (b), the requests which tried to be inserted into the same vehicle k will be sorted depending on regret values. Let r_k^{regret} and r_k^{second} (if exist) represent the request with the highest and second-highest regret value among all requests which are tending to be inserted into route k. If r_k^{regret} only uses vehicle k, then it can be inserted. If r_k^{regret} uses multiple vehicles, for example k and l, the operator will check whether there are other requests that intend to use l. If only r_k^{regret} intends to use l, r_k^{regret} can be inserted. Otherwise, if the regret values of r_k^{regret} bigger than or equal to regret values of r_l^{regret}, r_k^{regret} will be inserted; if smaller, r_k^{second} (if exist) will be inserted when r_k^{second} only use k. Other requests will not be inserted in this step.

Most Constrained First Insertion operator sorts the requests depending on the following weighted function of the distance between pickup and delivery terminal when using trucks ($d_{p(r)d(r)}^{\text{truck}}$), load, and time windows:

$$C_r = \varpi_1 d_{p(r)d(r)}^{\text{truck}} + \varpi_2/(|b_{p(r)} - a_{p(r)}| + |b_{d(r)} - a_{d(r)}|) + \varpi_3 q_r \tag{3.54}$$

where ϖ_1, ϖ_2, and ϖ_3 are the corresponding weights (Danloup et al. 2018, Qu and Bard 2012). Note that each component needs to be normalized by dividing the largest value of all requests. The larger the value of C_r, the harder request r fits into a route. Therefore, this operator considers the r with a larger C_r first.

Removal operators

All removal operators have a basic operation, i.e., removing one request. It means removing the pickup, transshipment, and delivery of this request from routes, and then recalculating the times of relevant routes. The main difference between these removal operators is that the chosen requests are different.

Worst Removal operator removes the requests with the highest cost in each route (Ghilas et al. 2016, Wolfinger 2021).

Random Removal operator selects part of vehicles and removes one request from each vehicle randomly (Danloup et al. 2018, Qu and Bard 2012).

Related Removal operator removes a request r randomly and then removes part of similar requests r' according to distance, time, load, and vehicles which can serve r and r' (Danloup et al. 2018, Ropke and Pisinger 2006).

History Removal operator uses historical information to remove requests which may be in the wrong position and guides insertion operators to insert requests which may be inserted at a lower cost.

All insertion operators record all insertion costs, and reserve the lowest insertion cost c_r^{lowest} for each r. History Removal operator calculates the gap Δc_r between current insertion cost c_r^{current} and c_r^{lowest} and sorts the requests in descending order according to Δc_r. If there is no request whose $\Delta c_r > 0$, then the algorithm goes to the next iteration directly. If there are n requests whose $\Delta c_r > 0$, this operator removes $max\{\sigma n, 1\}$ (σ is the removal proportion) requests from these n requests. Requests which are not inserted at the lowest-cost position may also make it possible for other requests to be inserted cheaply, and thus allow an overall cheaper solution. Therefore a removal proportion of σ is used in this operator.

Route Removal Insertion operators may not be able to find feasible solutions based on a small number of removals in a short time. In this case, the route needs to be cleared, which means all requests in a route are removed to the request pool. Another idea behind this operator is to guide the search in the direction of minimizing the number of used vehicles and making full use of capacity.

First, this operator obtains a random number n with a given numerical distribution $[x_1, x_2, ..., x_3]$ for $[1, 2, ..., m]$, where m is the number of routes which served requests, $x_1 = 1/\xi$ and $x_i = x_{i-1}/\xi$ when $i > 1$. Then, it chooses n vehicles according to a probability $\psi = u_k^{\text{ava}}/(\sum_{k\in K_{\text{serve}}} u_k^{\text{ava}})$, where u_k^{ava} is available capacity and K_{serve} is a set of vehicles which have served requests. The vehicle whose capacity has not been fully made use of will have a higher probability to be cleared. In an extreme case, all routes will be cleared and all requests fill the request pool. In this case, this operator may change the search direction from the beginning and thus provide a larger neighborhood for insertion operators.

Node Removal In most cases, barges and trains in ST carry multiple requests, therefore removing part of the requests may not change the routes of vehicles, as shown in Figure 3.7(a). However, the cost-savings are usually obtained from minimizing distance, i.e., changing the routes of vehicles. To obtain better solutions quicker, the Node Removal operator is designed, which deletes visited terminals in the routes, as shown in Figure 3.7(c). Similar to the Route Removal operator, this operator chooses n vehicles based on a distribution and probability ψ. One terminal of each route is randomly chosen and all requests which visit this terminal will be removed.

Swap operator

In the following cases, the requests will be wrongly placed in routes and it's difficult for the operators in previous sections to find the optimal solution:

1. When vehicle k is out of capacity but the served requests of vehicle k are not the most appropriate. For example, requests 1 and 2 should be served by vehicle k in the optimal solution, but vehicle k is occupied by requests 3 and 4 in the current solution.

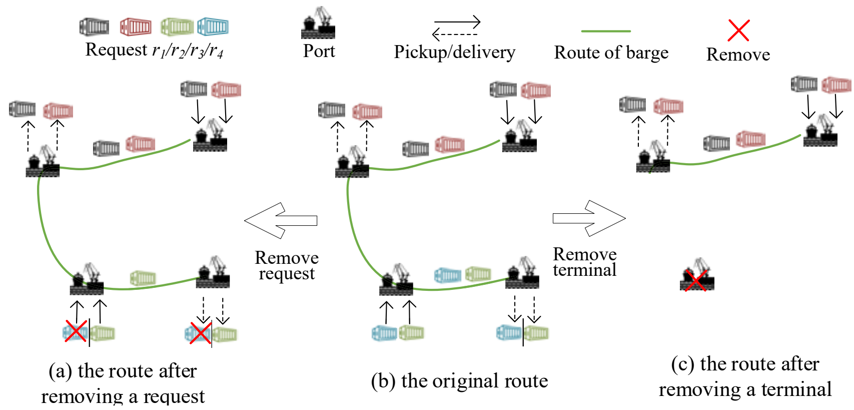


Figure 3.7: Difference between removing a request and a terminal in ALNS

However, operators in previous sections cannot remove requests 3 and 4 and insert 1 and 2 precisely.

2. When vehicle k has available capacity but requests cannot be served by vehicle k due to other constraints. For example, vehicle k goes to pickup terminal A of request 1 at time 20 and arrives at delivery terminal B at time 30. If request 2's due time is 20 at delivery terminal B, then it cannot be served by vehicle k because vehicle k needs to go to terminal A first. When there are more requests (requests 3-5) with a similar situation, the best solution should use vehicle k to serve requests 2-5 rather than only request 1 to make full use of its capacity.

The reason behind it is that Greedy Insertion and Worst Removal operators only care about whether the solution is the best one for the individual request, rather than overall requests. Regret Insertion considers that inserting which request will let us the most regret, but it still cannot find the best solution precisely. The Historical Removal operator removes the requests that are not in the historical best position, which may remove requests 1 and 2 in case 1. But it will not remove requests 3 and 4 because they are in their best position. Therefore, requests 1 and 2 still cannot be inserted into vehicle k because k's capacity is full. It's difficult to solve this problem using Random Insertion/Removal operators because they change routes randomly.

To make up for the shortcomings of existing operators, a Swap operator is designed. The Swap operator is a combination of History Removal and Greedy Insertion operators. It uses the History Removal operator to find the requests R_{swap} that are not served by the historical best vehicles K_{swap}, but only records them rather than removing them directly. As shown in Figure 3.8, for all requests $r \in R_{\text{swap}}$, the following steps will be iterated:

1. Identification: The Swap operator identifies requests R'^{r}_{swap} that may be swapped with r. Let $K^{r}_{\text{swap}} \subseteq K_{\text{swap}}$ represents historical best vehicles which serve request r. For each $k^{r}_{\text{swap}} \in K^{r}_{\text{swap}}$, if it is case 1, all requests served by vehicle k^{r}_{swap} belong to R'^{r}_{swap}; if it is case 2 and k^{r}_{swap} is not a fixed vehicle or truck, all requests served by vehicle k^{r}_{swap} also belong to R'^{r}_{swap}. No request belongs to R'^{r}_{swap} when

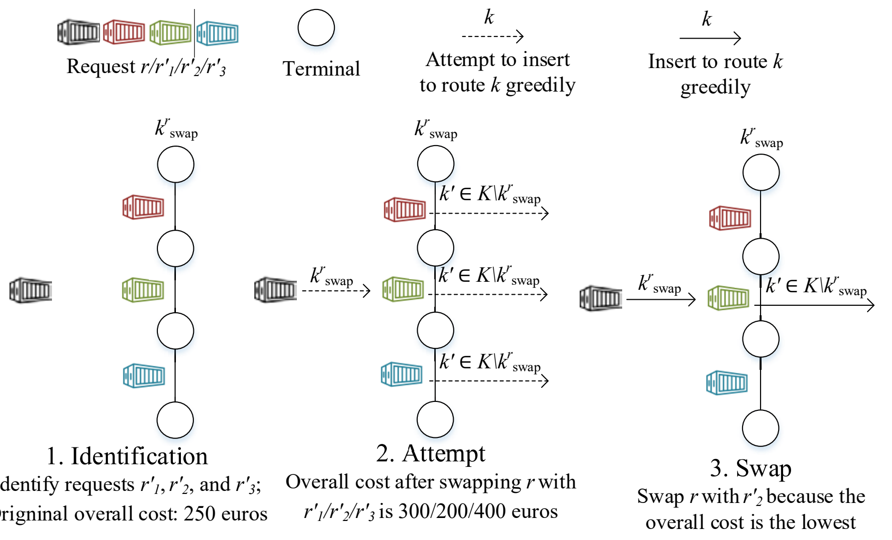


Figure 3.8: Three steps in the Swap operator

vehicle k^r_{swap} is a truck or fixed vehicle because requests served by truck fleet or using fixed schedule will not influence each other.

2. Attempt: All $r' \in R'^r_{\text{swap}}$ will be tried to be swapped with r one by one. In every attempt, firstly, the Swap operator removes request r and one possible request $r' \in R'^r_{\text{swap}}$; then, Greedy Insertion operator is used to insert request r/r' into vehicle $k^r_{\text{swap}}/k' \in K \setminus k^r_{\text{swap}}$; finally, the overall cost after the swap attempt is recorded and routes are restored as before.

3. Swap: If the lowest overall cost of all possible swaps is lower than the overall cost without swap, request r' with the lowest overall cost will be swapped with request r.

3.5.3 Feasibility check and synchronization

The insertion may cause infeasible solutions, e.g., the capacity constraints may be violated after an insertion. Both insertion and removal operators will affect the schedules of the operated route as well as the relevant routes. After the insertion of each request or segment, (a) the times of the operated route will be updated, (b) vehicles that influence each other will be synchronized, and (c) the feasibility of the current solution will be checked. After the removal of each request, the (a) and (b) will be executed but (c) is not required because removal will not cause infeasible solutions. In this section, feasibility checking and synchronization in ALNS are highlighted, and how to achieve flexible routing and schedule are illustrated in detail.

Same with the mathematical model, the following constraints will be checked in ALNS:

1. Subtour elimination constraints (3.10)-(3.12);

2. Capacity constraints (3.15);

3. Suitable routes constraints (3.24);
4. Time constraints (3.27)-(3.49).

Other constraints are satisfied automatically in the construction of routes, such as flow conservation (3.18)-(3.23), or preprocessing procedure, such as fixed routes constraints (3.25). The subtour elimination constraints can be guaranteed by checking whether there are duplicate terminals on the route. When picking up/delivering requests, the current load will increase/decrease by the quantity q_r. If the current load exceeds the capacity of the vehicle, the capacity constraints will be violated. The suitable route constraints are ensured by checking whether the adjacent terminals in the routes are the same as unsuitable routes.

The difficulty lies in satisfying the time constraints. The times in the proposed model include time windows of requests, open time windows of terminals for fixed vehicles, loading/unloading time, waiting time, storage time, delay time, fixed travel time of barges and trains, and time-dependent travel time of trucks. Detailed feasibility checking on time constraints is shown in flow charts in Appendix A.2. In this section, some key points are listed, including waiting time and infeasible cases for barges and trains, time-dependent travel time for trucks, and time synchronization.

The vehicle will wait when it departs earlier than the fixed departure time ($\bar{t}_j^k < b_j^k$), arrives before pickup time window ($t'^k_j < a_{p(r)}$), and arrives earlier than the containers at transshipment terminal ($t'^k_j < Td'^r_j$). If the vehicle's departure time is later than open time window ($\bar{t}_j^k > b_j^k$) or pickup time window ($\bar{t}_j^k > b_{p(r)}$), the route of vehicle k is infeasible.

At peak period, the travel time of trucks τ'^{kr}_{ij} will be longer than normal due to congestions, i.e., τ'^{kr}_{ij} is time-dependent. When the truck deliveries request at the transshipment terminal or delivery terminal, the time-dependent travel time τ'^{kr}_{ij} will be calculated depending on the departure time at the last terminal $\bar{t}_i^{kr}$ by function f_{truck}:

$$\tau'^{kr}_{ij} = \theta_m \bar{t}_i^{kr} + \eta_m \tag{3.55}$$

where θ_m and η_m are the slope and intersection of f_{truck} and can be calculated based on specific time period m within a day, $\bar{t}_i^{kr}$, and travel time at non-peak period τ_{ij}^k (Guo et al. 2020).

In ST with flexible services, vehicles are highly dependent on each other and synchronization is needed. The synchronization means that when a vehicle influences other vehicles, these vehicles' schedules will be re-planned and vehicles could cooperate to obtain the best solution. Such cooperation could be changing pickup/delivery time or extending/shortening the waiting or storage time. As shown in Figure 3.9, Vehicles l_1-l_3 load containers unloaded by vehicle k_1, therefore the changes on the route of vehicle k_1 will influence vehicles l_1-l_3. The routes of vehicles l_1-l_3 are called relevant routes of vehicle k_1. Similarly, routes of vehicles m_1-m_3/m_4-m_6/m_7-m_9 are relevant routes of vehicle l_1/l_2/l_3. A small change of a vehicle will cause a chain reaction on relevant routes. For example, at the transshipment terminal, if the pickup vehicle k_1 delivers request r_1 later than the planned time, the route plans of vehicles l_2 and m_5 need to be synchronized to find suitable arrival times to load request r_1. a chain reaction may be caused by a small change of one route, and all relevant routes need to be synchronized. When a new request r_2 is inserted into the route of vehicle l_2, the request r_1 will be influenced because it is transported by the relevant route m_5, and the schedule of r_2 will be recalculated using the information of k_1, l_2, and m_5. Algorithm 2 shows the synchronization on relevant routes, in which the initial input is the original changed route. To check all relevant routes shown in Figure 3.9, this function is a recursion function. Only when all relevant routes meet the time constraints, the current solution is feasible, otherwise, the synchronization will stop and return “infeasible”.

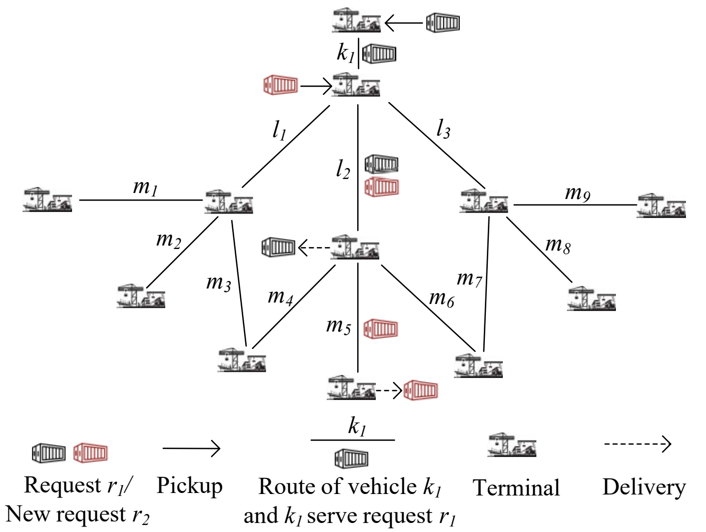


Figure 3.9: Chain reaction and synchronization.

Algorithm 2: Synchronization

Input: *relevant_routes*; **Output:** *feasibility*;
for *route* $\in$ *relevant_routes* **do**
  update pickup/delivery time and extend/shorten the waiting or storage time of influenced requests;
  if *route does not satisfy time constraints* **then**
    return *infeasible*
  else
    obtain *relevant_routes* of *route*;
    Synchronization(*relevant_routes)*
  end
end
return *feasible*;

3.5.4 Comparison with (A)LNS for PDPT in the literature

A detailed comparison between the developed ALNS and the existing (A)LNS for PDPT in the literature is presented in Table 3.3. When an operator is used in only one paper, it is called the special operator of this paper. Although some operators proposed in the literature have similar functions to the operators designed in this study, there are still some differences. For example, the Route Removal operator used by Danloup et al. (2018) chooses a route randomly or depending on the number of visited nodes, while in this study, it chooses a route depending on available capacity. Besides, in this study, we developed a Swap operator to enhance the local search, and the experiments (Section 3.6.5) show that the solution quality is improved by using this new operator. Several performance improvement methods are also used in this study, including preprocessing heuristics, hash table, and bundle insertion, and they are illustrated in Appendix A.3.

In freight transport, such as urban freight transport, all customer nodes are usually distinct, while many requests in ST share the same terminal. Therefore the maximum number of nodes in this study is fewer than others. Moreover, there are usually several dedicated transfer nodes in freight transport, which cannot be customer nodes. In comparison, almost all terminals are transshipment terminals in ST, which also have functions as pickup/delivery terminals. It increases the possibility of transshipments and the connections between vehicles. The number of requests in ST is also bigger than the number in freight transport. In Table 3.3, the maximum number of requests is 100 in the literature, while there are up to 1600 requests in the case studies in this work. A large proportion of transshipment terminals together with a large number of requests make the routes of vehicles in ST highly dependent on each other. In an extreme case, a small change in one route may cause changes in several dozens of vehicles because this change will influence subsequent terminals in this route and each terminal may cause a chain reaction as in Figure 3.9. Therefore, ST brings more complexity to freight transport when there are many requests. To address this issue, we propose the synchronization algorithm (Algorithm 2), swap operator, and performance improvement methods.

Table 3.3: Comparison between the proposed ALNS and existing (A)LNS for PDPT in the literature

Article		Qu and Bard (2012)	Ghilas et al. (2016)	Danloup et al. (2018)	Wolfinger (2021)	this study
Removal operator	Worst	-	✓	✓	✓	✓
	Random	✓	✓	✓	✓	✓
	Route	✓	✓	✓	-	✓
	History	-	✓	-	-	✓
	Related	✓	✓	✓	✓	✓
	special	-	Late-arrival, Worst-distance	Cluster, Many-split	-	Node
Insertion operator	Greedy	✓	✓	-	✓	✓
	Random	✓	-	✓	✓	✓
	Regret	✓	-	-	✓	✓
	Most constrained	✓	-	✓	✓	✓
	Transshipment	-	✓	-	✓	✓
	special	-	Second best, Best λ feasible	-	-	-
Swap operator		-	-	-	-	✓
Choosing operator		adaptive	adaptive	random	random	adaptive
Acceptance criterion		best solution only	simulated annealing	fixed percentage of degradation allowed	fixed percentage of degradation allowed	simulated annealing
Performance improvement		hash table	-	-	-	preprocessing, hash table, bundle insertion
Transshipment location		dedicated location	dedicated location	dedicated location	dedicated location	transshipment terminals
Instance size	N	-	108	100	55	10
	T	1	5	5	5	10
	R	25	100	50	100	1600
	K	3	24	unlimited	6	116
Max. # of transshipments		once	allow twice	once	allow twice	allow twice

–: not considered or stated in the related paper; N/T/R/K: maximum number of nodes/transshipment nodes/requests/vehicles.

3.6 Numerical experiments

The proposed ALNS (Algorithm 1) is compared with the developed MILP model and two benchmark methods from the literature that do not consider flexible services, namely Demir et al. (2016) and Guo et al. (2020). The transport network information and request data can be found in these two papers. In the comparison with the MILP model, we compared the exact approach by the commercial solver (Gurobi) and ALNS in terms of the quality of solutions and computation time. In the benchmarking on small instances, firstly we compared with results in (Demir et al. 2016) under different weights for the individual objectives, then we designed a scenario using the transport network of Guo et al. (2020) to illustrate the function of flexible vehicles under congestion. In the benchmarking on large instances, we compared with the model in Guo et al. (2020) with up to 10 terminals, 116 services (vehicles), and 1600 requests. Most parameters are derived from Guo et al. (2020), Demir et al. (2016), and the rest parameters are defined by tuning ALNS. Part of the parameters is shown in Table 3.4.

Table 3.4: Parameters used in the paper

parameter	value	parameter	value	parameter	value
c^1_{truck}	30.98	c^1_{train}	7.54	c^1_{barge}	0.6122
$c^{1'}_{\text{truck}}$	0.2758	$c^{1'}_{\text{train}}$	0.0635	$c^{1'}_{\text{barge}}$	0.0213
c^2_{truck}	3	c^2_{train}	18	c^2_{barge}	18
c^3_{truck}	1	c^3_{train}	1	c^3_{barge}	1
c^4_{truck}	8	c^4_{train}	8	c^4_{barge}	8
c^5_{truck}	1	c^5_{train}	1	c^5_{barge}	1
e_{truck}	0.8866	e_{train}	0.3146	e_{barge}	0.2288
γ_{1-4}	0.25	ξ	1.3	σ	0.5
ς	1.1	ρ	0.2	φ	1.3
t_1	0	t_2	5	t_3	7
t_4	9	t_5	13	t_6	13
t_7	17	t_8	19	t_9	21
t_{10}	24	α	2	β	1.5
ϖ_1	0.5	ϖ_2	0.2	ϖ_3	0.3

Note that the cost parameters in Table 3.4 are used in the comparison with results of Guo et al. (2020). Demir et al. (2016) use different cost parameters for different vehicles/terminals. The values of other parameters which have different values for different vehicles/requests/terminals and all instances can be found at a research data website[3]. All experiments are implemented in Python 3.7 and run on Linux with 62 GB of memory and an Intel Xeon E5 CPU with a 2.40GHz core.

We consider three levels of flexibility with an increasing degree:

1. Level 0 (L_0): all vehicles are fixed except the flexibilities considered by Demir et al. (2016) and Guo et al. (2020) when compared with them;

[3]https://figshare.com/s/2bbc4c63fd9a7200594f

2. Level 1 (L_1): trucks have flexible routes and schedules, including flexible due time, waiting time, storage time, and departure time;

3. Level 2 (L_2): both trucks and barges have flexible routes and schedules.

At Level 0, the initial solution is obtained by the Regret Insertion operator. Except for Level 0, the initial solution is obtained in three different ways, as mentioned in Section 3.5.1. It is worth mentioning that the proposed model allows more specific flexibility levels, e.g., only part of the barges can be flexible. This study mainly shows the potential of flexibility and specific flexibility levels are not considered. The maximum number of segments of a request is also adjustable in the proposed model and it is set to three in the case studies.

3.6.1 Comparison with the exact approach

Table 3.5 shows the comparison between the exact approach (by Gurobi) and ALNS. All instances are based on the transport network with 116 vehicles published in Guo et al. (2020). There are ten terminals in the lower Rhine-Alpine corridor, and two or five of them are selected as transshipment terminals randomly. One, three, and five request(s) are randomly chosen from instances in Guo et al. (2020) and tested under different flexibility levels. All experiments are repeated three times to obtain the average values of costs and computation time. For all instances in Table 3.5, there are significant differences in both costs and computation time. ALNS gets the best solution in a few seconds, while the exact approach needs 5 min for the smallest instance. When the numbers of requests and transshipment terminals increase, the computation time of the exact approach increases dramatically and no solution is obtained in a limited time (12h) when there are five requests at L_2. Increasing the number of transshipment terminals decreases the costs of ALNS, while costs of the exact approach may be higher because it cannot find the optimal solution in the limited time. Moreover, at L_0, both the exact approach and ALNS can find the optimal solution, although the exact approach needs an obviously longer time. At L_1, the exact approach cannot find the optimal solution within 12 hours when there are five transshipment terminals and more than three requests. At L_2, the exact approach cannot find the optimal solution for all instances in Table 3.5, while ALNS finds solutions with significantly lower costs.

3.6.2 Optimization with and without flexibility under different weight combinations

The transport network studied by Demir et al. (2016) is located in the Danube region between Hungary and Germany, which consists of 10 terminals including inland waterway ports and railway terminals and 3 barge, 18 train, and 11 truck services. Demir et al. (2016) assume trucks can depart with a flexible time and they also consider storage time but storage cost is not included in the objective, i.e., $F_3 = 0$ in their model. To make a fair comparison, we do not consider storage cost in the objective function when comparing with Demir et al. (2016). Moreover, they compare results under different weights for service cost, penalty cost, and emissions cost. Therefore, the objective is as follows:

$$F = w_1(F_1 + F_2 + F_5) + w_2 F_6 + w_3 F_4 \tag{3.56}$$

Table 3.5: The comparison between exact approach and ALNS

			Avg. Cost (EUR)		Avg. CPU (s)	
T	R	L	Exact approach	ALNS	Exact approach	ALNS
2	1	L_0	3585	3585	343.26	0.18
2	1	L_1	3585	3585	461.56	0.18
2	1	L_2	1315	994	43200.00*	0.12
2	3	L_0	8935	8935	3790.64	0.36
2	3	L_1	8935	8935	4383.69	2.68
2	3	L_2	8851	6074	43200.00*	2.26
2	5	L_0	16491	16491	12921.26	0.37
2	5	L_1	16491	16491	15941.14	3.15
2	5	L_2	–	12986	43200.00*	2.62
5	1	L_0	2098	2098	385.46	0.13
5	1	L_1	2098	2098	431.34	0.14
5	1	L_2	3775	994	43200.00*	0.06
5	3	L_0	5828	5828	5793.62	0.35
5	3	L_1	6859	5828	43200.00*	1.24
5	3	L_2	11226	5828	43200.00*	1.23
5	5	L_0	13383	13383	11050.79	0.59
5	5	L_1	13738	13383	43200.00*	1.70
5	5	L_2	–	11345	43200.00*	2.37

T: number of transshipment terminals; R: number of requests; L: flexibility level
$*$ time limit reached (12 hours). $-$ no solution is found due to time limitation.

The weights enable the reflection of individual preferences regarding different costs. The impact of preferences can also be analyzed with different weights.

ALNS finds all best solutions reported by Demir et al. (2016) under the same setting and hence not reported in this study. The barge services in Demir et al. (2016) are three consecutive services operated by one barge, therefore the route of the barge is fixed and barges' timetables and truck services could be flexible. In Table 3.6, results with and without flexibility are compared under cases with different weight combinations for multiple objectives. There are 32 services (vehicles) and 5 requests, and their numbers are the same with Demir et al. (2016). All used services/vehicles of five requests and costs of objectives are listed and the cost saving is shown in brackets. Table 3.6 shows that ALNS with flexibility finds better solutions on all cases except case 1, where it finds the same solution. The differences are marginal in some cases because the solution found in the case without flexibility is also optimal under flexibility. Although in some cases the differences between sub-costs are 0%, the differences in the total cost are always larger than 0% except for case 1, where our approach finds the same solution with Demir et al. (2016). In case 3, routes for requests are the same but the delay penalty is lower due to the flexible schedule. Sometimes the proposed model sacrifices part of the objectives for a better overall solution, such as case 6. In all other cases, by using flexible vehicles, the proposed model provides better solutions from the perspectives of all objectives under different weight combinations. Moreover, all the best solutions can be found in few seconds by ALNS.

The results are always in line with the preferences (weights) on the objectives. For example, in case 3, the decision-maker prioritizes the minimization of emissions, and the electric trains (services 4-21) are chosen as much as possible, which causes a delay for request 3 and more waiting time for request 5. In this case, the total emissions cost is the lowest, but the service and penalty costs are higher than case 8 when there are no preferences (all weights equal to 1). When the decision-maker has preferences on service cost (cases 1, 4, 6, and 8) and penalty cost (cases 2, 5, and 7), the cheaper modes (barges and trains, i.e., services 1-21) and faster modes (trucks, i.e., services 22-32) are chosen, respectively. The preferred costs usually are compensated by other higher costs, but the flexibility makes the compensation as low as possible compared with the cases without flexibility.

Table 3.6: Comparison on results with flexibility (the proposed model) and without flexibility (Demir et al. 2016)

Case	Weights			Services/Vehicles					Total service	Total penalty	Total emissions	Total
	w_1	w_2	w_3	1	2	3	4	5	costs (EUR)	costs (EUR)	costs (EUR)	costs (EUR)
1⋆	1	0	0	1,2,3	1,2,3	31,5	2,3	21	17179	6720	782	24681
1	1	0	0	1,2,3	1,2,3	31,5	2,3	21	17179 (0%)	6720 (0%)	782 (0%)	24681 (0%)
2⋆	0	1	0	22	22	22,26	23	28,30	32284	0	1634	33919
2	0	1	0	1,2,3	1,2,3	23	2,3	25	24152 (25%)	0 (0%)	1287 (21%)	25439 (25%)
3⋆	0	0	1	31,5,25	31,6,25	31,7	2,3	21	22435	12200	594	35229
3	0	0	1	31,5,25	31,6,25	31,7	2,3	21	22435 (0%)	11900 (2%)	594 (0%)	34929 (1%)
4⋆	0.4	0.4	0.2	1,2,3	1,2,3	31,5	2,3	28,30	19171	3220	894	23285
4	0.4	0.4	0.2	1,2,3	1,2,3	31,5	2,3	27	18543 (3%)	3220 (0%)	865 (3%)	22629 (3%)
5⋆	0.2	0.6	0.2	1,2,3	1,2,3	22,26	2,3	28,30	24707	0	1303	26010
5	0.2	0.6	0.2	1,2,3	1,2,3	1,22	2,3	27	22739 (8%)	0 (0%)	1248 (4%)	23987 (8%)
6⋆	0.6	0.3	0.1	1,2,3	1,2,3	31,5	2,3	21	17179	6720	782	24681
6	0.6	0.3	0.1	1,2,3	1,2,3	31,5	2,3	27	18543 (-8%)	3220 (52%)	865 (-11%)	22628 (8%)
7⋆	0.1	0.8	0.1	1,2,3	1,2,3	22,26	2,3	28,30	24707	0	1303	26010
7	0.1	0.8	0.1	1,2,3	1,2,3	1,22	2,3	27	22739 (8%)	0 (0%)	1248 (4%)	23987 (8%)
8⋆	1	1	1	1,2,3	1,2,3	31,5	2,3	28,30	19171	3220	894	23285
8	1	1	1	1,2,3	1,2,3	31,5	2,3	27	18543 (3%)	3220 (0%)	865 (3%)	22628 (3%)
9⋆	1	10	10	1,2,3	1,2,3	31,8,27,26	2,3	28,30	25081	0	1098	26179
9	1	10	10	1,2,3	1,2,3	1,22	2,3	27	22739 (9%)	0 (0%)	1248 (-14%)	23987 (8%)

⋆ means benchmark by Demir et al. (2016), in which all vehicles follow fixed routes and schedules except the truck's departure time is flexible.

3.6.3 Optimization with and without flexibility under congestion

The flexibility considered in this study is helpful for mitigating congestions in ST. Two types of congestions are considered: arc congestion and node congestion, which are concerned with the limited capacities of roads and terminals, respectively. For arc congestion, we consider the congestions in peak periods on roads. As shown in Figure 3.10, there are several time breakpoints in one day, i.e., b_1, b_2, b_3, b_4, b_5, b_6, b_7, b_8, b_9, b_{10} $= 0, 5, 7, 9, 13, 13, 17, 19, 21, 24$. Between b_2 and b_9, there are congestions adjusted by coefficients α and β, which represent multiples of time spent in the peak period compared with the travel time in the normal period (τ^k_{ij}). According to Guo et al. (2020), when α is 2, double travel time will be needed on the road when departing at 5 pm. More congestion will cause higher costs when we take the time-dependent travel time into account by replacing

Equation (3.2) with:

$$F_1 = \sum_{k \in K} \sum_{(i,j) \in A} \sum_{r \in R} (c_k^1 (\bar{t}_i^{kr} - t_i^{kr}) + c_k^{1'} d_{ij}^k) q_r y_{ij}^{kr} \tag{3.57}$$

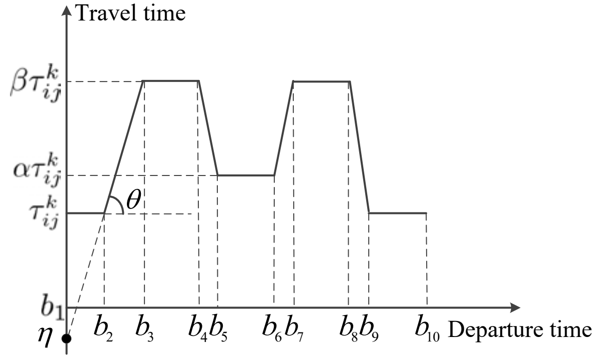


Figure 3.10: Time-dependent travel times of truck services (source: Guo et al. (2020))

For node congestion, terminal a will be unavailable for vehicles when the served vehicles/containers exceed its capacity, i.e., the following constraints are added:

$$\sum_{j \in N} x_{aj}^k = 0 \quad \forall k \in K \tag{3.58}$$

$$\sum_{i \in N} x_{ia}^k = 0 \quad \forall k \in K \tag{3.59}$$

Because the time horizon of the synchromodal transport planning is usually longer than one day, we use hours beginning from 0 to represent the time. For example, time 25 means 1 am on the second day. A simple but illustrative scenario using the data in Guo et al. (2020) is designed to show the function of flexibility under congestions. There are three terminals, two services, and one request:

- Terminals A, B, and C, and all terminals are connected with roads and waterways. The road/waterway distances between A and B, A and C, and B and C are 15km/15km, 270km/262.5km, 262.5km/255km, respectively.
- A truck fleet service with begin and end depots of terminals B and C respectively and a speed of 75km/h.
- A barge service, whose begin depot is terminal A (fixed departure time is 66), end depot is terminal C (fixed arrival time is 83.5), speed is 15 km/h, and capacity is 160 TEU.
- A request, whose pickup terminal is B (pickup time is 63), delivery terminal is C (due time is 85), and load is 12 TEU.

There is no fixed service on other roads/waterways because the demand is low. As shown in Figure 3.11 (a), at L_0, the only solution is using the truck to serve this request because both truck and barge routes are fixed. However, because the pickup is at 3 pm (normalized by time 63), the truck will depart at peak time and there will be congestion on road. At L_1, the best solution uses the combination of the truck and barge (Figure 3.11 (b)), which means the request is picked up by the truck, transferred from truck to barge at terminal A, and delivered by barge. This solution can mitigate the impact of congestion by using inland waterways. Table 3.7 shows the comparison between costs of L_0 and L_1 at different congestion levels. When the congestion level increases, the cost increase of L_0 is much greater than the increase of L_1. When $\alpha = 14$, the road is disrupted due to severe congestion and there is no feasible solution at L_0.

Table 3.7: Costs under congestions

Congestion level α	Cost of L_0 (EUR)	Cost of L_1 (EUR)
2	3240	906
6	5842	1050
10	8444	1194
14	–	1338

– means there is no feasible solution.

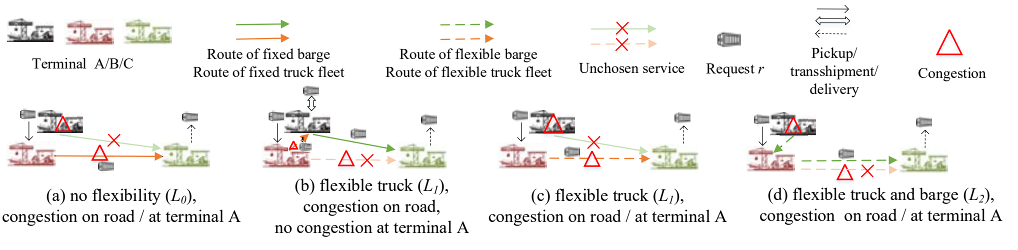


Figure 3.11: Optimal routes under congestions on road and at the terminal

Furthermore, if the truck and barge cannot use terminal A to transfer containers because too many containers are piled up at the terminal or no crane is available at the terminal (node congestion), we can only use the truck to serve the request at L_0 and L_1, as shown in Figure 3.11 (a) and (c). However, at L_2, we can use the barge to serve this request even though terminal A is unavailable. As shown in Figure 3.11 (d), The barge will go to terminal B to pick up containers first and then deliver the request to terminal C directly with a cost of only 628€.

3.6.4 Benchmarking on large instances

Guo et al. (2020)'s instances are based on a transport network operated by European Gateway Services[4], which offers a wide variety of synchromodal transport services between the ports of Rotterdam and Antwerp and the leading economic centres of Western and Central Europe. The instances contain 116 vehicles (49 barges, 33 trains, and 34 trucks), 10 terminals (3 deep-sea terminals in Port of Rotterdam and 7 inland terminals in the Netherlands,

[4]https://www.europeangatewayservices.com/en

Belgium, and Germany), and 10 transshipment terminals. The origins and destinations of requests are independently and identically distributed among deep-sea terminals 1, 2, 3 with probabilities 0.66, 0.2, 0.14 and inland terminals 4, 5, 6, 7, 8, 9, 10 with probabilities 0.306, 0.317, 0.153, 0.076, 0.071, 0.034, 0.043, respectively. The container volumes of requests are drawn independently from a uniform distribution with range [10, 30] and the average container volume is 20 TEU. The earliest pickup time $a_{p(r)}$ of requests is drawn independently from a uniform distribution with range [1, 120]; the latest delivery time $b_{d(r)}$ of requests is generated based on its $a_{p(r)}$ and lead time LD_r, i.e., $b_{d(r)} = a_{p(r)} + LD_r$, and the lead time of requests is independently and identically distributed among 24, 48, 72 (unit: hours) with probabilities 0.15, 0.6, 0.25. Since Guo et al. (2020) do not use time windows, we set $b_{p(r)}$ and $a_{d(r)}$ equal to $b_{d(r)}$ and $a_{p(r)}$, respectively. The objective in Guo et al. (2020) is as same as the objective in this study. Guo et al. (2020) assume that there are unlimited storage spaces at terminals and loading/unloading infrastructure is always available for multiple vehicles. In the original paper, Guo et al. (2020) provide results with 5-30 requests and 700-1600 requests. To obtain a complete comparison, we asked the authors to run their model again, and then we got the results with 50-400 requests.

Tables 3.8 to 3.10 show the results of different levels of flexibility with different methods to obtain the initial solution. In each table, the number of requests increases from 5 to 1600, and results of different levels of flexibility are obtained for each instance. At $L_0^\star$ (benchmark) and L_0, the delay penalty is charged when vehicles deliver containers later than the due time, while other flexibilities, such as flexible routing and flexible waiting time, are not considered. In Table 3.9, there is no results under L_0 because the initial solution given by matching model is optimal under L_0. All experiments are repeated 10 times and Tables 3.8 to 3.10 show average values of results. The time limitation for all experiments is 48 hours. The computation time of the benchmark is not provided because we use different computers and software with Guo et al. (2020). The Cost Savings column shows the gap in percentage between the cost of ALNS's solution and cost of solutions in Guo et al. (2020).

Based on the results, we obtain the following insights:

1. Initial solution:

   (a) When using the best solution of the predefined schedule (method M) as the initial solution, the costs are lower than other ways in most cases. Therefore, adjusting the plan based on a predefined schedule is the most appropriate way for transport operators because there will be no significant changes and better solutions can be found quicker than optimization from scratch.

   (b) For small instances (less than 50 requests), optimization based on an initial solution provided by method S is better than other methods because method S can find the (near) optimal solution under L_1. However, for instances with more than 50 requests, method S performs worse than method M because the initial solution obtained by method S may be worse than the optimal solution under L_0, which is the initial solution of method M.

Table 3.8: Comparison of results with different levels of flexibility (obtain the initial solution by method R)

		Avg. Costs (EUR)							# of	Avg. Mode Share (%)			Avg. CPU (s)		Cost
R	L	F	F_1	F_2	F_3	F_4	F_5	F_6	Vehicles	barge	train	truck	initial	best	Savings (%)
5	$L_0^\star$	4386	1532	2562	269	23	0	0	5	60	0	40	–	–	–
5	L_0	4385	1531	2562	269	23	0	0	5	60	0	40	0.2	0.0(0%)	0
5	L_1	4270	967	2994	290	18	0	0	6	66	0	33	0.4	0.0(0%)	2
5	L_2	3808	482	3312	0	14	0	0	4	100	0	0	0.9	0.0(0%)	13
10	$L_0^\star$	25988	14560	6990	2158	186	0	0	14	50	29	21	–	–	–
10	L_0	25988	14559	9084	2158	186	0	0	14	50	28	21	0.6	0.0(0%)	0
10	L_1	25985	14559	9084	2155	186	0	0	14	50	28	21	1.6	0.3(32%)	0
10	L_2	24838	15847	8304	450	211	25	0	12	69	7	23	2.9	23.7(1%)	4
20	$L_0^\star$	44198	20870	16218	5003	287	0	1820	23	57	18	25	–	–	–
20	L_0	44221	20604	15990	5527	279	0	1820	22	57	23	19	1.1	0.0(0%)	0
20	L_1	42786	22342	15210	4940	293	0	0	21	53	23	23	4.5	0.0(53%)	3
20	L_2	36737	19757	15324	1270	276	108	0	20	70	16	12	8.5	105.5(0%)	16
30	$L_0^\star$	65126	36953	22896	4794	483	0	0	35	50	11	39	–	–	–
30	L_0	65126	36953	22896	4794	482	0	0	35	50	11	38	1.5	0.4(0%)	0
30	L_1	64905	35873	23712	4845	473	0	0	33	51	11	37	7.8	18.2(68%)	0
30	L_2	51665	26691	24258	15	415	285	0	29	74	2	23	11.8	419.5(15%)	20
50	$L_0^\star$	135679	88930	23919	9350	1069	0	0	46	42	14	44	–	–	–
50	L_0	139819	96241	33396	9050	1131	0	0	47	41	15	42	2.9	2.1(0%)	-3
50	L_1	131605	84662	35357	10568	1017	0	0	37	41	16	41	19.7	50.9(69%)	2
50	L_2	106728	64815	38058	2493	885	476	0	40	75	6	18	25.0	639.1(17%)	20
100	$L_0^\star$	181204	92873	53580	15838	1297	0	0	56	56	12	32	–	–	–
100	L_0	183818	97853	68880	15748	1337	0	0	56	56	12	30	6.9	60.8(1%)	-1
100	L_1	176074	89282	69852	15688	1251	0	0	49	55	14	30	45.3	258.4(69%)	2
100	L_2	142721	68150	71016	1812	1115	614	13	57	79	5	15	72.7	3507.9(46%)	20
200	$L_0^\star$	497380	316980	97149	29648	3950	0	0	70	45	12	43	–	–	–
200	L_0	502851	325703	142016	30880	4002	0	248	72	44	13	41	13.8	1824.2(11%)	-1
200	L_1	481192	298941	146606	31694	3741	0	210	69	45	15	38	130.7	2620.3(67%)	3
200	L_2	374768	216237	146145	7683	3194	934	574	73	71	4	24	138.6	7351.4(70%)	24
400	$L_0^\star$	1100758	754771	194634	62051	8848	0	0	95	40	19	41	–	–	–
400	L_0	1115227	777999	265497	61787	9066	2	875	96	39	18	42	47.4	14492.7(64%)	-1
400	L_1	1117930	773891	270943	61765	9023	0	2308	89	40	18	41	427.2	9695.9(80%)	-1
400	L_2	925230	623500	268031	22206	8109	1399	1984	82	63	6	29	855.8	29465.0(77%)	15
700	$L_0^\star$	1060077	723033	197406	57334	8483	0	1815	104	39	18	43	–	–	–
700	L_0	1070117	740118	261762	57451	8647	0	2138	102	39	17	43	102.6	48788.1(76%)	-1
700	L_1	1071214	735499	267561	57209	8613	0	2330	98	40	17	41	1293.7	27376.0(82%)	-1
700	L_2	943710	654660	249363	25799	8242	1530	4115	90	60	7	31	2448.5	99186.4(85%)	10
1000	$L_0^\star$	1017669	692260	189822	62025	8146	0	850	101	41	16	43	–	–	–
1000	L_0	1028469	713238	245619	59702	8327	0	1581	100	39	15	45	140.7	95235.4(75%)	-1
1000	L_1	1024973	704195	251533	59992	8257	0	996	93	40	15	44	1318.5	60259.9(79%)	-1
1000	L_2	934731	630058	255919	35646	7427	1213	4465	99	59	7	32	4788.3	159355.5(72%)	7
1300	$L_0^\star$	1042481	704457	196548	58404	8336	0	1974	103	42	16	41	–	–	–
1300	L_0	1057118	721333	262740	62029	8486	0	2528	102	41	17	41	629.1	111229.6(63%)	-1
1300	L_1	1052389	707281	270223	63145	8357	0	3380	94	42	17	40	3019.4	111889.8(84%)	-1
1300	L_2	985232	689334	236429	34801	8471	1304	14891	97	55	8	36	7610.4	135318.0(82%)	5
1600	$L_0^\star$	1020075	671262	201825	62765	7961	0	408	100	43	21	37	–	–	–
1600	L_0	1031499	687488	269642	65989	8110	0	269	101	42	20	37	294.5	146337.4(83%)	-1
1600	L_1	1036620	690889	269330	67511	8156	0	735	95	43	19	37	6522.0	126142.0(83%)	-1
1600	L_2	991122	705891	229860	33201	8482	1023	12663	99	52	11	36	6763.0	140737.1(84%)	3

R: number of requests; L: flexibility level; $L_0^\star$: benchmark; L_0: flexibility Level 0, i.e., same with benchmark; L_1: flexibility Level 1, i.e., trucks are flexible; L_2: flexibility Level 2, i.e., trucks and barges are flexible; F: total cost, F_1: transit cost, F_2: transfer cost, F_3: storage cost, F_4: carbon tax, F_5: waiting cost, F_6: delay penalty, barge: proportion of requests served by barge, train: proportion of requests served by barge, truck: proportion of requests served by barge, initial: running time of the initial solution, best: running time of the best solution, and the percentage in bracket equals the running time of the best solution divided by the total running time;

size of segment: 20 iterations; cooling rate $c = 0.99$; 200 iterations; time limit: 48 hours.

Table 3.9: Comparison of results with different levels of flexibility (obtain the initial solution by method M)

		Avg. Costs (EUR)							# of	Avg. Mode Share (%)			Avg. CPU (s)		Cost
R	L	F	F_1	F_2	F_3	F_4	F_5	F_6	Vehicles	barge	train	truck	initial	best	Savings (%)
5	$L_0^{\star}$	4386	1532	2562	269	23	0	0	5	60	0	40	–	–	–
5	L_1	4266	967	2994	286	18	0	0	6	66	0	33	0.3	0.9(10%)	2
5	L_2	3792	782	2993	0	16	0	0	5	84	0	16	0.3	0.8(6%)	13
10	$L_0^{\star}$	25988	14560	6990	2158	186	0	0	14	50	29	21	–	–	–
10	L_1	25988	14559	9084	2158	186	0	0	14	50	28	21	0.8	0.0(0%)	0
10	L_2	22912	13458	8801	436	184	32	0	11	64	19	16	0.8	14.7(29%)	11
20	$L_0^{\star}$	44198	20870	16218	5003	287	0	1820	23	57	18	25	–	–	–
20	L_1	42751	22450	15301	4703	296	0	0	21	53	21	25	0.6	16.2(34%)	3
20	L_2	36604	20099	14969	1256	278	0	0	22	66	16	16	0.6	35.0(38%)	17
30	$L_0^{\star}$	65126	36953	22896	4794	483	0	0	35	50	11	39	–	–	–
30	L_1	64938	35862	23724	4877	473	0	0	34	51	11	37	0.9	13.1(12%)	0
30	L_2	50111	25233	24356	29	398	94	0	30	72	4	22	0.9	264.0(62%)	22
50	$L_0^{\star}$	135679	88930	23919	9350	1069	0	0	46	42	14	44	–	–	–
50	L_1	131171	84358	35309	10486	1017	0	0	40	42	15	42	2.8	83.9(54%)	2
50	L_2	106530	65774	37017	2515	888	336	0	42	71	8	20	2.8	401.3(55%)	21
100	$L_0^{\star}$	181204	92873	53580	15838	1297	0	0	56	56	12	32	–	–	–
100	L_1	175830	88962	70025	15594	1249	0	0	52	55	14	30	4.1	435.4(55%)	2
100	L_2	135866	59862	72136	2273	1031	563	0	60	78	6	14	4.1	2164.2(76%)	24
200	$L_0^{\star}$	497380	316980	97149	29648	3950	0	0	70	45	12	43	–	–	–
200	L_1	480191	298177	148325	29863	3750	0	74	72	45	14	40	9.1	1373.4(62%)	3
200	L_2	375251	215376	147082	8383	3175	848	387	73	70	5	24	9.1	11530.6(76%)	24
400	$L_0^{\star}$	1100758	754771	194634	62051	8848	0	0	95	40	19	41	–	–	–
400	L_1	1094750	744197	280991	60806	8755	0	0	97	40	18	40	29.1	7950.8(68%)	0
400	L_2	921991	616403	272201	23052	7991	1226	1117	88	61	8	29	29.1	31958.4(81%)	15
700	$L_0^{\star}$	1060077	723033	197406	57334	8483	0	1815	104	39	18	43	–	–	–
700	L_1	1054526	714839	273176	56286	8409	0	1815	104	40	17	42	38.4	17466.6(75%)	0
700	L_2	921924	617128	262654	28483	7896	1230	4532	101	56	11	31	38.4	97319.8(82%)	12
1000	$L_0^{\star}$	1017669	692260	189822	62025	8146	0	850	101	41	16	43	–	–	–
1000	L_1	1010503	679957	261160	60443	8045	0	898	101	41	15	42	78.9	32804.0(75%)	0
1000	L_2	919037	621175	253311	33110	7700	1098	2640	104	52	12	35	78.9	151032.2(86%)	9
1300	$L_0^{\star}$	1042481	704457	196548	58404	8336	0	1974	103	42	16	41	–	–	–
1300	L_1	1038067	693346	276066	58614	8241	0	1798	105	42	16	40	158.6	89314.2(65%)	0
1300	L_2	971182	661358	258441	37425	8147	1041	4768	109	50	13	35	158.6	129940.4(73%)	6
1600	$L_0^{\star}$	1020075	671262	201825	62765	7961	0	408	100	43	21	37	–	–	–
1600	L_1	1017824	666952	280231	62303	7929	0	407	102	43	20	36	302.4	142784.8(82%)	0
1600	L_2	961277	651516	258086	39327	7965	905	3477	111	50	17	32	302.4	132404.6(74%)	5

R: number of requests; L: flexibility level; $L_0^{\star}$: benchmark; L_0: flexibility Level 0, i.e., same with benchmark; L_1: flexibility Level 1, i.e., trucks are flexible; L_2: flexibility Level 2, i.e., trucks and barges are flexible; F: total cost, F_1: transit cost, F_2: transfer cost, F_3: storage cost, F_4: carbon tax, F_5: waiting cost, F_6: delay penalty, barge: proportion of requests served by barge, train: proportion of requests served by barge, truck: proportion of requests served by barge, initial: running time of the initial solution, best: running time of the best solution, and the percentage in bracket equals the running time of the best solution divided by the total running time;
size of segment: 20 iterations; cooling rate $c = 0.99$; 200 iterations; time limit: 48 hours.

Table 3.10: Comparison of results with different levels of flexibility (obtain the initial solution by method S)

		Avg. Costs (EUR)							# of	Avg. Mode Share (%)			Avg. CPU (s)		Cost
R	L	F	F_1	F_2	F_3	F_4	F_5	F_6	Vehicles	barge	train	truck	initial	best	Savings (%)
5	$L_0^\star$	4386	1532	2562	269	23	0	0	5	60	0	40	–	–	–
5	L_0	4385	1531	2562	269	23	0	0	5	60	0	40	0.2	0.0(0%)	0
5	L_1	4269	967	2994	289	18	0	0	6	66	0	33	0.2	2.1(14%)	2
5	L_2	3793	757	3020	0	16	0	0	5	85	0	15	2.3	1.9(10%)	13
10	$L_0^\star$	25988	14560	6990	2158	186	0	0	14	50	29	21	–	–	–
10	L_0	25988	14559	9084	2158	186	0	0	14	50	28	21	0.7	0.0(0%)	0
10	L_1	25988	14559	9084	2158	186	0	0	14	50	28	21	0.7	0.0(0%)	0
10	L_2	21907	12389	8854	456	175	32	0	11	67	16	16	0.7	34.6(55%)	15
20	$L_0^\star$	44198	20870	16218	5003	287	0	1820	23	57	18	25	–	–	–
20	L_0	44221	20604	15990	5527	279	0	1820	22	57	23	19	1.6	0.0(0%)	0
20	L_1	42776	22344	15210	4929	293	0	0	20	53	23	23	1.6	10.2(14%)	3
20	L_2	36603	20119	14934	1270	278	0	0	23	66	16	16	11.8	41.4(38%)	17
30	$L_0^\star$	65126	36953	22896	4794	483	0	0	35	50	11	39	–	–	–
30	L_0	65126	36953	22896	4794	482	0	0	35	50	11	38	2.4	0.8(0%)	0
30	L_1	64938	35862	23724	4877	473	0	0	34	51	11	37	3.0	16.8(17%)	0
30	L_2	50468	25638	24307	11	402	109	0	29	73	4	23	19.9	304.5(71%)	21
50	$L_0^\star$	135679	88930	23919	9350	1069	0	0	46	42	14	44	–	–	–
50	L_0	139796	96241	33396	9027	1131	0	0	47	41	15	42	3.6	11.4(8%)	-3
50	L_1	131556	84339	35596	10607	1013	0	0	39	41	16	42	15.1	149.8(57%)	2
50	L_2	104722	64172	37027	2306	870	346	0	42	69	9	21	164.8	622.4(68%)	22
100	$L_0^\star$	181204	92873	53580	15838	1297	0	0	56	56	12	32	–	–	–
100	L_0	183818	97853	68880	15748	1337	0	0	56	56	12	30	7.6	63.0(11%)	-1
100	L_1	176277	89606	69740	15677	1253	0	0	51	55	14	30	65.1	273.3(49%)	2
100	L_2	136570	60699	72043	2251	1041	534	0	60	78	6	14	338.4	2571.0(67%)	24
200	$L_0^\star$	497380	316980	97149	29648	3950	0	0	70	45	12	43	–	–	–
200	L_0	503213	326231	141763	30962	4008	0	248	72	44	13	41	16.6	1744.5(57%)	-1
200	L_1	480447	298048	146909	31575	3735	0	180	73	45	15	39	1761.1	2212.3(70%)	3
200	L_2	375011	216329	145604	8830	3184	847	217	72	69	5	24	3973.4	9941.7(76%)	24
400	$L_0^\star$	1100758	754771	194634	62051	8848	0	0	95	40	19	41	–	–	–
400	L_0	1116016	778088	265674	62092	9056	0	1105	96	39	18	41	55.9	18595.5(79%)	-1
400	L_1	1109777	765050	273158	61491	8947	2	1128	94	40	18	41	14840.2	11397.8(65%)	-1
400	L_2	927872	621526	271452	23902	8022	1189	1780	87	62	8	28	21199.0	32510.2(84%)	15
700	$L_0^\star$	1060077	723033	197406	57334	8483	0	1815	104	39	18	43	–	–	–
700	L_0	1069477	738691	261757	58154	8643	2	2230	102	39	17	42	117.0	40557.4(79%)	-1
700	L_1	1064366	726571	269101	57923	8539	2	2229	101	40	17	41	33041.7	20013.7(67%)	-1
700	L_2	933777	636168	256529	27271	8038	1347	4423	96	58	9	31	29483.4	45423.0(77%)	11
1000	$L_0^\star$	1017669	692260	189822	62025	8146	0	850	101	41	16	43	–	–	–
1000	L_0	1028896	713804	245254	60155	8333	0	1349	101	39	15	45	136.3	43698.0(74%)	-1
1000	L_1	1021288	697265	253339	61216	8192	0	1275	101	40	15	44	39740.6	39115.2(68%)	0
1000	L_2	931311	643213	243915	32493	7892	1202	2595	104	50	12	37	82678.7	49847.9(84%)	7
1300	$L_0^\star$	1042481	704457	196548	58404	8336	0	1974	103	42	16	41	–	–	–
1300	L_0	1057678	722566	262007	62183	8494	0	2426	102	41	17	41	232.6	30366.8(51%)	-1
1300	L_1	1053422	711026	268448	62944	8392	0	2611	100	42	17	40	25422.0	35414.2(60%)	-1
1300	L_2	1016902	690033	244096	39575	8410	1214	33572	102	52	10	37	25292.9	41472.2(68%)	2
1600	$L_0^\star$	1020075	671262	201825	62765	7961	0	408	100	43	21	37	–	–	–
1600	L_0	1032359	689402	268823	65788	8129	0	217	100	42	20	37	345.0	47730.8(78%)	-1
1600	L_1	1031410	686880	270284	65872	8112	0	260	100	42	19	37	45326.4	32501.3(54%)	-1
1600	L_2	1009904	706790	237215	40799	8449	898	15752	103	48	13	37	29850.2	49071.6(78%)	0

R: number of requests; L: flexibility level; $L_0^\star$: benchmark; L_0: flexibility Level 0, i.e., same with benchmark; L_1: flexibility Level 1, i.e., trucks are flexible; L_2: flexibility Level 2, i.e., trucks and barges are flexible; F: total cost, F_1: transit cost, F_2: transfer cost, F_3: storage cost, F_4: carbon tax, F_5: waiting cost, F_6: delay penalty, barge: proportion of requests served by barge, train: proportion of requests served by barge, truck: proportion of requests served by barge, initial: running time of the initial solution, best: running time of the best solution, and the percentage in bracket equals the running time of the best solution divided by the total running time;

size of segment: 20 iterations; cooling rate c = 0.99; 200 iterations; time limit: 48 hours.

2. Costs:

    (a) Higher degree of flexibility usually leads to more cost savings, but sometimes ALNS at L_1 cannot find better solutions than ALNS at L_0 when the solution space is larger but the better solution is harder to find, as in the cases with 400, 700, and 1600 requests in Table 3.8.

    (b) The cost savings increase when the number of requests increases from 5 to 200 requests. When there are more than 200 requests, the cost savings decrease because of two reasons: (i) the solutions are tighter due to limited capacities; (ii) ALNS cannot find (near) optimal solutions in a limited time due to the complexity of larger size instances.

    (c) By using flexible vehicles, cost savings of up to 24% (200 requests at L_2) and 170,000€ (400 requests at L_2) are obtained compared with the cost without flexible vehicles. On average, the proposed model at L_2 reduces the cost by 14% compared with the best solutions without flexibility. It is worth noting that the cost savings are related to parameters and may differ from one instance to the other.

    (d) The cost savings mainly come from the reduction in transit cost, storage cost, and carbon tax. The transfer cost, waiting cost, and delay penalty usually increase slightly when the total cost decreases because more transshipments and more barges are used.

    (e) The carbon tax decreases when there are more flexibilities because more barges are used. This insight is obtained when there is no restriction on the schedules of barges. If the schedules were very restricted we would not be able to have emissions reductions as we would be stuck with trucks in many cases.

3. Number of vehicles and mode share:

    (a) At Level 1, trucks are flexible but the mode share of trucks will decrease and the mode share of trains and barges will increase in most cases. Using more trucks will not reduce cost, but flexible trucks increase the possibilities of using more trains and barges by intermodal transport. The number of used vehicles may decrease because fewer trucks are used.

    (b) At Level 2, the requests will be shifted from trucks to barges. However, the number of used vehicles sometimes increases compared with Level 1, especially for instances with 1000 to 1600 requests, because more barges and transshipments are used.

    (c) Using more barges may cause more waiting time and a little delay, but will reduce costs significantly.

4. Computation time:

    (a) For instances with 5-30 requests, the best solution is found in 3 s, 30 s, and 8 min at L_0, L_1, L_2, respectively. For instances with 50-400 requests, the best solution is found in 5 h, 3 h, and 10 h at L_0, L_1, L_2, respectively. This time is 41 h, 40 h, and 39 h for instances with 700-1600 requests. Therefore, for small instances, a higher degree of flexibility means longer computation time. For large instances, using limited resources to serve a large number of requests in the most appropriate way is difficult when no flexibility is considered. More alternatives are provided when more flexibility is considered, therefore the best solution may be found in a shorter time compared with the lower degree of flexibility.

(b) When using the best solution of the problem with fewer flexibilities as the initial solution, the total computation time is obviously longer than the other ways because it spends significant time to obtain the initial solution. However, the running time of the best solution (time after the initial solution is found) is less than other methods for large instances, although the best solution may not be better than other methods.

(c) For small instances, the best solution is found in the early iterations of ALNS. When the instance size increases, more iterations are needed.

(d) The computation time of large instances reflects the real-time optimization ability of the proposed model. Take the instance with 50 requests as an example, the best solution can be found in less than 15 min, which means the proposed model is able to handle 50 changed requests every 15 min under the same hardware used in this study.

At L_0 and L_1, ALNS is stable and the differences among multiple optimization runs of ALNS are usually less than 1%. At L_2, the differences of runs are bigger due to larger solution space and limited running time. Figure 3.12 shows the box plots of different numbers of requests at L_2. The cost savings compared with the benchmark is calculated and different methods for the initial solution are compared. The proposed model provides better solutions on all instances at L_2 when using methods R and M to obtain the initial solution. When using method S, all solutions are better except for the instance with 1300 requests. When there are 5 to 400 requests, the proposed model with flexible vehicles reaches at least 4% and up to 24% cost savings. When there are 700 to 1600 requests, the cost savings are between 0% and 16% except for the instance with 1300 requests and the S method. From the perspective of overall performance, method M performs better than the other two methods in cost savings. For instances with 10 and 50 requests, method S is the best one. For instances with less than 100 requests, method R has very stable performance, although it performs worst. For instances with 200 requests to 1000 requests, methods S and R have similar performances. When there are more than 1300 requests, method R performs better than method S but not stable. According to the results, adjusting the original plan (method M) is more appropriate than making a plan from scratch (methods R and S) for transport operators who consider flexible services.

3.6.5 Evaluations on the customized operators

As illustrated in Section 3.5.2, a new Swap operator is proposed and some operators are customized depending on the characteristics of ST. Using instances with 5-100 requests in Section 3.6.4, Figure 3.13 shows the comparison on the (a) results with and without Swap operator and (b) results of inserting one/multiple request(s) in one construction step in Regret Insertion operator. In Figure 3.13(a), the cost and computation time of the optimal

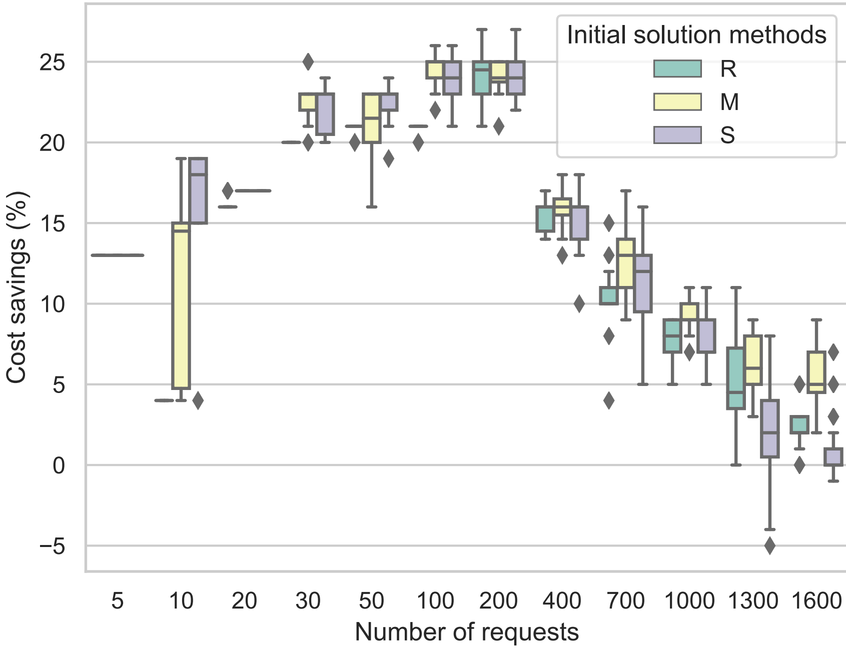
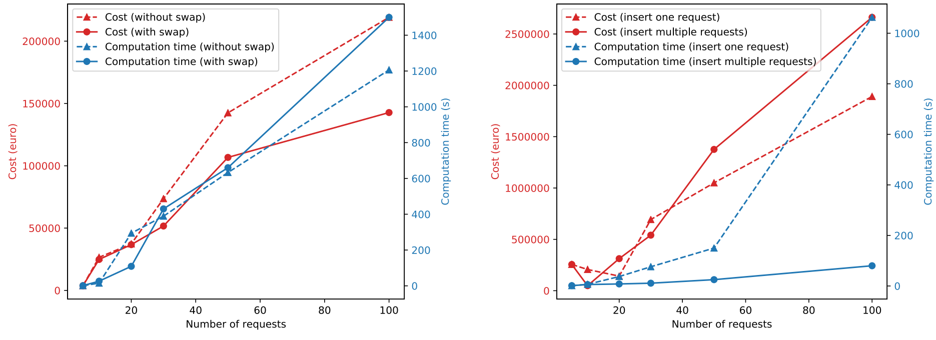


Figure 3.12: Box plots of different numbers of requests at L_2. The y-axis is the cost savings compared with the benchmark.

solution are compared. In Figure 3.13, solutions are obtained by the Regret Insertion operator from scratch and only results of the initial solution are presented to avoid influences from other operators. Figure 3.13(a) shows that the cost with Swap operator is always lower than without Swap operator, except the instance with 5 requests, where the costs are the same. Moreover, the cost gap is increasing with the number of requests and reaches 35% on the instance with 100 requests. The reason behind it is that the Swap operator inserts more requests into better positions for a larger instance. Therefore, it is shown that the Swap operator has an important role in obtaining superior solutions, although it slightly increases the computation time. Figure 3.13(b) shows that inserting one request in Regret Insertion operator does not always obtain a lower cost than inserting multiple requests, such as instances with 10 requests and 30 requests. In contrast, the computation time is decreased dramatically by inserting multiple requests in one step, especially on large instances. For example, the computation time is reduced by 92% on the instance with 100 requests.

3.6.6 Summary

By comparing with the exact approach, the results verify that ALNS reduces computation time significantly. Compared with existing models in the literature (Demir et al. 2016, Guo et al. 2020), the proposed model provides considerable cost savings by using flexible vehi-



(a) (b)

Figure 3.13: Evaluations on the customized operators. (a) Comparison on results with and without Swap operator; (b) Comparison on inserting one/multiple request(s) in Regret Insertion operator.

cles. When allowing flexibility, the requests will be shifted to low-cost and low-emission modes, especially inland waterways. The cost savings are mainly due to the better utilization of capacities of low-cost vehicles, such as trains and barges. Additional cost savings for small instances are usually obtained by avoiding unnecessary trips and transshipments. For large instances, reducing storage costs by flexible vehicles is another important source of cost savings.

The proposed model performs well under different weights for the individual objectives and generates better solutions compared with solutions in the literature (Demir et al. 2016). When there are congestions, the proposed model can mitigate the impact of congestions by using flexible vehicles. In large instances, solutions with lower costs (benchmark by Guo et al. (2020)) can always be found when allowing flexibility. Moreover, the proposed model performs consistently well on different transport networks published in the literature.

In addition, the results show that the ALNS with customized operators performs better than those without these operators.

3.7 Conclusions

In order to address the research question Q1, a novel MILP model is formulated and a customized Adaptive Large Neighborhood Search (ALNS) is proposed to solve the problem efficiently. The features of synchromodal transport, such as multiple modes, transshipment, the mix of fixed and flexible vehicles, complex schedules, and synchronization are considered in the proposed model. To achieve flexible synchromodal transport, vehicle and request routes are planned simultaneously. In order to benefit from the proposed model for realistic size instances, several customized operators are designed and performance improvement methods are proposed in ALNS. The proposed model performs well under different weights for individual objectives and can mitigate congestions by using flexible vehicles. When attributes of requests change, the proposed model can also switch transport modes flexibly in (near) real-time according to the latest information. By comparing with models published in the literature, the results demonstrate that the proposed model can reduce cost by 14% on average when using flexible vehicles. Moreover, the proposed model performs consistently well on large instances and different transport networks. Mode share of barges increases obviously and the carbon tax is reduced when using flexible vehicles, therefore the proposed model is promising for green transportation.

The proposed model provides an optimization framework for synchromodal transport with flexible services and shows promising potential for cost savings and emissions reduction by exploiting the flexibility. The transport operators can use the proposed model to make schedules for the mix of fixed and flexible vehicles and achieve economic and sustainable transport operations. Based on the experimental results, the following managerial insights are obtained:

1. Utilizing service flexibility can reduce costs under given resources and enables the transport operator to be more competitive. More cost savings need a higher degree of flexibility, which allows containers to be shifted to low-cost modes by utilizing the capacity of barges and trains. However, blindly pursuing low cost will cause delays and longer waiting times. The proposed model can be used to make decisions taking into account the trade-off between costs, emissions, delays and waiting times.

2. Flexible services facilitate the modal shift in synchromodal transport. When trucks are flexible, the mode share of trucks will decrease because it increases the possibilities of using more trains and barges by transshipments. Moreover, flexible barges are necessary for reducing emissions because many requests are still stuck with trucks when only trucks are flexible.

3. Considering the types of cargoes and the characteristics of companies, different transport operators have different preferences about transportation. Many of them consider multiple objectives to optimize, yet, the importance of different objective terms may be different. Satisfying one sub-objective is often detrimental to other sub-objectives, while flexible services make the detriment as low as possible.

4. When there are congestions, especially severe congestions, the impacts can be alleviated more with a higher level of flexibility because more options are provided.

5. Compared with planning from scratch, adjusting the transport plan with predefined schedules is the best way for transport operators to adopt flexible services, which will not change the original plan significantly and provide more cost savings.

This chapter focuses on static synchromodal transport planning. Uncertainties exist in the operations of synchromodal transport. Transport operators might be able to handle uncertainties in a better way by allowing flexibility. For example, when unexpected events occur at terminals, the request cannot be served or only be served at high delay penalty by predefined schedules but can be served without delay when considering flexible routes of vehicles. Therefore, Chapter 4 develops a dynamic planning approach to handle uncertainty.

Chapter 4

Re-planning under service time uncertainty with reinforcement learning

Chapter 3 has studied static synchromodal transport planning. However, as discussed in Chapters 1 and 2, the service time uncertainty creates challenges in the implementation of the solutions derived from static synchromodal transport planning. The service time uncertainty can result in delays, inefficiencies, and reduced satisfaction for shippers. Therefore, this chapter aims to address research question Q2: How can a real-time planning approach be developed for carriers to provide reliable services while taking into account uncertainties in service time?

This chapter is organized as follows: Section 4.1 introduces the service time uncertainty in synchromodal transport. Section 4.2 presents a brief literature review. Section 4.3 formalizes the studied problem. Section 4.4 proposes the model-assisted RL approach for the synchromodal transport re-planning. In Section 4.5, simulation experiments and results are provided, and the ability of the approach to handle unexpected events in different scenarios is evaluated. Section 4.6 concludes this chapter.

4.1 Introduction

Synchromodal transport planning is often faced with various uncertainties, such as service time uncertainty, which can significantly impact the transportation system's efficiency (Delbart et al. 2021, SteadieSeifi et al. 2014). Service time in synchromodal transport refers to the duration of picking up, delivering, or transferring goods at terminals, including time for loading/unloading and related activities. Synchromodal transport strives for seamless and efficient transfer of goods between modes, however, the service time uncertainty at terminals caused by unexpected events poses a significant challenge to achieving this goal. Unexpected events, such as congestion, bad weather, and equipment malfunctions, can cause long waiting times or changes in the duration of service, leading to uncertainty in service time. This uncertainty can trigger delays and infeasible transport plans, causing low efficiency, high cost, and request cancellation. One necessary task of synchromodal transport is to adapt to service time uncertainty at terminals (including ports, train/truck stations, and transshipment terminals).

To tackle transport planning problems under uncertainty, most of the existing approaches in the literature are based on robust optimization (Abbassi et al. 2019), re-planning (Hrušovskỳ et al. 2021), or stochastic programming (Guo et al. 2021b). Robust optimization evaluates the solutions using worst-case realizations of uncertain parameters and may generate unused excess capacities (Gabrel et al. 2014). Re-planning refers to adjusting transport plans and schedules in response to unexpected events. The re-planning is usually carried out after significant delays without predicting when and how long a delay will be. Stochastic programming approaches rely on prior assumptions on probability distributions for travel times or demands. They do not account for possible deviations from an assumed distribution (Farahani et al. 2021). These approaches usually assume that distribution information about the uncertainty is available a priori before an action is taken. This is not always a realistic assumption because the information about uncertainty is usually incrementally revealed during the transport process. Moreover, using historical distributions without detecting changes in an environment, the planning performance may decline (Phiboonbanakit et al. 2021). Therefore, a dynamic learning ability that updates the planning model is required for dealing with uncertainty in the environment.

Online scheduling and routing problems arise naturally in many application areas and have received increasing attention in recent years. Contrary to offline optimization, data is not assumed available a priori in online optimization. Rather it is collected during algorithm execution (Bent and Van Hentenryck 2005). Thanks to the development of digital platforms and the rise of concepts such as synchromodal transport, a carrier is more and more able to collect real-time information from the transport network (through port authorities, terminal operators and/or sensors) about uncertainties.

The complexity and size of a transport network make it difficult for carriers to retain and learn from events. Advanced models and algorithms, specifically deep Reinforcement Learning (RL), have the potential to be instrumental in handling unexpected events. RL has been proven to be able to achieve human or superhuman skill in tasks such as Atari games (Mnih et al. 2015) and the game Go (Silver et al. 2018). In synchromodal transport, the pattern of service time uncertainty refers to the regularities or associations that are related to factors that have an impact on the duration of service. Such factors include but are not limited to the mode of transport, current time, terminal, and type of event. The collected information from port authorities, terminal operators, and sensors can be used to learn the pattern of uncertainties by RL. By learning online, RL can handle the uncertainty and help operators take better decisions in a re-planning framework. As opposed to traditional methods of re-planning that lack an adaptive learning component, the utilization of RL for re-planning enables learning from experience and adjusting transport plans accordingly using continuously updated policy.

It is widely recognized that RL algorithms can be challenging to implement due to the "curse of dimensionality" (Gosavi 2009). This term refers to the difficulty of training RL agents when the dimension of the environment state or control action is high. This challenge is compounded in the context of synchromodal transport planning, which involves a large state space due to the need to consider routing and scheduling across multiple transport modes, as shown in Figure 4.1. The decisions in synchromodal transport are also complex, which include both discrete actions (e.g., vehicle selection) and continuous actions (e.g., shipment scheduling). To address these challenges and enhance the convergence of RL training, we propose a model-assisted RL approach in this paper. Instead of relying solely on the RL agent to make control decisions without guidance, we integrate a transport planning model to provide assistance. Specifically, we employ Adaptive Large Neighborhood Search (ALNS) to aid the RL, which helps to reduce the size of both actions and states and thus accelerates the training process. In this way, an optimization algorithm that has the domain knowledge for synchromodal transport and a machine learning technique for unexpected events are integrated to handle the synchromodal transport re-planning under service time uncertainty.

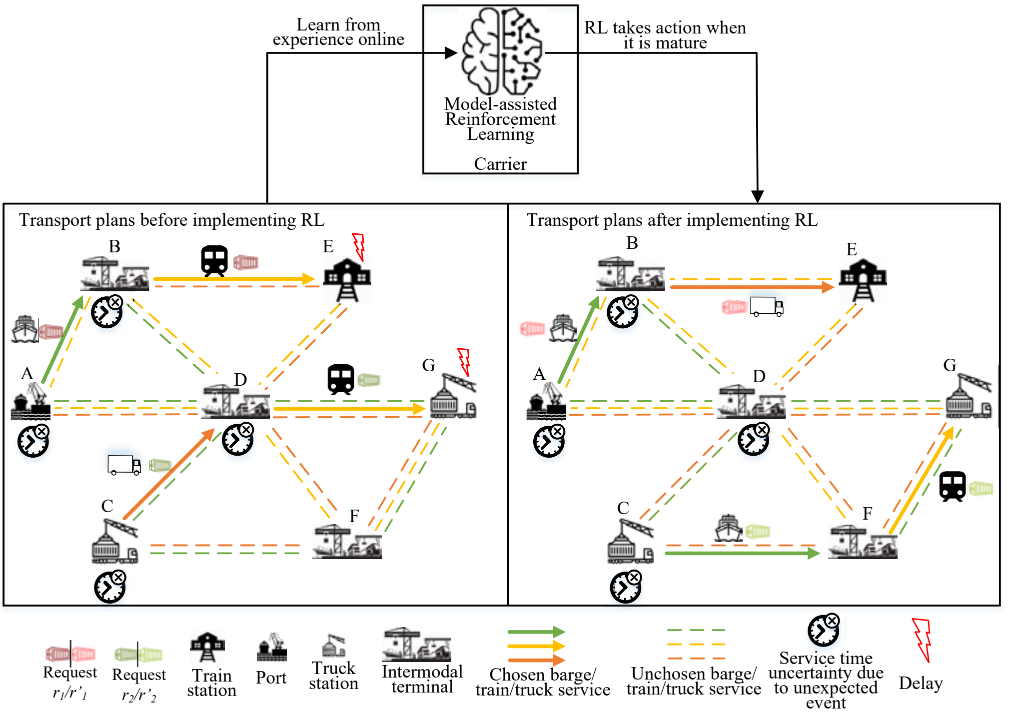


Figure 4.1: Synchromodal transport planning under service time uncertainty.

As shown in Figure 4.1, there are delays in terminals due to unexpected events, such as congestion, bad weather, and equipment malfunctions, and the carriers need to take appropriate actions when such delays occur. The problem is that a carrier usually does not know how long an unexpected event will last. Therefore, a model-assisted RL approach is proposed to find suitable actions by learning from the historical experiences of all vehicles in the transport network. The proposed RL is not provided with any transportation information in advance. It learns from nothing but the state input, the reward, and the taken actions—just as a carrier in practice would. In Figure 4.1, when the RL is not implemented, requests r_1 and r_2 are scheduled for transportation from terminals A and C to terminals E and G, respectively. However, unexpected events at terminals A, B, C, and D result in service time uncertainty and both requests arrive with a delay. When RL is implemented, new requests r_1' and r_2' need to be transported with the same origin and destination as r_1 and r_2. The RL adjusts the transport modes and routes based on its experience with requests r_1 and r_2. The mode of transportation between terminals B and E for request r_1' is changed from train to truck for improved speed. The route for request r_2' is altered from C-D-G to C-F-G to avoid service time uncertainty in terminal D. Both requests r_1' and r_2' are eventually delivered without delay. By using RL, our approach is able to adapt to unexpected events and make decisions in real time based on the current state of the transportation system. We demonstrate the effectiveness of our approach through a series of simulation experiments, illustrating that the approach could significantly improve the efficiency of synchromodal transport re-planning compared to traditional non-learning methods.

The main contributions of this paper are summarized as follows: (a) we introduce a synchromodal transport re-planning problem under service time uncertainty; (b) we propose a synchromodal transport re-planning framework that can accommodate different strategies; (c) under the re-planning framework, we develop a model-assisted RL approach to handle the service time uncertainty online; (d) we evaluate the performance of the proposed approach under different scenarios using a realistic transport network, including scenarios with disturbance and disruptions, scenarios with multiple types of events, and scenarios with perfect and imperfect severity level.

4.2 Literature review

We first review existing studies for synchromodal transport planning under uncertainty and then review the learning approaches under uncertainty in vehicle routing problems.

4.2.1 Synchromodal transport planning under uncertainty

At the operational level, synchromodal transport is required to adapt to uncertainty in a dynamic environment (SteadieSeifi et al. 2014). Therefore online planning is needed based on real-time information that becomes available over time (Yee et al. 2021). In the literature, some studies do re-planning when an unexpected event occurs, while the uncertainty is not considered. For example, Van Riessen et al. (2015c) measure the effect of a disturbance and update suitable paths in an intermodal transport network to adapt to occurring disturbances, such as early or late service departure and cancellation of services. Li et al. (2015b) use the receding horizon intermodal container flow control approach to control and reassign intermodal container flows under disturbances in transportation demand and travel time. Qu et al. (2019) re-plan the synchromodal transport by shipment flow rerouting, service rescheduling, and transshipment when the release time, container volume, and travel time change.

Some studies consider demand uncertainty. For example, Van Riessen et al. (2016) adopt decision trees to make real-time container transport planning based on offline obtained optimal solutions. Rivera and Mes (2017) propose a look-ahead planning method for the intermodal long-haul round-trips under the uncertainty of the arrival of new orders.

Travel time uncertainty is an important issue related to the efficiency of transportation. Different approaches have been developed to handle it, including stochastic programming (Demir et al. 2016, Guo et al. 2021b), Markov decision process (Yee et al. 2021), and RL

(Guo et al. 2022). Most of them focus on travel time on transport arcs, including roads, railways, and waterways. In synchromodal transport, the service time uncertainty at terminals, including ports, train/truck stations, and transshipment terminals, is very common due to unexpected events, such as congestion, weather conditions, late arrivals of services, and late releases of empty containers. However, the service time uncertainty does not attract enough attention and few studies (Demir et al. 2016) propose approaches to handle it.

4.2.2 Learning approaches for vehicle routing problems under uncertainty

In vehicle routing problems with uncertainty, studies mainly use RL to handle the demand uncertainty. Basso et al. (2022) use RL to learn the stochastic demand and energy consumption offline for an electric vehicle routing problem. Pan and Liu (2023) design a real-time decision support system that consists of a deep neural network and an RL algorithm to control the value function of the VRP with demand uncertainty. Balaji et al. (2019) propose an RL benchmark for a VRP of an on-demand delivery driver, where orders are generated with a constant probability. Phiboonbanakit et al. (2021) use RL to discover strategies for VRP with delivery incidents and the results show that RL can quickly adapt to demand uncertainty by identifying patterns of abnormalities and rearranging shipments.

The Vehicle Routing Problem with Stochastic Travel Times (SVRP) has received considerable attention in the operations research (OR) community since its introduction by Laporte et al. (1992). Recently, the computer science (CS) community also found that RL is a potentially ideal approach to solve the SVRP, especially for dynamic SVRPs (Hildebrandt et al. 2021). The OR methodology can be used to model the SVRP with as much practical consideration as possible, such as time windows, capacity, precedence constraints, etc. The CS methodology can tackle the challenging stochastic part of the SVRP with a learning approach. In this way, a hybrid approach that combines methodologies from both OR and CS communities can provide a powerful tool to search the action space and evaluate actions in SVRP efficiently.

4.2.3 Summary

Table 4.1 provides a summary of the reviewed papers. In synchromodal/intermodal transport, only Demir et al. (2016) consider service time uncertainty, while they do not propose an online planning approach. Service time is crucial in synchromodal transport because a delay at one terminal could propagate to other terminals due to transshipment, hence causing numerous consequences, such as delays and reductions in shipper/customer satisfaction. Previous studies in synchromodal transport have focused on predefined arcs or paths, without considering the flexibility of vehicle routing (Zhang et al. 2022b). However, in this study, the ability to choose routes and switch to available vehicles under uncertainty freely is taken into account, which is a critical characteristic of synchromodal transport (Giusti et al. 2019, Tavasszy et al. 2017). In VRP, although integrating RL from CS and approaches from OR is promising, handling the uncertainties of the transport environment using RL has not been well-addressed, and existing studies mainly focus on dealing with demand uncertainty (Hildebrandt et al. 2021, Phiboonbanakit et al. 2021). Moreover, most studies require prior information, such as distribution and historical demands, while the proposed approach learns online and does not need such information.

Guo et al. (2022) is the most similar study to our work. Guo et al. (2022) use the Q-learning algorithm to learn the policy of matching a shipment with a service in synchromodal transport. There are five differences that distinguish our work from Guo et al. (2022): (a) we tackle the service time uncertainty at terminals, while Guo et al. (2022) consider the travel time uncertainty on arcs; (b) Guo et al. (2022) assume that probability distributions of uncertainties are available, while the proposed model in our work does not need the distribution to train the RL; (c) Guo et al. (2022)'s RL approach uses offline simulation to learn, while our model utilizes online learning, allowing it to adapt and improve as new information is revealed during transportation. This enables our model to better handle uncertainty in real-world scenarios; (d) Guo et al. (2022) use a tabular Q-learning approach and the obtained policy cannot be generalized to events that have never been encountered before, while our model can handle events with similar features by using a deep neural network as a function approximator to estimate the action-value function; (e) our study proposes a model-assisted RL, which integrates a heuristic with RL to let RL only focus on the uncertainty part, and the size of the state is reduced compared to Guo et al. (2022).

Table 4.1: Comparison between the proposed model and existing approaches in the literature.

	Problem characteristics					**Methodologies**			
Article	Mode	Problem	Vehicle routing	Uncertainty	Event location	Approach	Learning	Re-planning	Required prior information
Synchromodal transport									
Li et al. (2015b)	road, railway, inland waterway	STP		–	–	RHC	–	periodical	–
Van Riessen et al. (2016)	road, railway, inland waterway	STP		demand	–	DT	✓, offline	real-time	historical requests
Demir et al. (2016)	road, railway, inland waterway	STP		travel/service time, demand	arcs	SO		–	–
Rivera and Mes (2017)	road, inland waterway	STP		demand	–	MDP		periodical	distribution
Yee et al. (2021)	road, railway, inland waterway	STP		travel time	arcs	MDP		periodical	distribution
Qu et al. (2019)	road, railway, inland waterway	STP		–	–	LP		real-time	–
Guo et al. (2021b)	road, railway, inland waterway	STP		travel time and demand	arcs	SO		periodical	distribution
Guo et al. (2022)	road, railway, inland waterway	STP		travel time	arcs	RL	✓, offline	periodical	distribution
Vehicle routing problems									
Balaji et al. (2019)	road	VRP	✓	demand	–	DRL	✓, online	–	none
Pan and Liu (2023)	road	VRP	✓	demand	–	DRL	✓, online	real-time	none
Basso et al. (2022)	road	VRP	✓	demand	–	RL	✓, offline	real-time	historical data
This research	road, railway, inland waterway	STP	✓	service time	terminals	model-assisted DRL	✓, online	real-time	none

–: in the "Required prior information" column, it means that no information is required as uncertainty is not taken into account; in other columns, it means that the relevant item is not mentioned in the article.
RHC: Receding horizon control; STP: Synchromodal transport planning; VRP: Vehicle Routing Problem; MDP: Markov decision process; DT: Decision trees; LP: Linear programming model; SO: Stochastic optimization.

4.3 Problem Description

Besides the problem setting in Chapter 3, we consider service time uncertainty in this chapter. During the transportation, unexpected events ue may occur with starting time t_{ue} and ending time $\bar{t}_{ue}$. The starting and ending times are unknown when designing the initial transportation plan. Due to unexpected events, the duration of service time at each terminal $i \in N$ is uncertain. If a vehicle k arrives at terminal i and cannot transport request r as planned, the request r is an affected request. If the vehicle k continued as originally planned, the delivery time of request r could exceed $b_{d(r)}$ and a delay penalty will be charged. To avoid delay, the best action needs to be taken. Specifically, the following questions need to be considered:

1. Should the affected requests be served by the current vehicle?

2. If not, which vehicles can be used for serving them?

In question 1, if request r is served by one vehicle, only the schedule of the current vehicle needs to be evaluated. If two or more vehicles are used, the schedules of subsequent vehicles also need to be considered. If the request is removed from the schedule of a vehicle, then question 2 is considered. After inserting the removed request into a new route of vehicle k', the schedules of vehicle k' and vehicles that have transshipment operations with k' need to be re-evaluated. Since multiple requests could be influenced by the same unexpected event, the above re-evaluation needs to be iterated until all affected requests have either been confirmed to keep the original plan or have been re-planned.

The severity of unexpected events may differ. Some events may cause severe disruptions and some may only disturb the schedules of vehicles. For different terminals, the factors that influence the duration of unexpected events are various, such as weather conditions, equipment malfunctions, or traffic congestion. Therefore, the duration of unexpected events at different terminals may be of different types. Multiple events of different types may happen in a single terminal. Moreover, the severity level of the event may be provided by the port authority or terminal operator (for example based on the source of the event), and the severity level may be inaccurate. The performance of the model under severity level with inaccurate information needs to be evaluated. Therefore, different scenarios need to be considered to evaluate the effectiveness of the proposed approach.

4.4 Proposed planning approach

Solving vehicle routing problems by RL is challenging because the size of the state is very large, especially for synchromodal transport with multiple modes and transshipment (Guo et al. 2022). RL can be computationally expensive and may not always find the optimal solution, especially in such large and complex environments. Different from approaches that solely use RL to solve vehicle routing problems (James et al. 2019, Nazari et al. 2018, SteadieSeifi et al. 2021), this study integrates RL and ALNS to make use of the strengths of both, namely the data-driven strength of the former and the domain knowledge from the latter, as shown in Figure 4.2. ALNS is a metaheuristic optimization algorithm that is widely used to solve vehicle routing problems, and the ALNS used in this study is extended from Chapter 3. ALNS can be very effective in finding good solutions quickly when uncertainty is not considered. By integrating RL and ALNS, we can potentially make use of the strengths of both approaches. ALNS can provide efficient search and optimization capabilities for the static problem, while RL can provide real-time adaptability and decision-making capabilities under uncertainty. This can potentially allow the integrated approach to find good solutions quickly and adapt to unexpected events in real-time. Different from the ALNS in Chapter 3, in this study, ALNS is used to build schedules, provide information on states, check feasibility to provide rewards and guide RL operators by prioritizing vehicles. Benefiting from combining ALNS, the RL approach can focus on the uncertainty in real-time and the size of the state in RL can be reduced by only keeping critical factors that influence decisions.

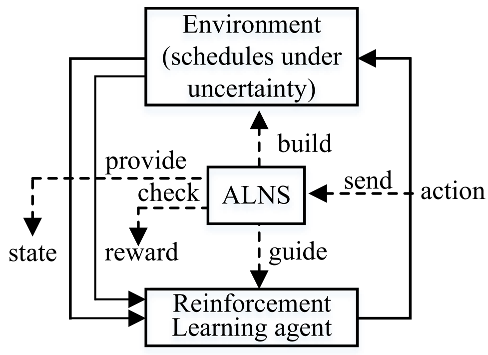


Figure 4.2: Model-assisted RL.

Section 4.4.1 introduces a re-planning framework that considers different strategies, one of which is the model-assisted RL. Section 4.4.2 presents the details of the model-assisted RL.

4.4.1 Synchromodal transport re-planning framework

This section presents a re-planning framework that accommodates different strategies: (a) waiting strategy, (b) average duration strategy, and (c) model-assisted RL strategy. The mathematical model for synchromodal transport planning under service time uncertainty is extended from Chapter 3. The objective of synchromodal transport planning is minimizing cost (Euro), as same as the objectives (3.1)-(3.7) in Chapter 3. When an unexpected event *ue* occurs prior to the planned service start time ($t_{ue} < t'^{kr}_i$), the service should start when the unexpected event *ue* is resolved, as shown in Constraints (4.1):

$$t'^{kr}_i \geqslant \bar{t}_{ue} \quad \forall i \in N,\ \forall k \in K_{ue},\ \forall r \in R \tag{4.1}$$

However, the event ending time $\bar{t}_{ue}$ in Constraints (4.1) is uncertain, which influences requests served by vehicle k at terminal i. If appropriate action is not taken, it may cause a long waiting time t^{wait}_{ki} at terminal i and hence severe delay t^{delay}_r at the delivery terminal $d(r)$.

With an event-triggered mechanism, the framework consists of two phases: re-planning when the unexpected event occurs at time step t_{ue} and evaluation/learning when the unexpected event ends at time step $\bar{t}_{ue}$. In order to address the two questions outlined in Section 4.3, the re-planning phase contains two sub-phases: the removal phase and the insertion phase. Three strategies (a), (b), or (c) are employed to determine the actions in these sub-phases. In the removal phase, the actions are to either wait or remove a request from the vehicle's schedule. In the insertion phase, the actions are to either insert a request into the schedule or not insert it.

As presented in Algorithm 3, in strategy (a), all vehicles just wait during the unexpected event mimicking the traditional planning in practice. When an unexpected event finishes, if there is a delay and re-planning is possible, the affected request will be re-planned. As presented in Algorithm 4, strategy (b) collects the duration of unexpected events online and then assumes that the current expected event's duration equals the average duration of these records and is updated as more information is received. This strategy mimics carriers who also learn from experience, but in a simpler way compared to RL.

Strategy (c) integrates re-planning and learning using a model-assisted RL, as presented in Algorithm 5. The re-planning phase stores information about the situation at time step t_{ue}. Since RL cannot immediately receive a reward for its actions when events occur, we allow the RL agent to learn when events end. As illustrated in Figure 4.3, when an event begins, the situations faced by all vehicles at different terminals are stored. When the event ends, RL is trained by simulating the situation when the event occurred. Since the duration of the event is known at the end, the reward for the taken action can be calculated. During the learning phase, the re-planning process relies on ALNS. For strategy (c), we also consider RL with and without severity level in the state.

Algorithm 3: Waiting strategy

Input: K, R, G; **Output:** X, R_{pool}; `// ` X/R_{pool} `represents the solution/request pool.`

obtain the initial routes by the static ALNS in Chapter 3 (Zhang et al. 2022b);

if *an event ue finishes* **then**

    get the set of affected requests R_{ue};

    add the event duration to schedules of R_{ue} and check feasibility of R_{ue}'s schedules;

    if requests in R_{ue} cannot be delivered on time and re-planning is possible, re-plan using Algorithms 6 and 7 and update solution X

end

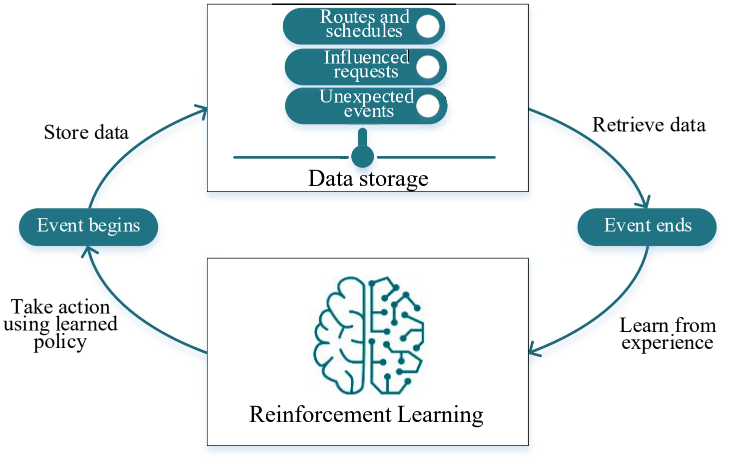


Figure 4.3: Data storage and learning.

Algorithm 4: Average duration strategy

```
Input: K, R, G; Output: X, R_pool;            // X/R_pool represents the
  solution/request pool.
obtain the initial routes by the static ALNS in Chapter 3 (Zhang et al. 2022b);
set the average duration DU as zero;
if an event ue occurs and enough historical durations are collected then
    get the set of affected requests R_ue;
    for r in R_ue do
        add average duration DU to r's schedule;
        check feasibility of request r's schedule;
        if r's schedule is infeasible then
            remove and reinsert request r using Algorithms 6 and 7 and update
              solution X
        end
    end
end
if an event ue finishes then
    the average duration DU is updated with the event duration;
    get the set of affected requests R_ue;
    add the event duration to schedules of R_ue and check feasibility of R_ue's
      schedules;
    if requests in R_ue cannot be delivered on time and re-planning is possible,
      re-plan using Algorithms 6 and 7 and update solution X;
end
```

Re-planning when the unexpected event occurs

The initial solution for the synchromodal transport re-planning is generated using ALNS (Zhang et al. 2022b). However, unexpected events during transportation may require the initial solution to be modified through re-planning. The synchromodal transport re-planning process proceeds as follows:

1. Find affected requests R_{ue}: When an unexpected event ue occurs at terminal i at time t_{ue}, the first step is to determine which transport mode w_{ue} is affected by the event. Then, for each vehicle k in the set $K_{w_{ue}}$, the process checks whether the vehicle passes terminal i. If it does, the process identifies all requests R_k^i that have operations at i. For each request r in R_k^i, if the planned service start time is larger than the event occurring time ($t'^{kr}_i > t_{ue}$), then the request is added to the set of requests R_{ue} that are affected by the unexpected event.

2. Collect RL state information: If the RL strategy is being used, for each request r in R_{ue}, the process collects the state information as described in Section 4.4.2.

3. Take action: For strategy (a), the waiting action is always taken when an unexpected event occurs and the schedules are not changed. For strategy (b), the average duration is added to the schedules, and the feasibility is checked. If the request is infeasible,

Algorithm 5: RL strategy

```
Input: K, R, G; Output: X, R_pool;            // X/R_pool represents the
  solution/request pool.
obtain the initial routes by the static ALNS in Chapter 3;
if an event ue occurs and RL is mature then
    get the set of affected requests R_ue;
    for r in R_ue do
        send the state of request r to RL and obtain the action from RL;
        if the action is removal then
            remove request/segment r using Algorithms 6 and update solution X;
            for k in suitable vehicles K' for request/segment r do
                try to insert r to vehicle k using Algorithm 7; send the state of k and
                  r to RL and receive action from RL;
                if the action is insertion then
                    keep the insertion, update solution X, and break the loop;
                end
            end
        end
    end
end
if an event ue finishes then
    update the RL's policy using the approach in Section 4.4.2;
    get the set of affected requests R_ue;
    add the event duration to schedules of R_ue and check feasibility of R_ue's
      schedules;
    if requests in R_ue cannot be delivered on time and re-planning is possible,
      re-plan using Algorithms 6 and 7 and update solution X;
end
```

it is removed and re-inserted using Algorithms 6 and 7. For strategy (c), RL is used to make decisions (see details in Section 4.4.2). The ALNS sends the state to RL and waits for the action from RL. If the action is waiting, the process evaluates the next affected request. If the action is removal, the process uses Algorithms 6 and 7 to remove and insert the request/request segment, respectively. When strategies (b) and (c) are not implemented, the vehicles will wait.

4. The above steps are repeated until all requests have been delivered.

Evaluation/learning when the unexpected event finishes

When unexpected event *ue* finishes, the duration is known. The RL agent can then learn from the experience of affected requests R_{ue} during the event. All routes, unserved requests, and state s_t are retrieved from the data storage to simulate the same situation at time step t. The ALNS sends the state s_t to RL and RL gives the action. Similar to the procedures in the previous section, if the action is removal, the request/request segment is removed and re-inserted using Algorithms 6 and 7. If the action is non-removal, the vehicle will wait until the event finishes. After the action is taken, the reward is determined by the methods in Section 4.4.2 and sent to RL for learning.

If RL is implemented, the performance of the action a_t taken by RL is evaluated. For each affected request r in R_{ue}, the routes, removal action a_t and insertion action a'_t (if any) at time step t are restored to recreate the same situation. The reward is then determined by checking the feasibility after taking the action a_t using the approaches in Section 4.4.2.

If strategy (b) is used, the duration is collected. The performance of strategies (a) and (b) are evaluated in a similar way to the evaluation of RL.

Removal and insertion methods

There are two types of synchromodal transport re-planning: re-planning for requests with and without transshipment. Requests without transshipment involve the transportation of goods using only one mode of transportation. If an unexpected event occurs at a terminal along the route of a vehicle transporting such a request, the vehicle may need to wait at the terminal until the event is resolved. This can cause delays in the delivery of the goods and may result in decreased efficiency and increased costs. In this case, re-planning may involve adjusting the route or waiting at the terminal until the event is resolved, depending on the specific situation. Requests with transshipment in synchromodal transport involve the transfer of goods from one mode of transportation to another at a specific terminal. If an unexpected event occurs at the transshipment terminal, it may affect the availability of the next mode of transportation or the transfer of goods between modes. Therefore, the re-planning for requests with transshipment also needs to consider the case where only a segment of the request is affected, meaning that only the request segment after the transshipment terminal needs to be re-planned. This helps to minimize the impact of the re-planning on the initial plan. The cases of these two types are shown in Figures 4.4 and 4.5, respectively.

The key to successful re-planning is to identify the current location i_k of the vehicle k and the terminal i_{ue} with the unexpected event ue, and determine the possible actions. If i_k is a terminal after i_{ue}, vehicle k is not affected by the event ue. Except in the case where ue occurs at the delivery terminal, only the re-planning from i_{ue} is considered in order to minimize changes to the initial plan.

On the route of vehicle k, if i_{ue} is a previous terminal of the pickup terminal $p(r)$ or is $p(r)$, then it is case 1 in Figure 4.4. In this case, the entire request r will be removed to R_{pool} and re-planned. For case 2, i_{ue} is in the middle of $p(r)$ and $d(r)$, and the request can be segmented by i_{ue} and delivery time $t^r_{i_{ue}}$ at i_{ue} if the request cannot be delivered on time. This results in the request r being segmented into two segments: $r^1_{i_{ue}}$, which needs to be picked up in the time window $[a_{p(r)}, b_{p(r)}]$ at terminal $p(r)$ and delivered in the time window $[a_{p(r)}, t^r_{i_{ue}}]$ at transshipment terminal i_{ue}, and $r^2_{i_{ue}}$, which needs to be picked up in the time window $[t^r_{i_{ue}}, b_{d(r)}]$ and delivered in the time window $[a_{d(r)}, b_{d(r)}]$. The planning for $r^1_{i_{ue}}$ remains unchanged, while $r^2_{i_{ue}}$ is removed to R_{pool} and re-inserted. In case 3, the unexpected event occurs at the delivery terminal $d(r)$. If i_k is a previous terminal of $d(r)$, the request can be removed or segmented by i_k in a similar way as in cases 1 and 2. Otherwise, the request cannot be rescheduled.

There are five cases to consider when request r is transferred at transshipment terminal j, as shown in Figure 4.5. In case 4, similar to case 1, the unexpected event influences

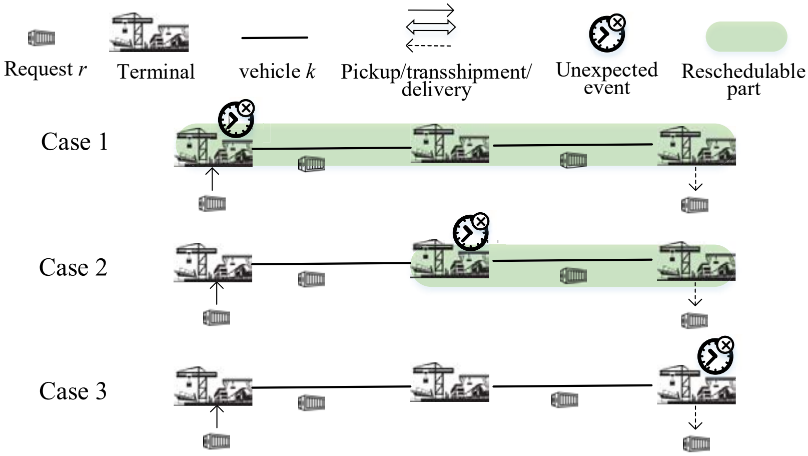


Figure 4.4: Reschedulable part when there is no transshipment.

the entire transportation of request r, and the request can be fully removed and re-planned. Cases 5 and 6 are similar to case 2, with the unexpected event occurring at a terminal between $p(r)$ and j (case 5) or at transshipment terminal j (case 6), resulting in the request segment from the affected terminal to $d(r)$ being removable. In case 7, the unexpected event occurs at a terminal between j and $d(r)$, and the request segment from the affected terminal to $d(r)$ can be re-planned, potentially requiring the use of three or more vehicles to serve the request. In case 8, the unexpected event occurs at the delivery terminal, and the request can be removed or segmented as in cases 4-7, depending on the location of vehicle k.

The removal and insertion algorithms are presented in Algorithms 6 and 7. Algorithm 6 removes the request or request segment based on the case it belongs to, while Algorithm 7 inserts the request into a route until the feasibility, as evaluated by ALNS/RL, is achieved.

Algorithm 6: Removal algorithm

Input: K, r, X_{current}, R_{pool}, *case*; **Output:** X_{removal}, R_{pool}; // $X_{\text{current}}/X_{\text{removal}}$ means the current solution/the solution after removal.

if *case == 1 or case == 4* **then**
  for *k in K* **do**
    if *k serves r* **then**
      remove r from k's schedule in X_{current} and obtain X_{removal}
    end
  end
  add r to R_{pool};
else
  remove the request segment from relevant routes of vehicles and obtain X_{removal};
  add the request segment to R_{pool};
end

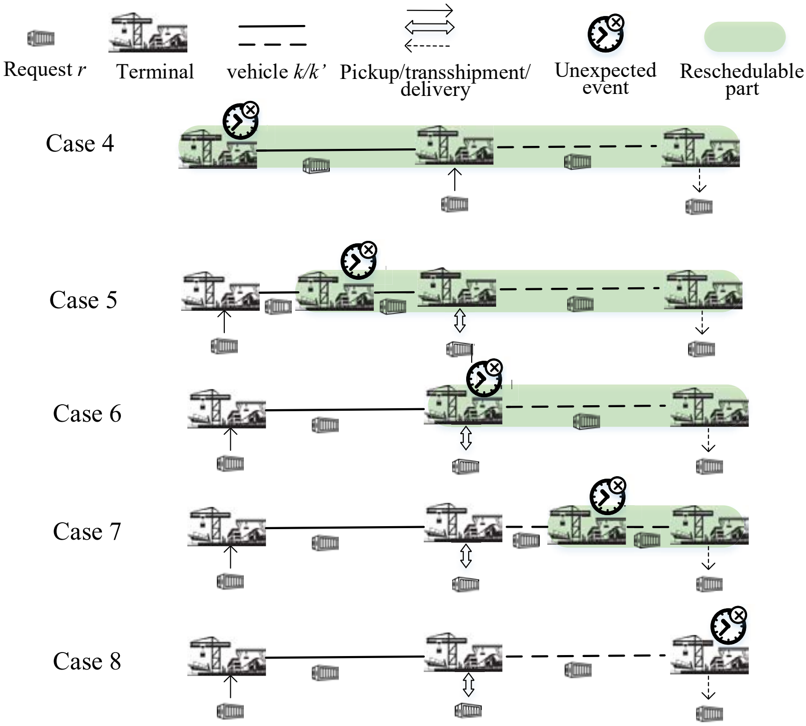


Figure 4.5: Reschedulable part when there is transshipment.

Algorithm 7: Insertion algorithm

Input: $k, r, X_{\text{current}}, R_{\text{pool}}$; ; `// k is the vehicle that is trying to be used, and r could be a request or a request segment.`

Output: $X_{\text{insertion}}, R_{\text{pool}}$;; `//` $X_{\text{current}}/X_{\text{insertion}}$ `means the current solution/the solution after insertion.`

for *position pos in all possible positions in k's route in $X_{current}$* **do**
  insert r to the position *pos*;
  check feasibility of the inserted route by the ALNS or RL;
  if *the solution after insertion is feasible* **then**
    keep the insertion and obtain $X_{\text{insertion}}$;
    remove r from R_{pool};
    stop
  else
    remove r from position *pos*;
    try next position
  end
end

4.4.2 Model-assisted Reinforcement Learning

The RL agent interacts with an environment $\mathcal{E}$ at each of a sequence of discrete time steps, $t = 0, 1, 2, 3, \ldots$. Besides the planning of all vehicles and requests, $\mathcal{E}$ contains the uncertain duration of the service time at terminals. For the unexpected event ue occurring at each time step t_{ue}, the RL agent receives a state s_t and chooses an action a_t from a set of possible actions $\mathcal{A}$ according to its policy $\pi = P(a_t|s_t)$. When the event finishes, the actual duration is known. ALNS checks the feasibility of schedules after adding the duration and gives the RL agent a scalar reward r_t. The goal of the RL agent is to maximize cumulative rewards R_t by selecting appropriate actions from each state s_t:

$$R_t = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots = \sum_{k=0}^{\infty} \gamma^k r_{t+k} \tag{4.2}$$

where γ is a discount factor.

In this RL approach, the state includes important information about the current time t, passed terminals that have unexpected events N_{ue}, the travel time τ_{ij}^k between adjacent terminals $i, j \in N_{ue}$, and the delay tolerance $t_r^{\text{tolerance}}$ of the request. The current time t helps the RL agent to evaluate how long the unexpected event will last. The decision for one request must consider not only the unexpected event at the current terminal but also events at later terminals. Therefore, we include all passed terminals that have unexpected events N_{ue} and the travel time τ_{ij}^k in the state. The delay tolerance $t_r^{\text{tolerance}}$ represents the maximum possible delay time and should not be smaller than the duration of the unexpected event, otherwise, there will be a delay in delivering the request and the request may need to be switched to another vehicle. As shown in Figure 4.6, there are two cases when calculating the delay tolerance. In both cases, the delay tolerance includes the duration between the latest delivery time and the planned delivery time $b_{d(r)} - t_r^{\text{delivery}}$. In case 1, the event begins after the service start time t'^{kr}_i, so the delayed time is equal to the duration of the event. In case 2, the event begins before t'^{kr}_i, and part of the duration $t'^{kr}_i - t_{ue}$ does not affect the service, which needs to be added to the delay tolerance. Therefore, the delay tolerance is calculated by:

$$t_r^{\text{tolerance}} = (t'^{kr}_i - t_{ue})^+ + (b_{d(r)} - t_r^{\text{delivery}}). \tag{4.3}$$

In order to provide more information about the event that is causing the service time uncertainty, we also consider the severity level of the event as a part of the state in the RL approach. The severity level is a measure of the impact of the event on the transport operation and can be obtained from the terminal operator or other sources. The severity level may not always be accurate due to incomplete information and measurement errors, therefore, the consideration of imperfect severity level is also incorporated. The inclusion of the severity level is only applied in complex scenarios, as demonstrated in Section 4.5.2.

Figure 4.7 shows the flowchart of the model-assisted RL, where dashed lines mean the interactions between ALNS and RL. When a request is influenced, firstly the RL agent decides whether the current vehicle is suitable to serve it or not in the removal phase. The first step involves generating the route for the request and sending the relevant state information to the RL agent. The RL agent then makes a decision about whether the request should be

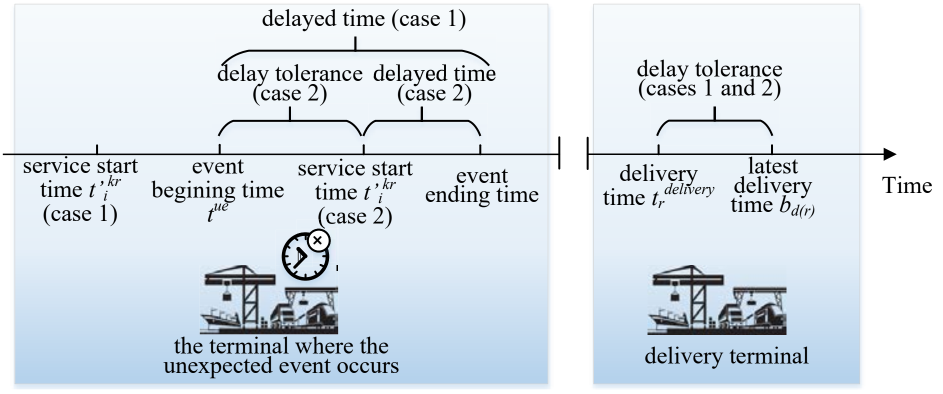


Figure 4.6: Delay tolerance in the state.

removed or if the vehicle should wait until the event finishes. ALNS then evaluates the feasibility of the original route based on the action taken by the RL agent and sends a reward to the RL agent based on whether or not the action avoided delay. If the action was removal and there was a delay when the event finished, or if the action was waiting and there was no delay when the event finished, the reward is 1. Otherwise, the reward is 0.

If the action in the removal phase is removal, RL will determine which vehicle is the most suitable for the affected request in the insertion phase. The insertion phase includes the following steps:

1. ALNS ranks the vehicles based on their unit cost. For each vehicle, it inserts the removed request into the route using the ALNS greedy insertion operator (Zhang et al. 2022b), and then sends the resulting state to RL. RL then returns an action, which can be either non-insertion (1) or insertion (0).

2. ALNS evaluates the action by checking the feasibility of the original route and sends a reward to RL. If the action is non-insertion (1) and there is a delay, or if the action is insertion (0) and there is no delay, the reward is 1. Otherwise, the reward is 0.

3. If the action is an insertion, the insertion phase is stopped and the affected request is inserted into the chosen vehicle. If the action is non-insertion, the process continues with the next vehicle until the request is inserted or there is no suitable vehicle left.

The actions and rewards in the insertion phase have a similar meaning to those in the removal phase but are referred to by distinct names. Therefore, the same RL approach can be utilized for both phases. If the action in the removal phase is waiting, then the insertion phase is not necessary. If the action is to remove the request, it may be necessary to perform additional iterations in the insertion phase to identify a suitable vehicle.

Once the RL approach has reached a certain level of maturity or a predetermined number of iterations, it will be used to make decisions for requests that are affected by uncertainty, while the ALNS heuristic will continue to handle constraint checking. As the RL approach continues to interact with the environment, it will continue to learn and improve its decision-making capabilities.

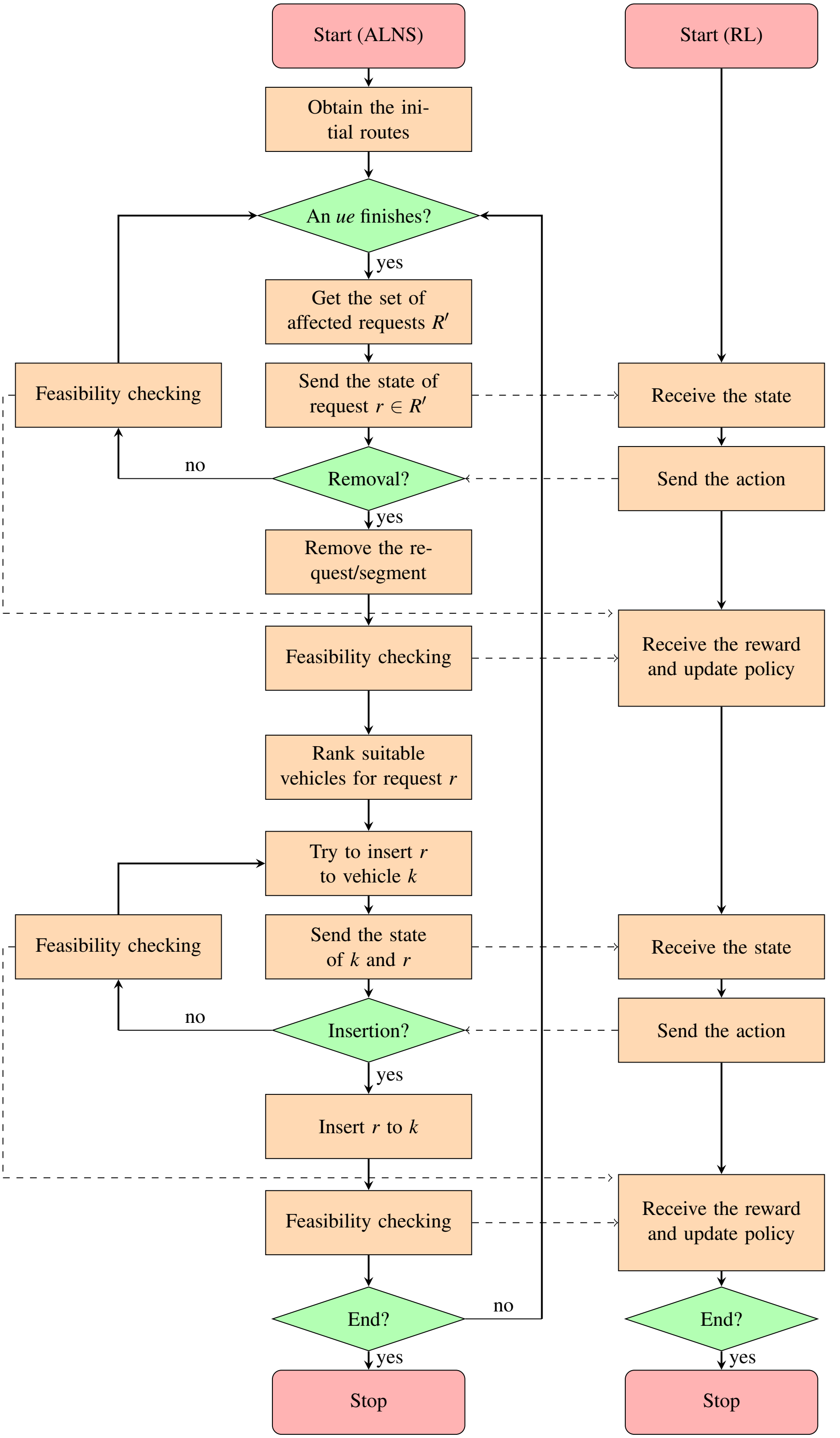


Figure 4.7: The flowchart of the model-assisted RL.

The proposed model-assisted RL framework can be built upon any RL algorithm. In this paper, we use the deep Q-network (DQN) (Mnih et al. 2015), a representative RL technique, as the RL algorithm. The action value $Q^{\pi}(s,a) = \mathbb{E}[R_t|s_t = s,a]$ is the expected return for selecting action a in state s and following policy π. The optimal value function $Q^*(s,a)$ gives the maximum action value for state s and action a for any policy. The $Q^*(s,a)$ obeys the Bellman equation:

$$Q^*(s,a) = \mathbb{E}_{s'}[r + \gamma \max_{a'} Q^*(s',a')|s,a]. \tag{4.4}$$

where s' and a' are the state and action at the next time step. The Bellman equation means that the optimal policy is to choose the action maximizing the expected value of $r + \gamma \max_{a'} Q^*(s',a')$ if $Q^*(s',a')$ of s' is known for all possible actions a'. In practice, finding $Q^*(s,a)$ is computationally expensive. Therefore, the DQN uses deep neural networks, called Q-network, as a nonlinear function approximator with parameters θ to estimate the action value function: $Q(s,a;\theta) \approx Q^*(s,a)$.

The algorithm for training DQN to approximate the optimal action-value function $Q^*(s,a)$ is presented in Algorithm 8. A target network $\hat{Q}(s,a;\theta^-)$ is cloned from Q using an older set of parameters θ^- in every C iterations and is used to generate the Q-learning targets y for the following C iterations. In the beginning, both Q and $\hat{Q}$ are initialized with random parameters θ. Then, for each iteration t, the DQN receives state s_t and selects an action a_t according to an ε-greedy policy (ε = 0.05). The action is sent to ALNS and reward r_t and state s_{t+1} is received. The target Q-value y is calculated using the Bellman equation (4.4) with $\hat{Q}$:

$$y = r_t + \gamma \max_{a'} \hat{Q}(s',a';\theta_t^-). \tag{4.5}$$

The predicted Q-value is obtained using the current parameters θ_t in the network $Q(s,a;\theta_t)$. At each iteration t, the $Q(s,a;\theta_t)$'s parameters θ_t are updated to minimize the mean-squared error between the target and predicted Q-values, i.e., the loss function:

$$L_t(\theta_t) = \mathbb{E}_{s,a,r,s'}[(y - Q(s,a;\theta_t))^2] \tag{4.6}$$

Differentiating (4.6) with respect to θ_t, we obtain the following gradient:

$$\nabla_{\theta_t} L(\theta_t) = \mathbb{E}_{s,a,r,s'}[(y - Q(s,a;\theta_t))\nabla_{\theta_t} Q(s,a;\theta_t)]. \tag{4.7}$$

These gradients are then used by optimization algorithms like stochastic gradient descent used in this study to update the parameters in a direction that minimizes the loss.

Besides, the DQN also makes use of different techniques to stabilize the learning with neural networks, including the replay buffer and gradient clipping, as introduced by Mnih et al. (2015).

The process of how the RL agent learns to make decisions in the presence of unexpected events is illustrated in Figure 4.8. A request is initially planned to be transported by truck and then transferred to a barge via transshipment. However, an unexpected event occurs at the transshipment terminal, requiring the RL agent to determine whether to remove the request from the barge and whether to insert it onto the train service as an alternative. If the request is removed from the barge and inserted onto the train, there will be no delay in

Algorithm 8: Deep Q-network

Initialize the Q-network Q parameters θ randomly;
Initialize the target Q-network $\hat{Q}$ parameters $\theta^- = \theta$;
repeat
  Receive state s_1 from ALNS;
  for $t = 1, 2, ..., T$ **do**
    Select a_t = $\arg\max_a Q(s_t, a; \theta)$ or a random action a_t with probability ε;
    Send action a_t to ALNS and receive reward r_t and state s_{t+1};
    Calculate the target Q-value using the Bellman equation (4.5) and the predicted Q-value using $Q(s, a; \theta)$;
    Compute the loss function (4.6) as the mean squared error between target and predicted Q-values;
    Perform a gradient descent step using equation (4.7) and update θ using stochastic gradient descent to minimize the loss function;
    Reset $\hat{Q} = Q$ in every C iterations;
    if *the RL is mature* **then**
      Return: Trained Q-network
    end
  end
until *the number of episodes is reached*;
Return: Trained Q-network

its transportation. In the removal phase, the RL agent receives a reward for removing the request from the barge service, as remaining on the barge would result in a delay. Through training, the RL agent continually tries different actions and receives rewards, eventually learning to make the decision to remove the request. Similarly, in the insertion phase, the RL agent is trained to ultimately make the decision to insert the request onto the train service. The required number of training iterations for effective learning depends on the size of instances. Further details can be found in Section 4.5.2.

4.5 Case Study

The European Gateway Services (EGS) network is selected as the real-world case to evaluate the effectiveness of the proposed planning approach. EGS network is located at the Rhine-Alpine corridor, which constitutes one of the busiest freight routes in Europe, around 138 billion tonne-kilometers of freight is transported along this corridor annually, accounting for 19% of the total GDP of the EU. Figure 4.9 presents the overall network of this study (Guo et al. 2020). It contains three terminals in the Port of Rotterdam and seven inland terminals in the Netherlands, Belgium, and Germany. In total 116 vehicles are used in the case study, which includes 49 barges, 33 trains, and 34 truck fleets. We assume a truck service is a fleet with an unlimited number of trucks and truck services are available between any of the two terminals. The origins and destinations of requests are distributed randomly among deep-sea terminals and inland terminals, respectively. Requests have random origins and destinations among deep-sea and inland terminals. The container volumes of requests are

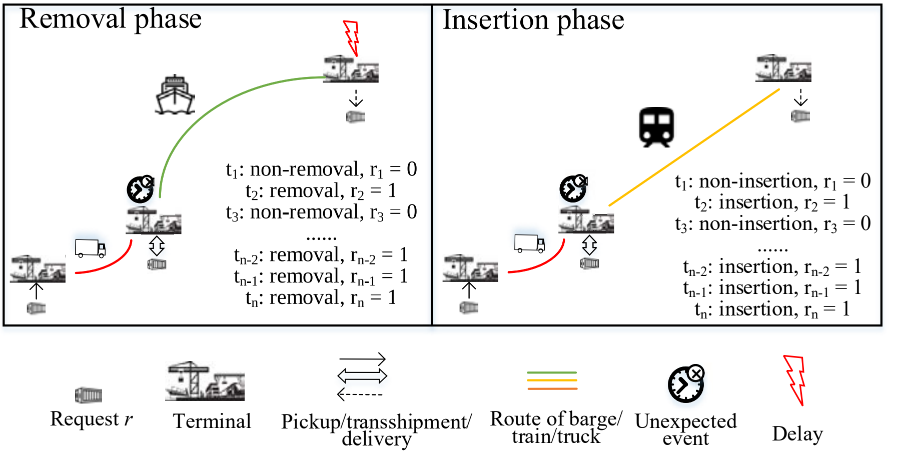


Figure 4.8: An example of how RL learns.

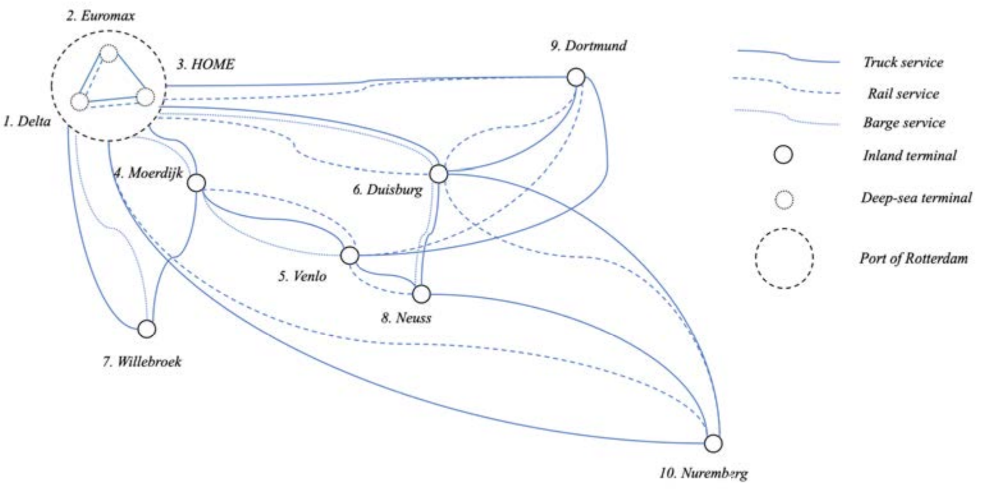


Figure 4.9: Transport network of EGS (source: Guo et al. (2020)).

drawn independently from a uniform distribution with range [10, 30] (unit: TEU). The earliest pickup time $a_{p(r)}$ of requests is drawn independently from a uniform distribution with range [1, 120]; the latest delivery time $b_{d(r)} = a_{p(r)} + LD_r$, where LD_r is the lead time and it is independently and identically distributed among 24, 48, 72 (unit: hours) with probabilities 0.15, 0.6, 0.25. Moreover, we set $b_{p(r)}$ and $a_{d(r)}$ equal to $b_{d(r)}$ and $a_{p(r)}$, respectively. Detailed information on how the instances are generated can be found in Guo et al. (2020). To evaluate the approach, instances with 5, 10, 20, 30, 50, and 100 shipment requests are designed. The time horizon of the transport planning is eight days. Before the transport, the model is used to generate transport plans for all requests. If unexpected events occur during the transportation, the model will be triggered for the re-planning of influenced schedules.

We consider scenarios with different types of unexpected events, which moreover follow different duration distributions. A duration distribution is a statistical representation of the distribution of time periods for a specific type of event. It describes the likelihood of the event taking a certain amount of time. In order to generate realistic unexpected events, we use truncated normal distributions to exclude negative durations, which are commonly used in the literature (Soltani-Sobh et al. 2016, Srinivasan et al. 2014). These distributions are not known to the RL algorithm. In terms of the severity level information in the state of RL approach, we have three cases: no severity level information, perfect severity level information (the level is accurate), and imperfect severity level (where some levels are not as expected). In Section 4.5.1, there is no severity level information. In Section 4.5.2, because the scenario with multiple events is complex, perfect and imperfect severity levels are considered.

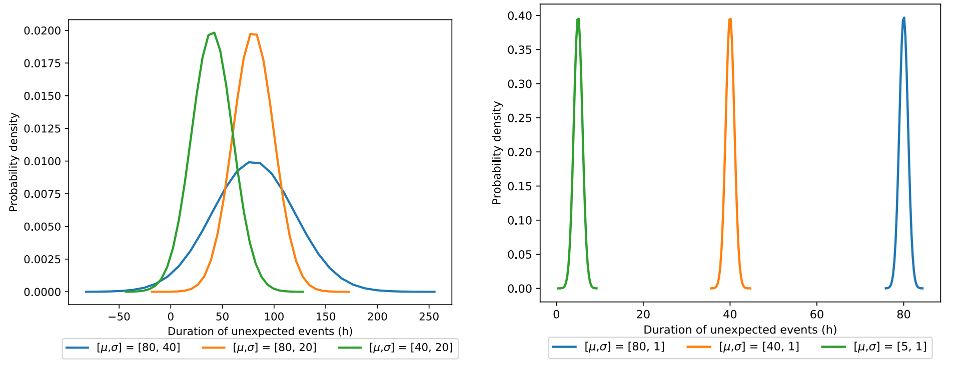
Unless otherwise specified, the maximum number of iterations in the learning phase is set to 5000, and the RL is evaluated every 100 iterations. During the evaluation, the RL is tested 10 times and the rewards are recorded. If the average reward is greater than 0.9 for five consecutive evaluations, we consider the RL to be mature and ready for implementation. During the implementation phase, the RL is used to make decisions for 200 iterations.

The performance is evaluated using two indicators: average reward of all iterations and total delay over all requests in the implementation phase. The performance indicators are evaluated from the carrier's perspective and consider all vehicles in the transport network. Rewards are given for actions that avoid delay (referred to as "correct actions"). A higher reward and lower delay indicate better performance. However, a high reward does not necessarily mean a low delay, as incorrect actions can result in substantial delays even if the majority of actions are correct and result in a high average reward. We also evaluate the proportion of rewards obtained through removal, waiting, non-insertion, and insertion actions, with higher proportions being favorable.

4.5.1 Results under disruptions and disturbances

To test the model under different types of unexpected events, several scenarios are designed, including (a) disturbances, (b) severe disturbances, (c) disruptions, and (d) a mix of disruptions and disturbances. The distributions used in each scenario are illustrated in Figure 4.10. In scenario (a), the mean value μ of the duration distribution is set to a small value of 5h, and the standard deviation σ is set to 1. This represents a situation where the duration of unexpected events is generally short but still somewhat variable. In scenario (b), the distribution is defined by the parameters [μ, σ] = [40, 20] or [40, 1]. In scenario (c), the mean value μ of the distribution is set to 80h, and the standard deviation σ is set to 40, 20, or 1. This allows us to evaluate the performance of the proposed approach under different levels of variability in the duration of unexpected events. In scenario (d), the terminals are divided into two groups. The first group (terminals 1-5) and the second group (terminals 6-10) experience different types of events in scenarios (a), (b), and (c). The information on these distributions is unknown to RL.

Figure 4.11 shows the proportion of actions and rewards among various strategies. Each rectangle of a distinct color represents a specific action, with the size of the rectangle indicating the proportion of that action. The filled portion of each rectangle represents the proportion of rewards obtained through the corresponding action, while the blank portion

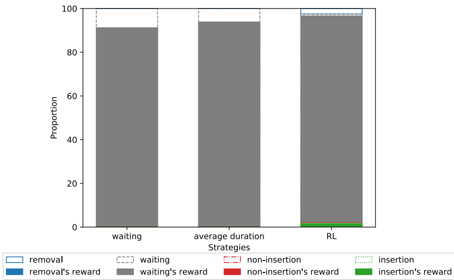


(a) (b)

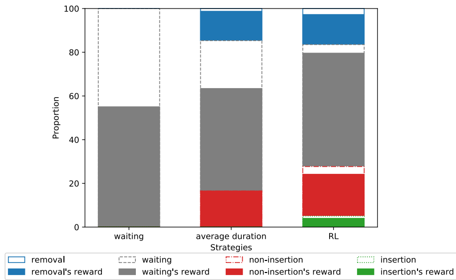
Figure 4.10: Normal distributions used in different scenarios (unknown to RL). These distributions are truncated at zero to avoid negative duration.

represents the proportion of the action that does not result in a reward. Across all scenarios, the RL strategy (strategy (c)) consistently performs the best, while the waiting strategy (strategy (a)) consistently performs the worst. The waiting strategy performs well only in the presence of disturbances in Figure 4.11(a), where the wait time is sufficient in most cases. As the severity of unexpected events increases, the waiting strategy performs increasingly poorly. The average duration strategy (strategy (b)) performs worse as the variation in the unexpected events becomes larger, as it becomes more difficult to utilize average duration to determine the optimal action in such circumstances. In the presence of disruptions, the proportion of non-insertion and removal actions increases as the strategy attempts to mitigate the disruptions and subsequent delays. The RL strategy uses more insertion and waiting actions compared to the average strategy, even in the presence of disruptions, because it is able to identify situations in which requests can still be serviced by vehicles despite the disruptions occurring frequently at terminals. This capability allows the RL strategy to earn more rewards compared to the other two strategies. The RL strategy also exhibits superior performance in terms of its ability to accurately recognize and execute non-insertion and removal actions.

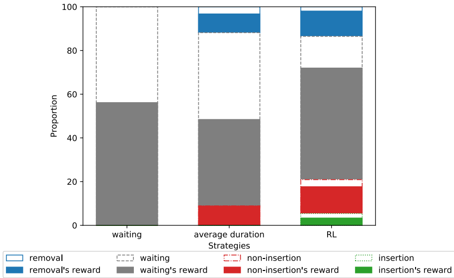
Figure 4.12 compares the delay (in hours) of different strategies under various numbers of requests and scenarios where the duration of unexpected events at all terminals follows the same distribution. It is observed that the delay of the waiting strategy is higher than other strategies in 75% of the cases. The RL strategy is relatively insensitive to increases in the variations or stochasticity of the duration of the events, and the total delay is the lowest in all scenarios, including disturbances, severe disturbances, and disruptions. As the severity of the events increases, the maximum delay for the waiting and average duration strategies increases significantly, while the maximum delay for the RL strategy remains below half of the maximum delay for the other strategies in the majority of cases. The delay of the RL strategy is lower than the other two strategies in 80% of the cases. In the remaining cases, the RL strategy performs better than at least one of the other two strategies in five out of seven cases. On average, the RL strategy reduces delay compared to the average duration



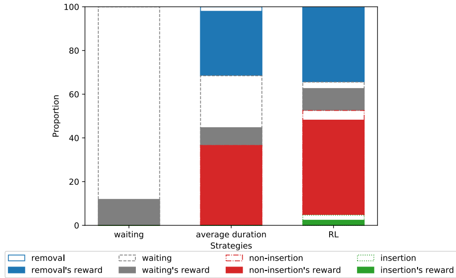
(a) disturbances



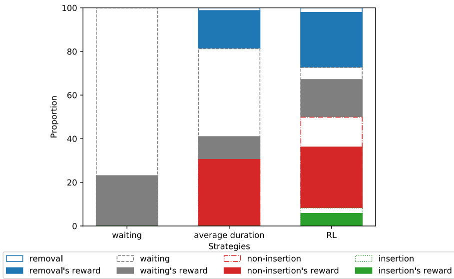
(b) severe disturbances



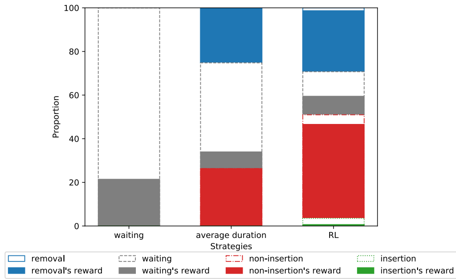
(c) severe disturbances with medium variations



(d) disruptions



(e) disruptions with medium variations

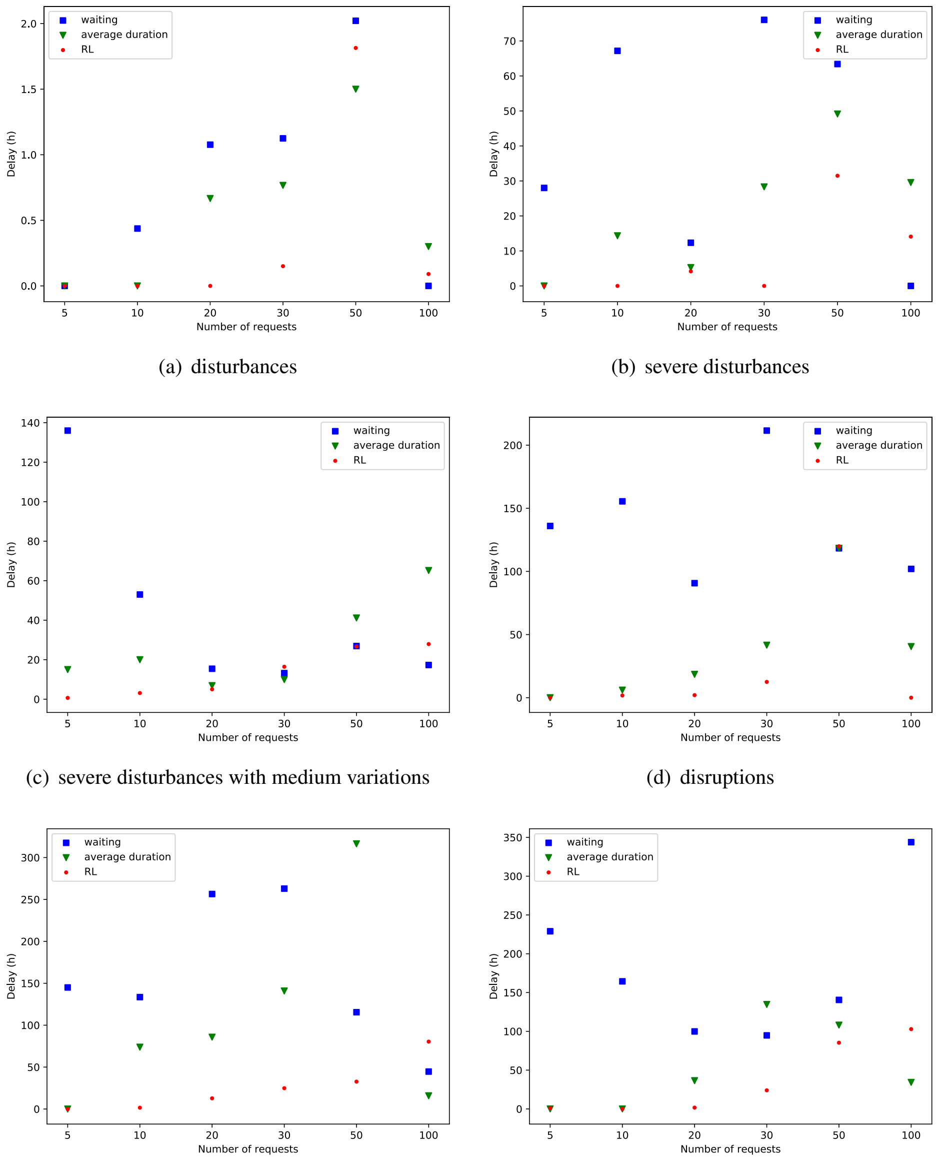


(f) disruptions with high variations

Figure 4.11: Proportion of actions and rewards under disturbances or disruptions.

strategy by 9.6% and the waiting strategy by 53.8%. This suggests that the RL approach is more effective at handling unexpected events and minimizing the delay compared to the waiting and average duration strategy.

Figure 4.13 depicts the distribution of actions and rewards under scenarios in which different types of events occur at different terminals. In Figure 4.13(a), the waiting strategy only effectively handles half of the cases in the scenario with both disturbances and severe disturbances. The average duration strategy performs better than the waiting strategy as it uses historical information, although it is still less accurate and yields fewer rewards compared to the learning strategy. In Figure 4.13(b), the performance of the waiting and average duration strategies is similar to that observed in Figure 4.13(a). In Figures 4.13(c) and 4.13(d), when disruptions occur at some terminals, the waiting strategy's performance

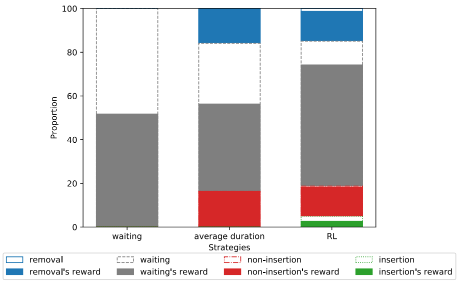


(a) disturbances
(b) severe disturbances
(c) severe disturbances with medium variations
(d) disruptions
(e) disruptions with medium variations
(f) disruptions with high variations

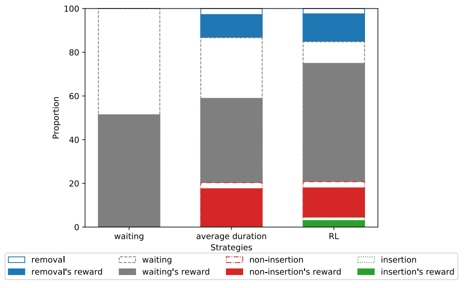
Figure 4.12: Total delay over all requests under disturbances or disruptions.

deteriorates significantly as it is unable to avoid delays caused by disruptions in the majority of cases. In contrast, the learning strategy is able to handle a mixture of disruptions and disturbances effectively, utilizing a range of actions appropriately based on the specific circumstances it encounters, and consistently earning the highest rewards.

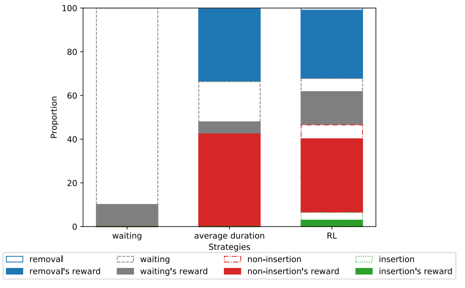
Figure 4.14 presents the total delay over all requests under scenarios in which different



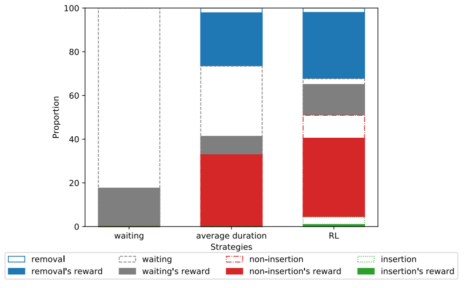
(a) disturbances and severe disturbances



(b) disturbances and severe disturbances with a medium variation



(c) disturbances and disruptions



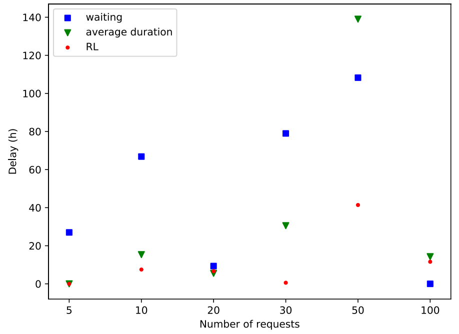
(d) disturbances and disruptions with a medium variation

Figure 4.13: Proportion of actions and rewards under different types of events occurring at different terminals.

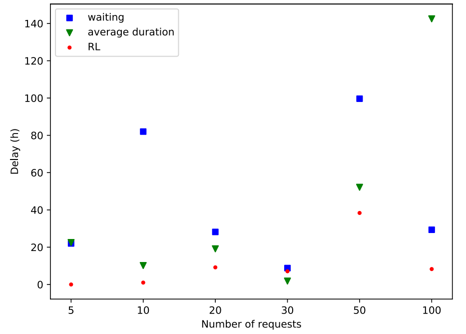
terminals experience different types of events. In 21 out of 24 cases, the RL strategy outperforms the other two strategies, while in the remaining three cases, the RL strategy performs comparable to the waiting or average duration strategy that has a better performance. Despite the presence of various types of events, including disturbances, severe disturbances, and disruptions, at different terminals, the RL strategy is able to effectively identify and implement strategies to avoid delay based on the terminal and its accumulated experiences at that terminal. The results indicate that when either the waiting or average duration strategy is the best-performing strategy, the RL strategy is able to obtain similar results. In cases where these strategies are not optimal, the RL strategy is able to devise a superior approach. On average, the RL strategy reduces delay compared to the average duration strategy by 22.1% and the waiting strategy by 73.8%.

4.5.2 Results under multiple events with perfect and imperfect severity level

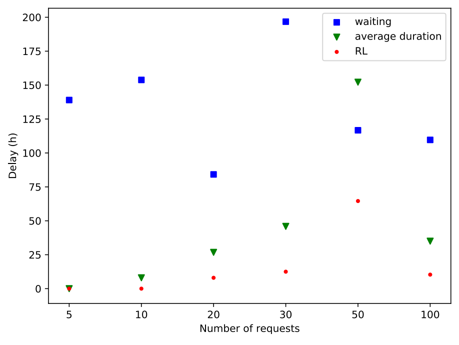
In previous experiments, we assumed that there was only one type of event at each terminal. However, it is possible for multiple types of events to occur at the same terminal, with some events causing disruptions and others causing disturbances. To tackle this issue, we created five scenarios incorporating 2-6 types of events occurring at the same terminal. In each



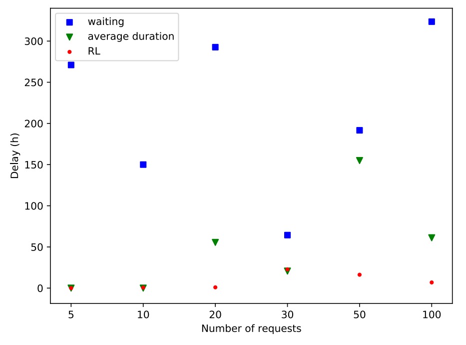
(a) disturbances and severe disturbances



(b) disturbances and severe disturbances with a medium variation



(c) disturbances and disruptions

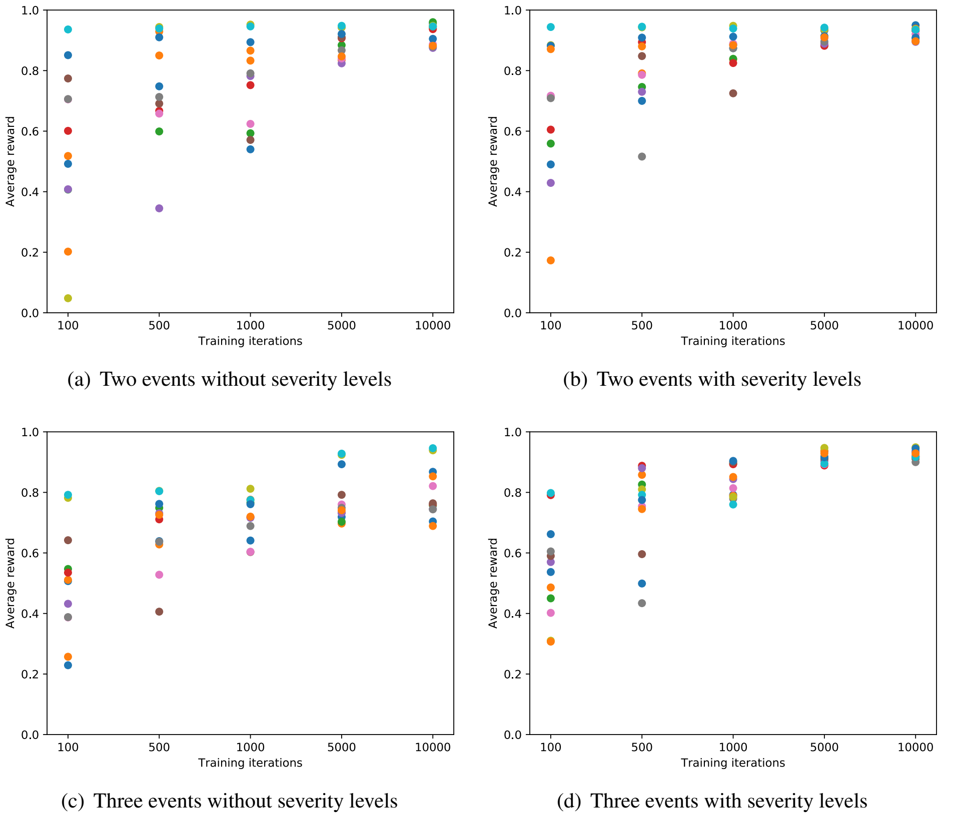


(d) disturbances and disruptions with a medium variation

Figure 4.14: Total delay over all requests under different types of events occurring at different terminals.

scenario, 12 cases are generated with different events, randomly chosen from the following types ([μ, σ]): disturbance ([5, 1]), severe disturbance [μ, σ], severe disturbances with a higher standard deviation ([40, 20]), disruption ([80, 5]), and disruptions with a higher standard deviation ([80, 40]). In majority of the cases, the types of events differ, but there are cases that contain the same type of events.

Figure 4.15 presents the average rewards obtained by all actions of the RL strategy with varying numbers of training iterations under scenarios involving different numbers of events occurring at the same terminal. It is observed that in the scenario with two events (Figure 4.15(a)), the RL's average rewards reach 0.9 when the number of training iterations is 10000, indicating that the RL is able to choose correct actions in more than 90% of cases. However, as the number of events increases, the performance of the RL declines, with the average reward unable to reach 0.8 in scenarios with six events. This suggests that the problem becomes increasingly complex as the number of events increases, and the RL is unable to effectively solve it without additional information. In order to measure the performance of RL in complex scenarios with multiple events at the terminal, the state has been augmented with the inclusion of a severity level. The severity level is labeled from 1 to 6 and is defined as follows: Level 1: duration time ≤ 20, Level 2: duration time $\in (20, 40]$, Level 3: duration time $\in (40, 60]$, Level 4: duration time $\in (60, 80]$, Level 5: duration time $\in (80, 100]$, Level 6: duration time > 100. The RL is only informed about the level as a label but does not know the duration. Figure 4.15 also presents the average rewards for scenarios after adding a severity level to the state. The results indicate that the average reward is able to reach 0.8 in most cases when the number of training iterations is 1000, and approaches or exceeds 0.9 when the number of training iterations is 5000. This suggests that incorporating a severity level into the state is beneficial in enabling the RL to choose correct actions, as it can help to differentiate between events with different levels of impact and allow for more informed decision-making.



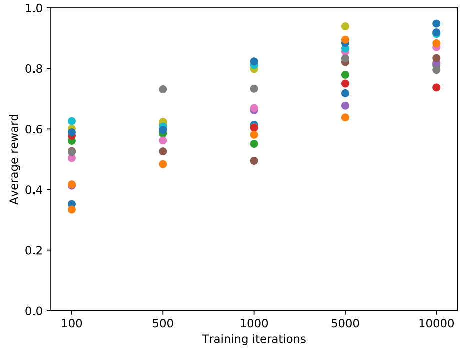
(a) Two events without severity levels

(b) Two events with severity levels

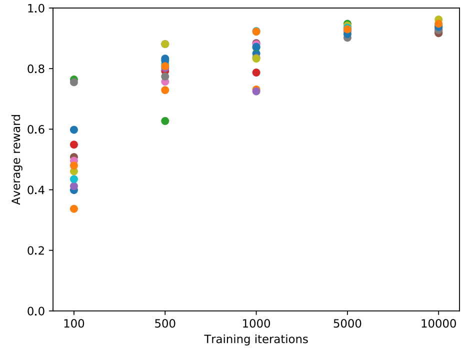
(c) Three events without severity levels

(d) Three events with severity levels

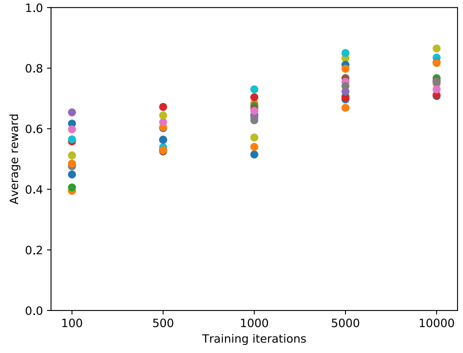
Figure 4.15: Average rewards under multiple types of events at the same terminal.



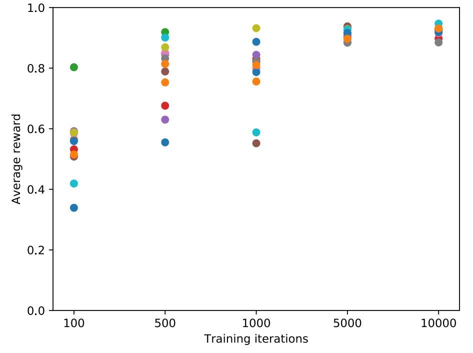
(e) Four events without severity levels



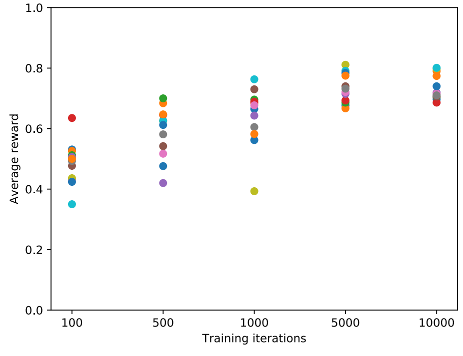
(f) Four events with severity levels



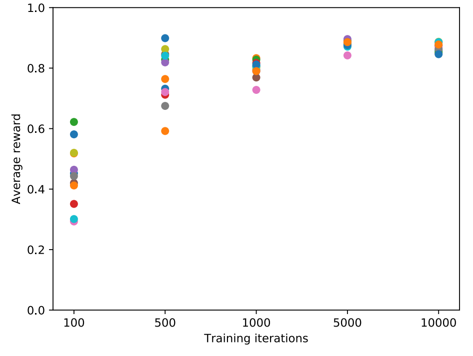
(g) Five events without severity levels



(h) Five events with severity levels



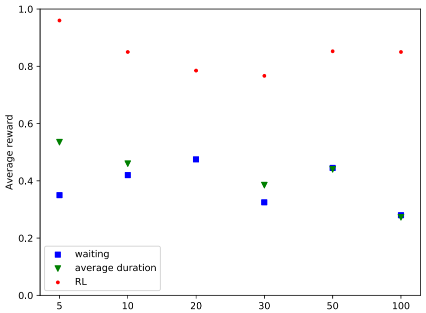
(i) Six events without severity levels



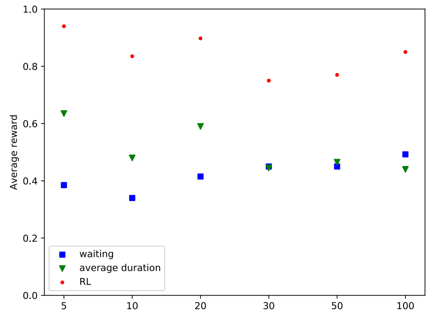
(j) Six events with severity levels

Figure 4.15: Average rewards under multiple types of events at the same terminal (cont.).

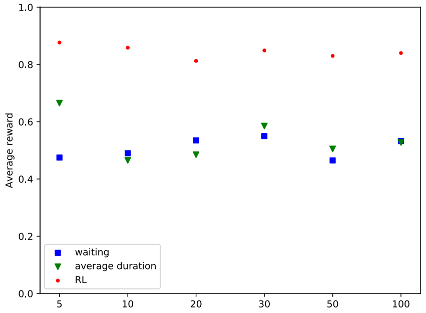
Figure 4.16 presents the average rewards of the three strategies under various numbers of requests in scenarios with multiple events and severity levels. Across all cases, the RL strategy's average rewards of handling all requests are higher than the waiting and average duration strategies. Figure 4.17 provides the proportions of actions and the corresponding rewards obtained by each action. This figure more clearly demonstrates the RL's ability to accurately utilize different actions in complex cases involving up to six events at a single terminal. Figure 4.18 compares the delay experienced by the different strategies. In 25 out of 30 cases, the RL strategy performs the best among the three strategies, and in the remaining four out of five cases, the RL's performance is similar to that of the other two strategies. The only exception is in the case with 100 requests under the scenario with four events (Figure 4.18(c)), where the RL strategy experiences a significantly larger delay due to a single incorrect action. On average, the RL strategy reduces delay compared to the waiting and average duration strategies by 52.8% and 29.0%, respectively.



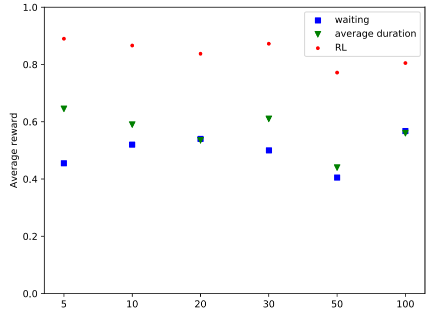
(a) two events



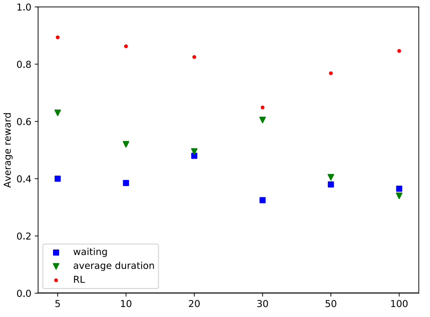
(b) three events



(c) four events

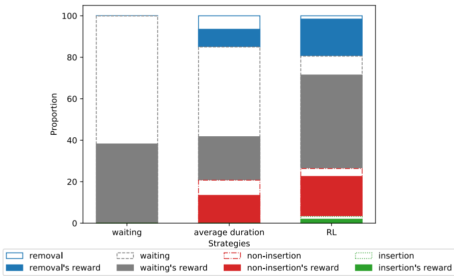


(d) five events

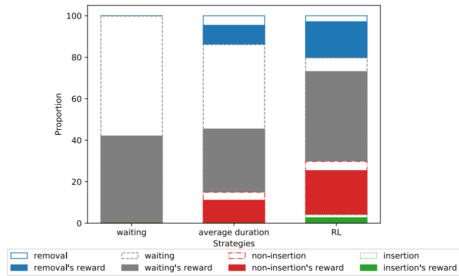


(e) six events

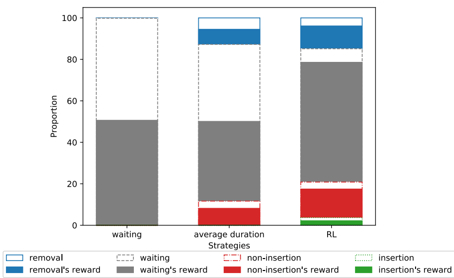
Figure 4.16: Average rewards of strategies under multiple events at the same terminal.



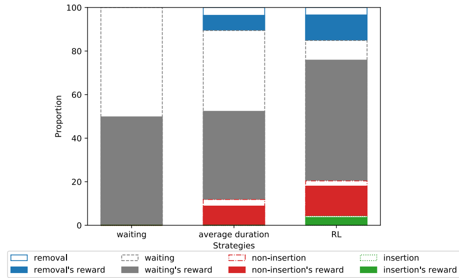
(a) two events



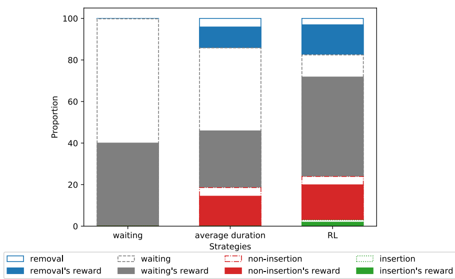
(b) three events



(c) four events

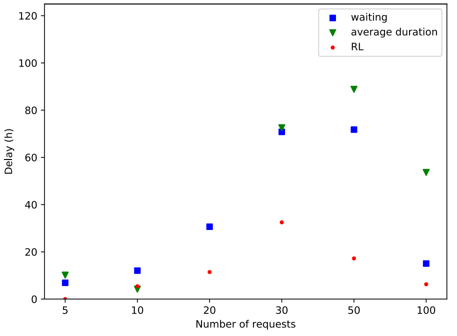


(d) five events

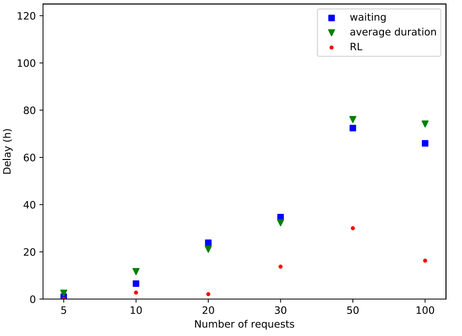


(e) six events

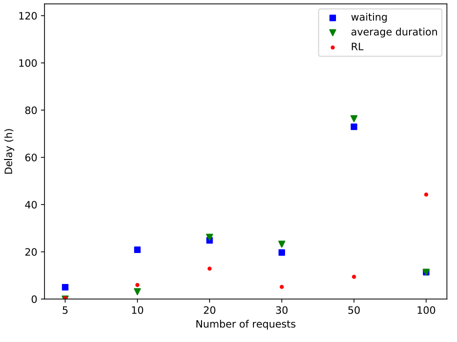
Figure 4.17: Proportion of actions under multiple events at the same terminal.



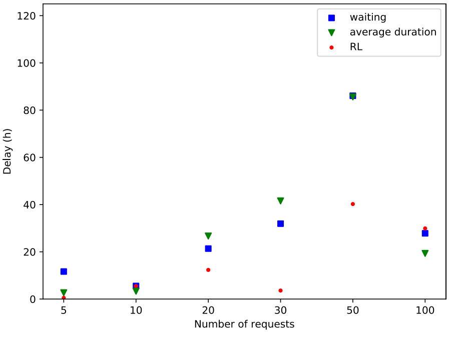
(a) two events



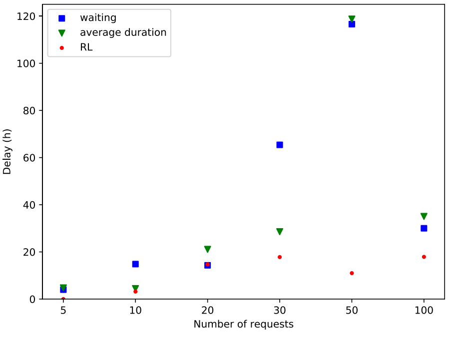
(b) three events



(c) four events



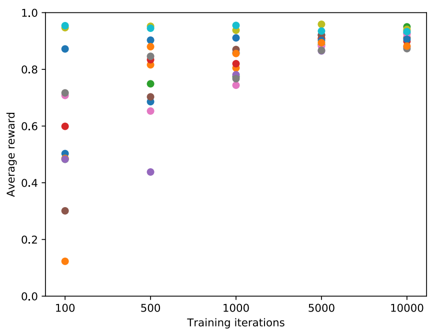
(d) five events



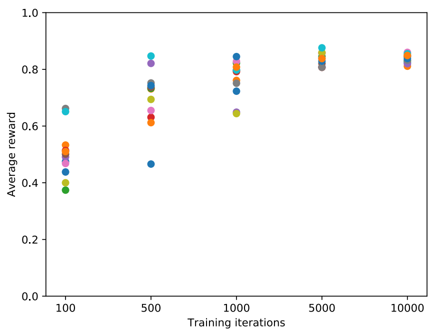
(e) six events

Figure 4.18: Total delay over all requests under multiple events at the terminal.

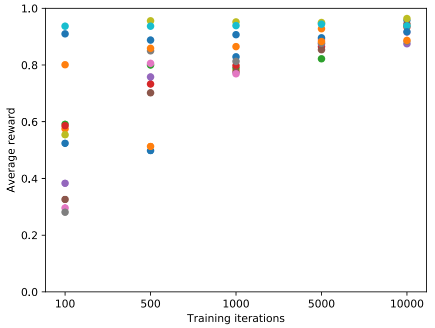
While incorporating severity levels can improve the performance of the RL, it is important to recognize that such knowledge may be imperfect, potentially incomplete or outdated, subject to interpretation, or prone to measurement errors. In these cases, the RL may make suboptimal decisions or take longer to learn an optimal policy. To assess the RL's performance under imperfect knowledge of severity levels, we designed scenarios that include random severity levels with a probability ranging from 0 to 0.5. The RL approach is evaluated under scenarios with two and six events, and the results are shown in Figure 4.19. For the scenario with two or six events, as the probability increases, the average reward decreases, but still reaches 0.8 or 0.7 with sufficient training iterations when half of the severity levels are randomly provided. The incorporation of imperfect knowledge can increase the complexity of the problem for the RL, requiring it to consider multiple potential states and incorporate uncertainty into its decision-making process. However, the use of deep neural networks in the RL allows the agent to adapt to changes in the environment, even with imperfect knowledge of the state, making it particularly useful in complex synchromodal transport environments where other methods may be ineffective.



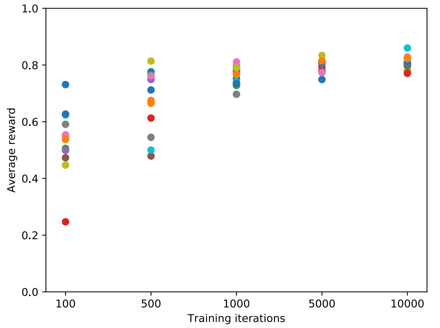
(a) two events, probability of imperfect levels: 0.2



(b) six events, probability of imperfect levels: 0.2

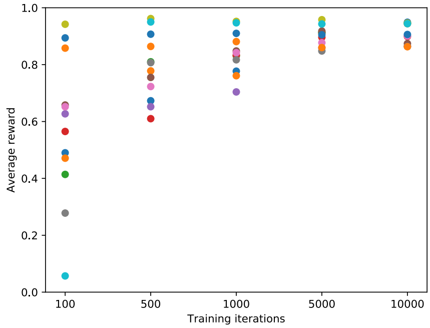


(c) two events, probability of imperfect levels: 0.3

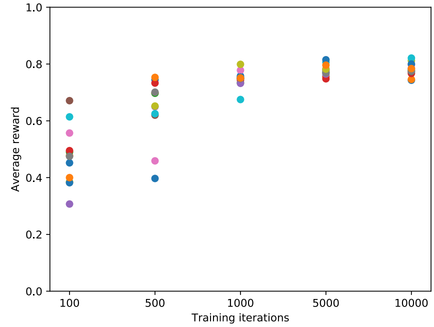


(d) six events, probability of imperfect levels: 0.3

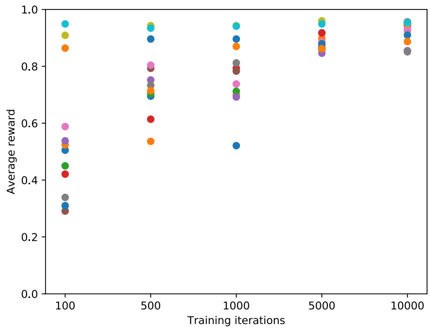
Figure 4.19: Average rewards under multiple events with imperfect severity levels (12 cases with different colors).



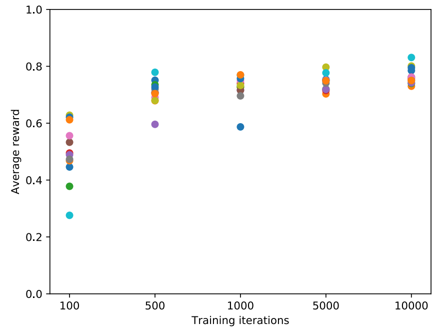
(e) two events, probability of imperfect levels: 0.4



(f) six events, probability of imperfect levels: 0.4



(g) two events, probability of imperfect levels: 0.5



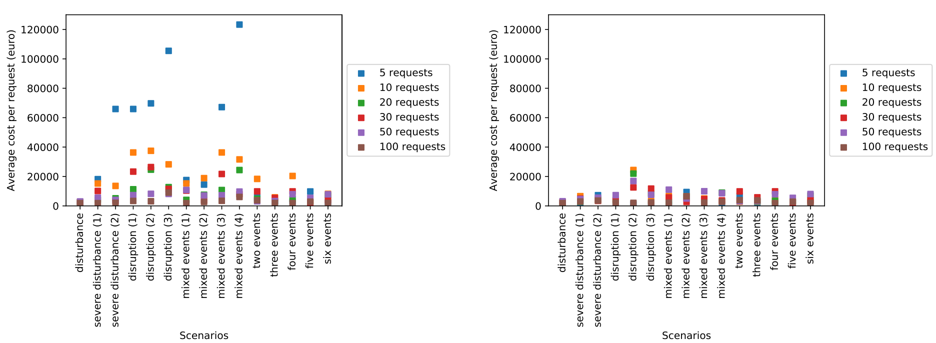
(h) six events, probability of imperfect levels: 0.5

Figure 4.19: Average rewards under multiple events with imperfect severity levels (12 cases with different colors) (cont.).

4.5.3 Analysis of other performance indicators: served requests, costs, emissions, waiting time, and training time

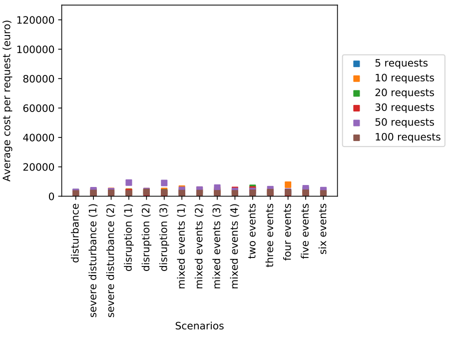
Besides delay and reward, there are several additional performance indicators that need to be considered, such as the number of served requests, costs, emissions, waiting time, and training time. The waiting strategy serves all requests even at the cost of a high delay penalty. The average duration and RL strategies may selectively unserve a limited number of requests in order to optimize overall performance in instances where delays are unavoidable and alternate services are more appropriate for other requests. In the average duration strategy, all requests are served in 91.2% of the experiments, in 7% of the experiments only one request is not served, and in the remainder 1.8% of the cases two requests are left unserved. The RL strategy has a higher rate of served requests, with all requests being served in 93.9% of the experiments, only one request being unserved in 5.7% of the experiments and two being unserved only in 0.4% of the cases. It is noteworthy that the experiments with unserved requests are mostly the larger ones such as those with 100 requests.

The performance indicators including average cost per request, average emissions, and average waiting time are presented in Figures 4.20, 4.21, and 4.22, respectively. These results are derived from the evaluation of different strategies under a variety of scenarios, including disturbance, severe disturbance, disruption, and mixed events in various terminals as discussed in Section 4.5.1, as well as multiple events at a single terminal in Section 4.5.2. In the scenario with multiple events, the RL strategy with severity level is used. The performance of the different strategies in terms of cost is shown in Figure 4.20. The average duration and RL strategies have demonstrated an improvement over the waiting strategy, reducing costs by 26.8% and 44.0%, respectively. This is attributed to the better handling of service time uncertainty, leading to a reduction in delay penalties and the effective adjustment of transport plans, avoiding the use of more expensive trucks in the late stages. Handling service time uncertainty not only leads to cost reduction, but also results in a decrease in emissions, particularly under scenarios with disruptions, mixed events, and multiple events, as shown in Figure 4.21. The waiting strategy, which only implements re-planning upon the occurrence of a significant delay, often leads to high-cost, high-emission vehicles to mitigate the delay at the last minute. On the other hand, the average duration and RL strategies reduce emissions by switching the shipment request to a suitable vehicle in the presence of unexpected events and reducing the need for high-emission vehicles at the last minute. As illustrated in Figure 4.22, the waiting time is significantly reduced when compared to the waiting strategy. The average duration and RL strategies have resulted in a reduction of 13.2% and 24.5%, respectively. The efficient handling of service time uncertainty allows for a more agile and flexible allocation of resources, leading to the avoidance of unnecessary wait times and the prompt adjustment of shipment requests to suitable vehicles. These results highlight the benefits of efficient handling of service time uncertainty, as it reduces the risk of missing the best time to switch vehicles and reduces costs, emissions, and waiting time. The training time for the RL strategy is presented in Figure 4.23. The total duration of training is no more than one hour when the size of the instance is small, such as the instance with 5 requests. The total training time increases proportionally with the size of the instance. The average training time per iteration is calculated to be a few seconds, with the longest being less than three minutes for the largest instance. As the duration of service time in the field of synchromodal transport often requires several hours, the training can be completed during this period and can be done online. Additionally, the time required for the RL approach to make a decision is less than 1 ms when the RL approach is implemented, making it an efficient solution for real-time decision-making.



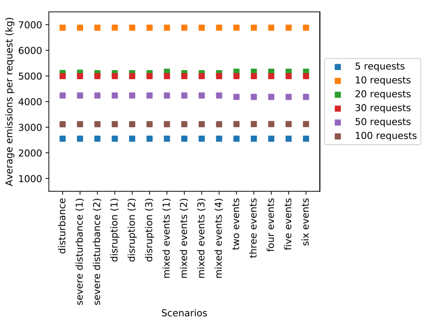
(a) waiting strategy (b) average duration strategy

Figure 4.20: Average cost per request in different scenarios with different strategies.

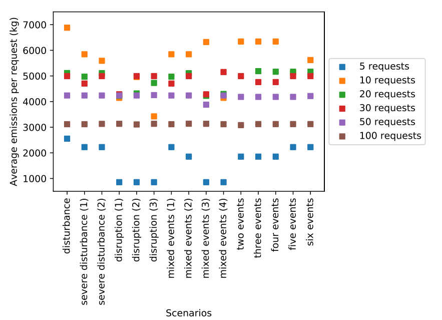


(c) RL strategy

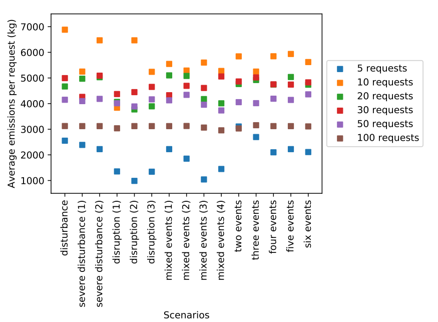
Figure 4.20: Average cost per request in different scenarios with different strategies (cont.).



(a) waiting strategy

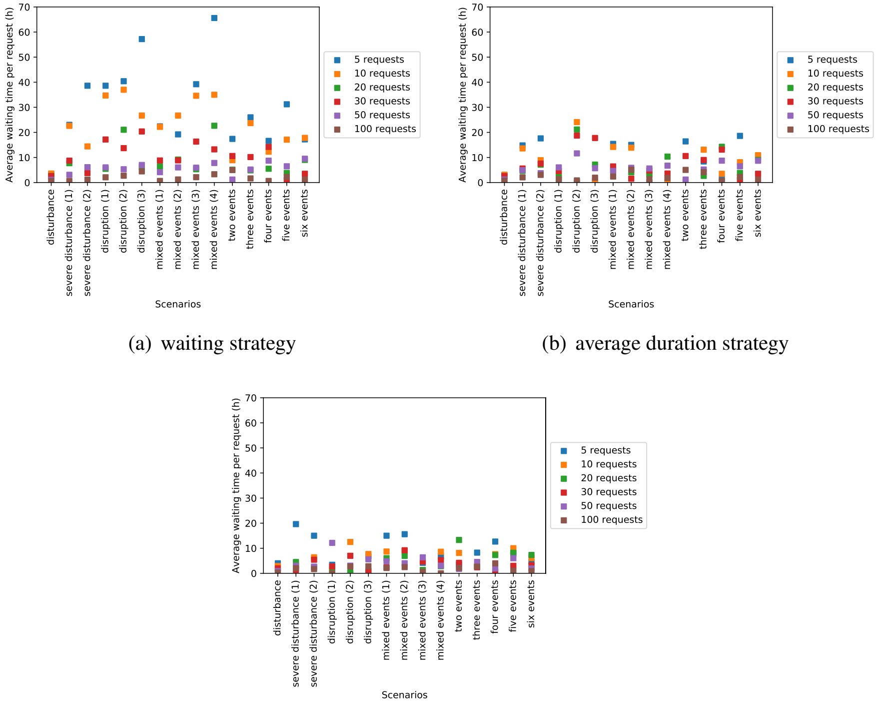


(b) average duration strategy



(c) RL strategy

Figure 4.21: Average emissions per request in different scenarios with different strategies.

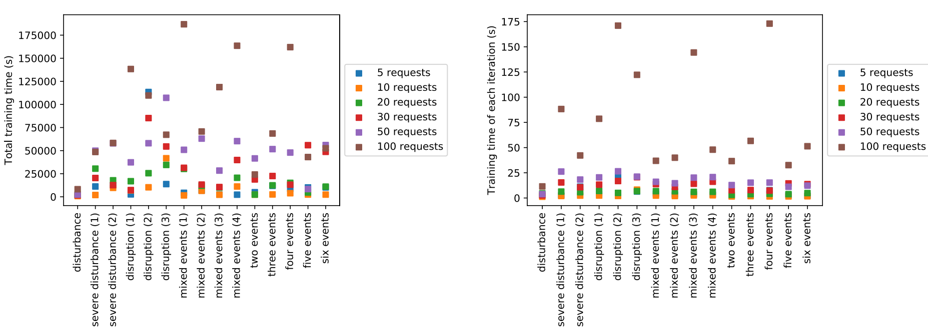


(a) waiting strategy

(b) average duration strategy

(c) RL strategy

Figure 4.22: Average waiting time per request in different scenarios with different strategies.



(a) total training time

(b) average training time of each iteration

Figure 4.23: Training time of RL strategy in different scenarios

4.6 Conclusions

It is important to consider the challenges of managing synchromodal transport operations in the presence of service time uncertainty due to unexpected events at terminals. Unexpected events, such as disruptions or disturbances, can have a significant impact on the efficiency and effectiveness of transportation processes, resulting in delays, high costs, and high emissions. These events are often difficult to predict and can be caused by a variety of factors, including weather, accidents, or maintenance issues. As a result, it is crucial for transport operators to have tools and strategies in place to mitigate the impact of such events and maintain the smooth operation of the transportation system.

To address research question Q2, we have proposed a Reinforcement Learning (RL) approach for online synchromodal transport planning that can handle uncertainty and determine whether requests should be switched to different vehicles in case of delays. The RL approach is assisted by an Adaptive Large Neighborhood Search (ALNS) heuristic, which provides state and reward information, makes changes on the transport plans, and checks the feasibility of schedules. The model-assisted RL approach learns in real time and adapts its recommendations for carriers dynamically based on the uncertain service time conditions in the environment. This approach can be used by synchromodal transport carriers through a digital platform, where the carrier receives information about unexpected events from port authorities and terminal operators.

Several scenarios that varied in the type and severity of unexpected events and the level of variability in their duration are investigated. The performance of each strategy was measured in terms of average reward and total delay. The results of this study indicate superior performance of RL on unexpected events, as it is able to adapt to unexpected events and effectively handle complex scenarios, resulting in significantly reduced delays and higher rewards compared to other strategies. The waiting strategy, on the other hand, is unable to effectively mitigate the impact of disruptions or severe disturbances. The RL strategy outperforms the waiting and average duration strategies in the majority of cases, particularly when dealing with disruptions, a mix of disruptions and disturbances, and multiple events in a single terminal. The efficient handling of service time uncertainty, as demonstrated by the RL approach, leads to a reduction in costs, emissions, and waiting time by reducing delay penalties, avoiding the use of more expensive and high-emission trucks, and allowing for a more agile and flexible allocation of resources. Therefore, transportation managers may consider implementing the RL strategy in their decision-making process to reduce delays and increase efficiency in their operations. It is worth noting that the RL strategy requires a longer training period compared to the other two strategies, but this is compensated by its superior performance in the long run. Therefore, transportation managers should also consider investing sufficient training time to fully optimize the RL strategy's performance.

The potential of incorporating knowledge of event severity into the decision-making process is a key managerial insight from this study. The results indicate that providing this type of information to the RL algorithm can significantly improve its performance. Transportation managers should prioritize regularly updating and accurately assessing event severity information in order to optimize their management systems. However, it is important to note that imperfect information on event severity is inevitable in complex synchromodal transport systems due to various factors such as outdated or incomplete information, subjective interpretation, or measurement errors. Despite this, the proposed RL approach is able to handle imperfect information and still achieve good performance.

Chapter 5

Transport planning considering carriers' preferences

The approaches for static and dynamic planning of carriers are discussed in Chapters 3 and 4. However, the preferences of carriers, which are crucial to synchromodal transport planning, have not been considered. This chapter considers the preferences of carriers. This chapter, in conjunction with Chapter 6, aims to answer research question Q3: How can the heterogeneous and vague preferences of shippers and carriers be incorporated into the planning approach?

This chapter is organized as follows: Section 5.1 introduces the carriers' preferences in synchromodal transport. Section 5.2 reviews the preference-based multi-objective optimization techniques and multi-objective optimization studies in synchromodal transport. In Section 5.3, we first present the ALNS for multi-objective optimization in Section 5.3.1 and then consider vague preferences in Section 5.3.2. In Section 5.4, experimental settings and results are provided. Section 5.5 concludes this chapter.

Parts of this chapter have been published in Zhang et al. (2022a)[1].

5.1 Introduction

In synchromodal transport, carriers have different preferences toward different objectives. Typically, the primary objective of carriers is to minimize the transport cost. Transport time also plays an important role in transport route optimization because it influences both cost and reliability. Moreover, the government stimulates stakeholders to minimize the total CO_2 emissions. To achieve synchromodal transport, it is necessary to consider multiple objectives and preferences and synthesize the best attributes of different modes in the optimization model for carriers. As shown in Figure 5.1, the carrier needs to find the most appropriate routes of multiple modes, including barges, trains, and trucks, according to the preferences. For example, when the carrier needs to transport perishable cargo for shippers,

[1]Zhang, Y., Atasoy, B., & Negenborn, R. R. (2022). Preference-based multi-objective optimization for synchromodal transport using Adaptive Large Neighborhood Search. Transportation Research Record, 2676(3), 71-87.

the time objective is important and the proportion of fast modes (such as trains and trucks) in transport planning will be higher. However, in the literature, most scholars ignore the different objectives and preferences of carriers in synchromodal transport (Van Riessen et al. 2015b, Zhu et al. 2014).

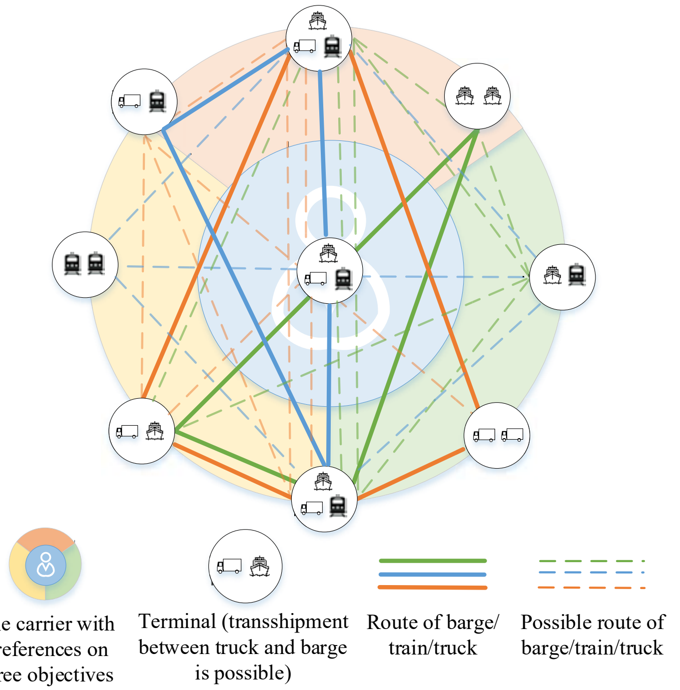


Figure 5.1: Vehicle routing for synchromodal transport considering preferences and synchronization

5.2 Literature Review

5.2.1 Preference-based multi-objective optimization

Wang et al. (2017) provide a summary of methods on how to incorporate preferences into multi-objective optimization (MOO), such as weighted sum method, reference point, reference direction, utility function, etc. According to Coello et al. (2007), preference-based MOO approaches (PMOO) are divided into three categories: Priori (Li and Liu 2015, Szlapczynska and Szlapczynski 2019), Progressive (Battiti and Passerini 2010, Gören et al. 2016), and Progressive (Ghodsi et al. 2016) Preference Articulations, which mean making decisions before, during, and after search, respectively. In synchromodal transport, it may be impractical for a carrier to completely specify their preferences before any alternatives are known. However, the carrier has at least a rough idea about reasonable trade-offs between different objectives, which is called *vague preferences*. For example, Szlapczynska and Szlapczynski (2019) propose a MOO model in ship weather routing, considering vague preferences of carriers in the form of weight intervals. Therefore, the Priori Preference Articulations approach is used in this paper and Pareto optimal solutions are obtained according to preferences. To solve the conflicts between objectives and obtain preferred solutions, the weight interval method proposed by Szlapczynska and Szlapczynski (2019) is used to add vague preferences to the MOO model.

The ε-constraint method is often used for multi-objective problems, which is based on minimizing/maximizing one of the objectives and restricting the rest of the objectives within predefined values (Kalinina et al. 2013). For heuristic approaches, evolutionary algorithms, such as NSGA-II (Nondominated Sorting Genetic Algorithm II) (Deb et al. 2002), are often used in MOO problems. Besides evolutionary algorithms, ALNS can also be used to solve the MOO problem. ALNS is more suitable for this study because it has been successfully applied to VRP and performs robustly in different instances due to its adaptive nature (Masson et al. 2013).

5.2.2 Multi-objective optimization for synchromodal transport

For synchromodal transport planning, two types of problems are considered in the literature. Service Network Design (SND) problem relates to choosing services and optimizing vehicle frequencies in the transport network. Route Optimization (RO) involves the planning decisions of routes and modes. The methods for solving MOO used in different articles are different. Table 5.1 provides a summary of models in the literature in order to position our work. As mentioned before, the vehicle routing component has many benefits, taking synchronization into account is conducive to making full use of limited resources, and considering preferences is important to solve the conflicts among objectives. However, vehicle routing, synchronization, and preferences are rarely considered in the literature and these are the core contributions of our paper. Furthermore, we use an ALNS algorithm to solve the problem and the procedures within ALNS are tailored specifically to the synchromodal case which is another distinction of our paper.

Table 5.1: Comparison with models in the literature.

Article	Problem definition	Objectives	Vehicle routing	Synchronization	Preferences	Solution method
Kalinina et al. (2013)	SND	c, e, t	×	×	×	ε
Xiong and Wang (2014)	RO	c, t	×	×	×	GA
Baykasoğlu and Subulan (2016)	SND	c, e, t	×	×	✓	CP, FGP
Ji and Luo (2017)	SND	c, t	×	×	×	HEDA
Mnif and Bouamama (2017)	SND	c, t	×	×	×	FA
Chen et al. (2019)	RO	c, t, cc	×	×	×	NNCM
Our paper	RO	c, e, t	✓	✓	✓	ALNS

c: cost; e: emission; t: time; cc: container usage cost; RO: Route Optimization; SND: Service Network Design; GA: Genetic Algorithm; FA: Firework Algorithm; HEDA: Hybrid Estimation of Distribution Algorithm; NNCM: Normalized Normal Constraint Method; ε: ε-constraint method; CP: Compromise programming; FGP: Fuzzy goal programming approach

5.3 Proposed approach

Compared with single-objective optimization, conflicts between objectives need to be considered in MOO. By taking preferences into account, the problem may be addressed. Carriers in synchromodal transport usually can not provide accurate preferences. Therefore, how to represent the vague preferences of carriers should be considered.

This section proposes approaches for the above research problem. Solving the MOO problem to optimality by the exact approach often needs multiple runs for different objectives and a long computation time. Therefore, the ALNS heuristic is used to solve MOO in Section 5.3.1. In order to consider vague preferences, the weight interval method is used in Section 5.3.2.

5.3.1 ALNS algorithm for PMOO

The considered multiple objectives are given by the Equations (5.1)-(5.3). Three objectives, i.e., minimizing cost, CO_2 emissions, and time, are considered as Equations (5.1)-(5.3) show. The cost objective consists of transportation cost of containers, fuel cost, transshipment cost, and cost associated with waiting, service, and transshipment time. The time objective includes the time on the route and waiting time at terminals. The constraints are identical to those in Chapter 3 except for constraints on time-dependent travel times, which are not considered in this study.

$$\begin{aligned} Minimize\ F_{cost} = & \sum_{k\in K}\sum_{(i,j)\in A}\sum_{r\in R}(c_k^1\tau_{ij}^k + c_k^{1'}d_{ij}^k + c_k^4 e_k d_{ij}^k)y_{ij}^{kr}q_r + \\ & \sum_{k,l\in K,k\neq l}\sum_{r\in R}\sum_{i\in T}c_k^2 q_r s_{ir}^{kl} + \sum_{k\in K}\sum_{(i,j)\in A}(c_k^5 t_{ki}^{\text{wait}} + c_k^6 d_{ij}^k x_{ij}^k) \end{aligned} \tag{5.1}$$

$$Minimize\ F_{emissions} = \sum_{k\in K}\sum_{(i,j)\in A}\sum_{r\in R} e_k q_r y_{ij}^{kr} d_{ij}^k \tag{5.2}$$

$$Minimize\ F_{time} = \sum_{k\in K}\sum_{(i,j)\in A}\tau_{ij}x_{ij}^k + \sum_{k\in K}\sum_{(i,j)\in A}t_{ki}^{\text{wait}} \tag{5.3}$$

Solving the MOO problem to optimality by the exact approach often needs multiple runs for different objectives and a long computation time. To solve the MOO problem and reduce the computation time, a preference-based ALNS is proposed, as shown in Algorithm 9.

The adaptive mechanism and insertion/removal procedures are the same as in Chapter 3. The distinction lies in the comparison of solutions during and after the search process. At the end of the iteration, the current solution $X_{current}$ obtained in this iteration will be compared with the last solution X_{last} obtained in the last iteration. If the current solution is worse than the last solution, it will be accepted with a probability p, which gradually declines in order

Algorithm 9: ALNS algorithm for PMOO

```
Input: K, R, N, A; Output: X_nd;
set X_initial as empty routes of K; set X and X_nd as empty sets; R_pool = R;
[X_initial, R_pool] = GreedyInsertion(X_initial, R_pool);
while R_pool is not empty do
    [X_initial, R_pool] = RandomRemoval(X_initial);
    [X_initial, R_pool] = GreedyInsertion(X_initial, R_pool);
end
X_last ← X_initial; Add X_last to X;
repeat
    refresh weights and choose operators at the beginning of every s iterations;
    X_current ← X_last;
    while R_pool is not empty do
        [X_current, R_pool] = RemovalOperator(X_current);
        [X_current, R_pool] = InsertionOperator(X_current, R_pool);
    end
    if Σ_{i=1}^n G_i(X_current, X_last) > 0 then
        X_last ← X_current;
    else
        X_last ← X_current with probability p;
    end
    Add X_last to X;
until a predefined iteration number;
for X in X do
    nd = 1 ;    // the solution is non-dominated solution when nd = 1
    for X' in X_{-X};          // X_{-X} means the solution set without X.
     do

    end
    if Σ_{i=1}^n G_i(X', X) > 0 then
        nd = 0; break ;     // X is dominated by X', break current loop
    end
    if nd == 1 then
        Add X to X_nd;
    end
end
```

to avoid local optima (Ropke and Pisinger 2006), as the following equation shows:

$$p = e^{\frac{\sum_{i=1}^{n} G_i(X_{current}, X_{last}) \cdot \sum_{n=1}^{n} F_i(X_{current})}{T_{\text{temp}}}} \tag{5.4}$$

where $T_{\text{temp}} > 0$ is a cooling down temperature with a cooling rate, c. n is the number of objectives and $F_i(X_{current})$ is the i_{th} objective of $X_{current}$. $\sum_{i=1}^{n} G_i(X_{current}, X_{last})$ represents the dominance degree between $X_{current}$ and X_{last}, which will be defined in Equation (5.7) when introducing the weight interval method.

After all solutions are obtained and stored in the solution set $\boldsymbol{X}$, $\boldsymbol{X}_{nd}$ is obtained by comparing all solutions through the dominance rule.

5.3.2 Weight interval method

MOO aims to yield a set of non-dominated solutions presenting the optimal trade-offs between different objectives. These solutions are obtained by the Pareto improvement, which means a change to a different solution that makes at least one objective better off without making any other objective worse off. When plotted in the objective space, the set of non-dominated solutions is called Pareto frontier (Bechikh et al. 2015). Figure 5.2 gives the Pareto frontier of bi-objective optimization for synchromodal transport, where different carriers have different preferred solutions. Carrier A mainly wants to minimize the cost, carrier C prefers to reduce the transport time, and carrier B wants to balance cost and time. Based on their preferences, they will choose their preferred solutions in the Pareto frontier.

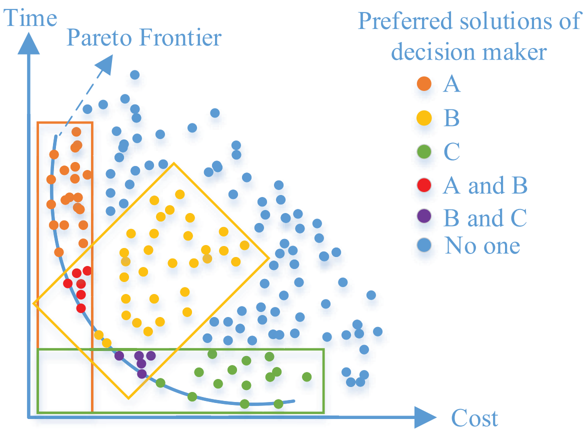


Figure 5.2: The Pareto frontier of bi-objective optimization for synchromodal transport

Integrating preferences into the MOO approach and guiding the search towards solutions that are considered relevant by the carrier may yield two important advantages:

1. Instead of a set of diverse solutions, many of which clearly irrelevant to the carrier, search guides toward the carrier's preferences will yield a more fine-grained and suitable selection of alternatives.

2. By focusing the search onto the relevant part of the search space, the objective space and the computation time can be reduced, especially when solving real-life MOO problems (Branke and Deb 2005, Szlapczynska and Szlapczynski 2019).

Using the weight interval method proposed by Szlapczynska and Szlapczynski (2019), the vague preferences are added to ALNS. The weight interval which is assigned to i_{th} objective is:

$$w_i \in (w_i^{min}, w_i^{max}) \tag{5.5}$$

where $0 \leq w_i^{min} < 1$, $0 < w_i^{max} \leq 1$, and $w_i^{min} \leq w_i^{max}$. The weight interval can represent vague preferences, such as linguistic terms. Under the vague preferences, the Pareto dominance rule is extended from traditional Pareto dominance (Szlapczynska and Szlapczynski 2019). In this chapter, solution X dominates X' when:

$$\sum_{i=1}^{n} G_i(X, X') > 0, \tag{5.6}$$

where:

$$G_i(X, X') = \begin{cases} w_i^{min}(F_i(X') - F_i(X)), & F_i(X') - F_i(X) \geq 0 \\ w_i^{max}(F_i(X') - F_i(X)), & F_i(X') - F_i(X) < 0 \end{cases} \tag{5.7}$$

and n is the number of objectives.

In ALNS, vague preferences are considered when comparing solutions. Before comparison, all objectives are normalized.

5.4 Case Study

The transport network information is obtained from Contargo company [2], which is a prominent intermodal container hinterland logistics network in Europe. It plays a leading role in integrating container transport between the western seaports, Germany's North Sea ports, and the European hinterland.

The parameters in ALNS need to be tuned before the optimization. In order to do that, the Pareto frontiers need to be compared in MOO instead of solutions comparison in the parameter tuning of single-objective optimization. The average value of all non-dominated solutions' objective function values represents the Pareto frontier in the frontiers comparison, as Equation (5.8) shows:

$$P = \frac{\sum_{j=1}^{m} \sum_{i=1}^{n} F_i(X_j)}{m} \tag{5.8}$$

where P is the value which represents Pareto frontier, m is the number of non-dominated solutions, n is the number of objectives, and $F_i(X_j)$ is the i_{th} normalized objective value of non-dominated solution X_j. The parameters which generate minimum value P will be used in the optimization.

The parameters to be tuned include the total iteration number, number of iterations for refreshing weights, initial temperature, and cooling rate. For example, the iteration number

[2] https://www.contargo.net/

influences the quality of results, as shown in Figure 5.3, which shows Pareto frontiers for 10 requests and 5 vehicles under two objectives (cost and emission). Because $P_{3000iterations}$ is less than $P_{50iterations}$, the Pareto frontiers with 3000 iterations are better than frontiers with 50 iterations. It's worth noting that these findings are only for this specific instance. Ideally, the parameters need to be tuned for each instance before the optimization.

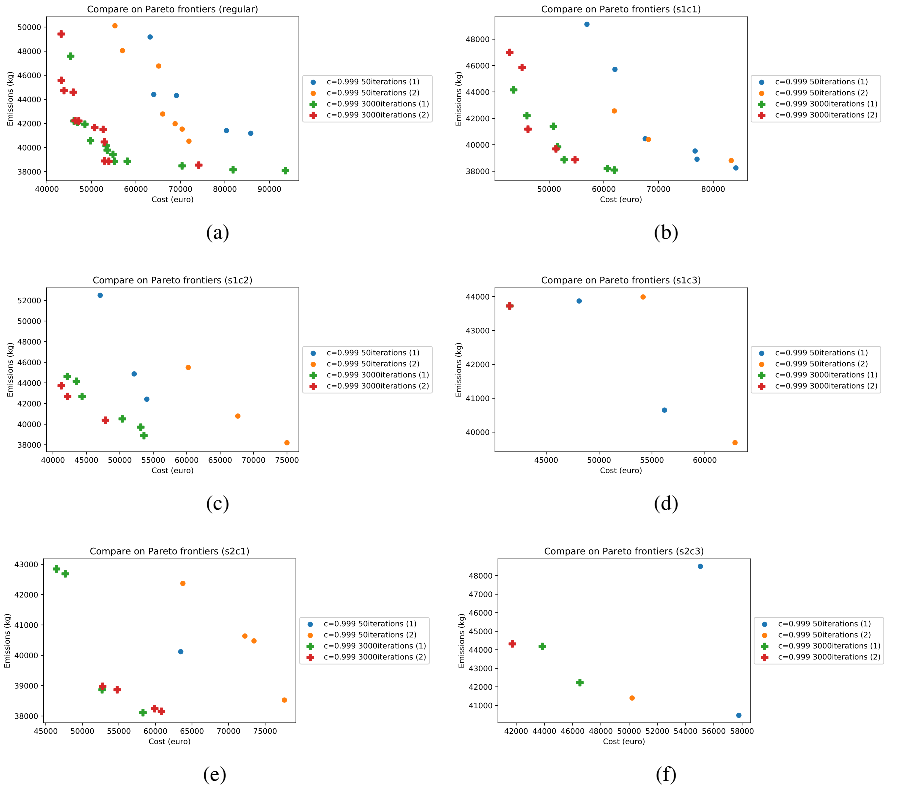


Figure 5.3: Pareto frontiers of bi-objective optimization under 50 iterations and 3000 iterations. (a) Regular Pareto frontier, (b) Cost&Emission: [0.1, 0.9], (c) Cost&Emission: [0.25, 0.75], (d) Cost&Emission: [0.33, 0.66], (e) Cost:[0.1, 0.5], Emission:[0.5, 1.0], (f) Cost:[0.5, 1.0], Emission:[0.1, 0.5].

The results for one of the experiments with 5 vehicles, 10 requests and 10000 iterations of ALNS are given in Figure 5.4. In this experiment, the objectives include cost and emissions. The requests and vehicles are randomly generated, and in total 19 terminals are used. The regular Pareto frontier, i.e., Pareto frontier without preferences, is shown in Figure 5.4(a). The other five figures compare the Pareto frontiers under different weight intervals with the regular Pareto frontier. Figures 5.4(b) to 5.4(d) show the results when the weight interval narrows down from [0.1, 0.9] to [0.33, 0.66]. As the weight interval narrows down, the relative importance of cost and emissions are similar to each other and therefore the trade-off between the objectives is more obvious. Figures 5.4(e) and 5.4(f) show two opposite situations. In Figure 5.4(e), the carrier prefers to reduce emissions. In contrast, the carrier favors reducing cost in Figure 5.4(f).

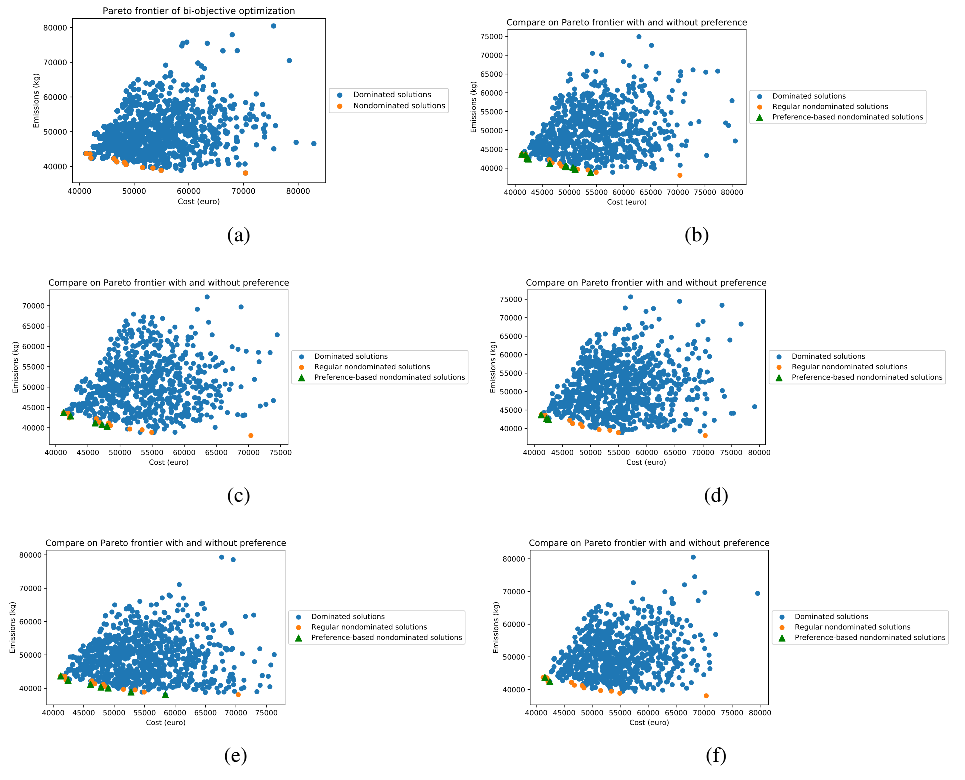


Figure 5.4: Pareto frontiers of bi-objective optimization. (a) Regular Pareto frontier, (b) Cost&Emission: [0.1, 0.9], (c) Cost&Emission: [0.25, 0.75], (d) Cost&Emission: [0.33, 0.66], (e) Cost:[0.1, 0.5], Emission:[0.5, 1.0], (f) Cost: [0.5, 1.0], Emission:[0.1, 0.5].

It is interesting to investigate the following research question: What mode/route will the carriers with different preferences choose? To answer this research question, a case study is designed and 5 terminals are used, including 2 seaports (Rotterdam and Antwerp) and 3 inland terminals (Duisburg, Worth, and Basel). Almost all modes can run between all terminals except for one situation: there is no train between Rotterdam and Antwerp. Tables 5.2 and 5.3 show the vehicle and request information, respectively. To guarantee that all modes have a similar chance to serve requests, different modes have the same number of vehicles, and there is no time window because vehicle speeds are different. Three objectives are considered, including cost, emissions, and time.

Ten instances are generated from ten requests, i.e., the i_{th} instance includes i request(s). For example, the 5th instance includes requests 0-4. Table 5.4 shows regular (means no preferences) non-dominated solutions with request 1. Except for Truck1 in Solution 5, which is empty from Antwerp to Rotterdam, other vehicles transport request 1 on their routes. Solution 1 is also the best solution for cost minimization (single-objective optimization) and the barge is used in this solution. From these non-dominated solutions, we can see that different modes and routes are used after emission and time objectives are considered. This insight is useful to see the impact of different policies on transportation networks in terms of environmental considerations.

Table 5.2: Vehicle information

Vehicle	Capacity (TEU)	Speed (km/h)	Begin depot	Fixed route
Barge1	100	15	Antwerp	free
Barge2	100	15	Rotterdam	free
Truck1	50	75	Antwerp	free
Truck2	50	75	Rotterdam	free
Train1	75	45	Antwerp	Antwerp-Duisburg -Worth-Basel
Train2	75	45	Rotterdam	Rotterdam-Duisburg -Worth-Basel

Table 5.3: Request information

Request	Pickup terminal	Delivery terminal	Time window	Load
0	Antwerp	Duisburg	free	25
1	Rotterdam	Duisburg	free	50
2	Antwerp	Worth	free	25
3	Rotterdam	Worth	free	50
4	Antwerp	Basel	free	25
5	Rotterdam	Basel	free	50
6	Duisburg	Worth	free	25
7	Duisburg	Basel	free	50
8	Worth	Basel	free	25
9	Antwerp	Rotterdam	free	50

Table 5.4: Regular non-dominated solutions

Solution	Cost (euro)	Time (h)	Emission (kg)	Vehicles and rotues
1	4379,309	27,16	2158,728	Barge1: Antwerp→Duisburg
2	5979,755	10,387	2968,251	Train1: Antwerp→Duisburg
3	6756,684	15,831	2753,751	Barge1: Antwerp→Rotterdam; Train2: Rotterdam→Duisburg
4	6004,381	23,716	2373,228	Train1: Antwerp→Rotterdam; Barge2: Rotterdam→Duisburg
5	11394,345	10,254	6935,071	Truck1: Antwerp→Rotterdam→Duisburg; Train1: Antwerp→Rotterdam
6	10351,813	7,032	8365,071	Truck1: Antwerp→Duisburg

Besides the regular case, 2 scenarios (each scenario includes 3 cases) with preferences are designed. The weight intervals of three objectives in the first scenario are the same but narrow down from case s1c1 (means scenario 1 case 1) to s1c3. The weight intervals of s1c1, s1c2, and s1c3 are [0.1,0.9], [0.25,0.75], and [0.33,0.66], respectively. In the second scenario, each case prefers one objective. Cases s2c1, s2c2, and s2c3 prefer minimizing cost, emissions, and time, respectively. The weight interval of the preferred objective is [0.5,1.0], and weight intervals of the other two objectives are [0.1,0.5]. For example, the weight intervals of s2c1 are Cost: [0.5,1.0], Emission&Time: [0.1,0.5].

Each experiment is repeated three times (30 experiments in total) and all results of these instances with different preferences are obtained. The share of used modes is calculated for every case, as shown in Table 5.5. The results show that the solution tends to be better when the weight narrows down in the first scenario (s1c1, s1c2, and s1c3) as the cost, emissions, and time reduce. The share of the barge of s1c3 is larger than s1c2 because s1c3 sacrifices time in exchange for better cost and emission, thus making the overall result better. In the second scenario, the minimum value of each objective is in line with preferences. The parameters used in this chapter set the barge has the lowest cost, emissions, and speed, and the truck is the fastest but needs the highest cost and emissions. Therefore, the barge is used the most when costs or emissions are prioritized. Nevertheless, when time is minimized (s2c3) the train's share becomes the highest because the barge speed is too low and the truck's cost and emissions are high. The results are sensitive to the cost, emissions, and time parameters. When the parameters change in reality, the share of modes may also change. In inland waterway transport, there are more uncertainties than in other modes, such as long waiting times, lock/bridge open time, and changing water level. In the meantime, compared with other modes, there may be limited depth and inadequate air draft in inland waterway transport. Therefore, although the results in this chapter show the advantages of barges and encourage carriers to choose barges, barges are not utilized as frequently in reality.

Table 5.5: Average objectives and mode shares of different cases

Name	Average cost (euro)	Average emission (kg)	Average time (h)	Share of barge	Share of train	Share of truck
regular	35710.5	31635.6	95.2	49.87%	39.58%	10.55%
s1c1	30283.7	28549.2	96.0	64.93%	33.97%	1.1%
s1c2	29628.0	28367.4	94.4	62.08%	37.40%	0.53%
s1c3	27546.1	27457.4	98.6	73.37%	26.16%	0.48%
s2c1	26966.5	27195.0	100.8	72.14%	27.86%	0
s2c2	28306.0	27068.6	103.0	72.13%	27.39%	0.48%
s2c3	33250.9	30068.9	85.7	42.57%	54.75%	2.68%
average	30241.7	28620.3	96.3	62.44%	35.30%	2.26%

5.5 Conclusions

To address research question Q3, a preference-based multi-objective optimization (PMOO) model is developed to address the conflicts among multiple objectives of carriers in synchromodal transport. The weight interval is incorporated into Adaptive Large Neighborhood

Search to represent the vague preferences of carriers. Vehicle routing and synchronization in synchromodal transport are also considered. The case study in the Rhine-Alpine corridor verified that the proposed model provides non-dominated solutions which reveal carrier preferences. Under different preferences in this chapter, the barge is the most popular transport mode due to its low cost and low emission. When carrier prefers to minimize transport time, transport modes with higher speed are used more frequently. It's worth noticing that which mode is used is dependent on the input parameters. When these parameters changed in another instance, the mode share may be different.

In a word, the proposed model is able to target a selected part of the Pareto frontier based on the carrier's vague preferences. It is a significant advantage for carriers in synchromodal transport because they can just enter their linguistic preferences and then obtain solutions that reveal their preferences. Using the proposed model, carriers do not need to struggle to solve conflicts between their objectives from a huge amount of solutions with different modes and routes. Compared with MOO without preferences, this model not only reduces the number of alternatives but also chooses solutions that are preferred by carriers.

The proposed model can be encapsulated in a software application in the synchromodal transport domain. Carriers enter transport network information, requests, and preferences into the software and then they will obtain preferred solutions. The model is designed for synchromodal transport, but it can also be applied to other transport domains if the shipments are non-splittable, i.e., they must remain intact as a whole and cannot be divided into multiple parts during transportation.

Chapter 6

Transport planning considering shippers' preferences

Ignoring shippers' preferences will negatively impact satisfaction and lead to the loss of shippers in the longer run. This chapter considers the preferences of shippers, and addresses the research question Q3: How can the heterogeneous and vague preferences of shippers and carriers be incorporated into the planning approach?

This chapter is organized as follows: Section 6.1 introduces the preferences in synchromodal transport. Section 6.2 presents a brief literature review. Section 6.3 describes the studied problem. In Section 6.4, we provide the mathematical model and Multiple Attribute Decision Making (MADM) approaches. Section 6.5 proposes a customized ALNS. In Section 6.6, experimental settings and results are provided, and the ability of the model to handle multiple attributes and different shippers is evaluated. Section 6.7 concludes this chapter.

Parts of this chapter have been published in Zhang et al. (2022d)[1].

6.1 Introduction

Synchromodal transport involves different stakeholders, including shippers, freight forwarders, and carriers, and their relationship is illustrated in Figure 6.1. A shipper is the entity that is responsible for starting the movement of cargo and making the decision on the total freight price. The freight forwarder organizes shipments for shippers to transport containers from origin to destination and usually plays a role between shippers and carriers. A carrier is the entity that actually transports cargo. This study proposes an optimization model for the freight forwarder. In cases where shippers work directly with carriers without a freight forwarder, the user of our proposed model could also be the carrier. In practice, the freight forwarder could be the third-party logistics provider, transport operator, or transport platform, and we refer to them collectively as "freight forwarder" in this study.

[1] Zhang, Y., Li, X., van Hassel, E., Negenborn, R. R., & Atasoy, B. (2022). Synchromodal transport planning considering heterogeneous and vague preferences of shippers. Transportation Research Part E: Logistics and Transportation Review, 164, 102827.

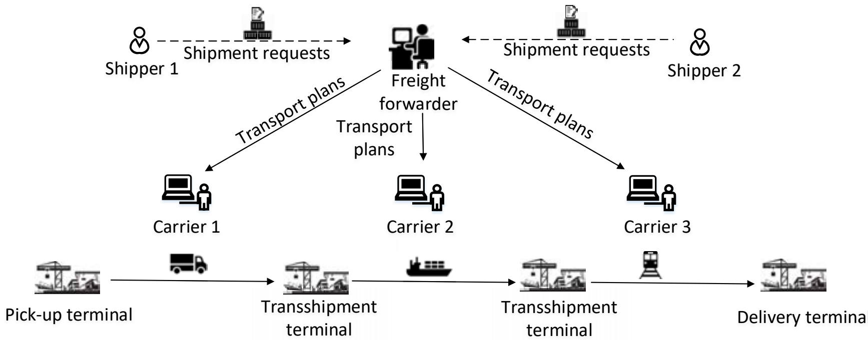


Figure 6.1: The relationships between shippers, carriers, and the freight forwarder in synchromodal transport.

Considering the preferences of shippers becomes more important in the context of synchromodal transport due to the modal-free booking nature. In synchromodal transport, transport plans can change dynamically to better match actual transport demand (Delbart et al. 2021, Tavasszy et al. 2017). It is therefore hard (and undesirable) for shippers to make mode choices and routing decisions. According to a large survey among global shippers (Khakdaman et al. 2020), two-thirds of shippers in synchromodal transport are willing to hand over control of the mode to freight forwarders. In other words, shippers in synchromodal transport accept a mode-free booking and only determine the price and quality requirements (Behdani et al. 2014). Freight forwarders with network-wide freedom can then fully utilize their authority on mode and route control to maximize the overall performance. However, it does not mean that freight forwarders will neglect the requirements and preferences of shippers. One aim of synchromodal transport is to provide demand-driven transport services by combining several transport modes (Khakdaman et al. 2020, Tavasszy et al. 2017), while considering shippers' preferences can match services and demands in a better way and improve the service level by utilizing advantages of different modes.

Over time, with the competition in product and service markets, shippers became concerned about service attributes such as cost, time, reliability, risk of damage, and sustainability (Kurtuluş and Çetin 2020). A freight forwarder works with multiple shippers with heterogeneous preferences due to their characteristics, such as product type, company size, firm location, etc. The most appropriate transport plan needs to be adopted based on a full understanding of the taste heterogeneity of service requirements from shippers. The term "taste heterogeneity" reflects that the shippers take different attributes into account or value the same attributes differently (Arunotayanun and Polak 2011). A full understanding of preferences will not only reduce unnecessary costs, but also improve the service level by the provision of customized services. However, understanding preferences is not easy because the preference information provided by shippers is usually subjective and vague due to the shippers' limited attention, time pressure, and lack of data. A rational approach toward decision-making should take into account human subjectivity, e.g., using fuzzy set theory to handle the vagueness of preferences (Chen and Hwang 1992). Furthermore, the freight forwarder also needs to resolve conflicts between the freight forwarder's objectives and shippers' preferences. Although much progress has been made on how to generate synchromodal services in a more efficient manner, less research focuses on how to better understand shippers' preferences and make the transport plan based on the preferences (Giusti et al. 2019, SteadieSeifi et al. 2014).

In a word, shippers' heterogeneous and vague preferences pose difficulties in setting up an appropriate transportation solution for freight forwarders in synchromodal transport. To improve the service level of freight forwarders and the satisfaction of shippers, this research establishes an optimization model. The focus of this research is to make synchromodal transport plans considering heterogeneous and vague preferences of shippers. The proposed model includes two parts: (a) synchromodal transport planning and (b) preference modeling. In part (a), a mathematical model is formulated for the synchromodal transport planning problem. In part (b), a MADM model is developed based on fuzzy set theory to handle heterogeneous and vague preferences. According to the preferences and actual values of attributes, the satisfaction of shippers is calculated. Part (a) incorporates part (b) by setting satisfaction as constraints, therefore the transport plans generated by part (a) are in line with shippers' preferences in part (b). Moreover, a heuristic algorithm, i.e., ALNS, is proposed to reduce the computation time.

The main contributions of this chapter are summarized as follows: (a) we develop a mathematical model for synchromodal transport planning and introduce the MADM integrating fuzzy set theory to capture heterogeneous and vague preferences; (b) we propose the ALNS algorithm to reduce the computation time; (c) we apply the proposed model to different scenarios using real-world data. In the case study, we compare results without preferences, with homogeneous preferences, and with heterogeneous preferences. Five attributes, i.e., cost, time, reliability, risk, and emissions, are considered. The attribute values, mode shares, and satisfaction values are also compared in these scenarios. Moreover, the performance of the ALNS is evaluated and the results of re-planning are analyzed.

6.2 Literature review

The number of studies that research optimization considering preferences in synchromodal transport is still limited (Delbart et al. 2021, SteadieSeifi et al. 2014). To the best of our knowledge, there is no study considering shippers' preferences at the operational level in the context of synchromodal transport planning.

Table 6.1 compares this study and the relevant studies in the literature. In road transport, such as package delivery, preferences of customers are considered at the operational level. Dumez et al. (2021), Los et al. (2018) consider the delivery location preferences by providing multiple options. Los et al. (2018) minimize the sum of costs and dissatisfaction values and Dumez et al. (2021) set the satisfaction of preference levels as constraints. Afshar-Bakeshloo et al. (2016), Baniamerian et al. (2018), Ghannadpour et al. (2014) take the fuzzy or soft time window preferences of customers into account and consider the satisfaction of customers in the objective. Zhang et al. (2013) use customer service level constraints to ensure the on-time shipment delivery preferences of customers.

Compared with customers in road transport who are recipients and focus on the delivery location or time, shippers in maritime, railway, or intermodal/synchromodal transport care more about the performance of the whole itinerary, such as cost, time, reliability, etc. Cheng and Wang (2021) address the container liner shipping network design and take shippers'

Table 6.1: Comparison between the proposed model and existing models in the literature.

Article	Field	Level	Problem	Heterogeneity	Vagueness	Preferences of whom	Preferences on what
Road transport (parcel delivery)							
Zhang et al. (2013)	Road	Operational	SVRPSTW	✓		recipient	On-time shipment delivery
Ghannadpour et al. (2014)	Road	Operational	DVRPFTW		✓	recipient	Time window
Afshar-Bakeshloo et al. (2016)	Road	Operational	S-GVRP		✓	recipient	Time window
Los et al. (2018)	Road	Operational	GPDPTWP			recipient	Delivery location
Baniamerian et al. (2018)	Road	Operational	VRPCDTWS			recipient	Time window
Dumez et al. (2021)	Road	Operational	VRPDO			recipient	Delivery location
Maritime, railway, or intermodal/synchromodal transport							
Duan et al. (2019)	Railway	Tactical	SNDP	✓		shipper	Time and Reliability
Zhang et al. (2020c)	Intermodal	Tactical	SNDP	✓		shipper	Cost, Time, Emission, Reliability, Frequency, Safety, Flexibility, and Traceability
Jiang et al. (2020)	Maritime	Tactical	LSSD			freight forwarder and shipper	Ship arrival time
Cheng and Wang (2021)	Maritime	Tactical	CLSNDP			shipper	Freight rate, Cost, and Time
Shao et al. (2022)	Intermodal	Operational	IFRP	✓		shipper	Cost, Timeliness, Reliability, and Flexibility
This chapter	Synchromodal	Operational	STPP-HVP	✓	✓	shipper	Cost, Time, Reliability, Risk of damage, and Emissions

SVRPSTW: Stochastic Vehicle Routing Problem with Soft Time Window constraints; DVRPFTW: Dynamic Vehicle Routing Problem with Fuzzy Time Windows; S-GVRP: Satisfactory-Green Vehicle Routing Problem; GPDPTWP: Generalized Pickup and Delivery Problem with Time Windows and Preferences; VRPCDTWS: Vehicle Routing Problem with Cross-Docking and Time Windows considering customer Satisfaction; VRPDO: Vehicle Routing Problem with Delivery Options; SNDP: Service Network Design Problem; LSSD: Liner Shipping Schedule Design; CLSNDP: Container Liner Shipping Network Design Problem; IFRP: Intermodal Freight Routing Problem; STPP-HVP: Synchromodal Transport Planning Problem with Heterogeneous and Vague Preferences.

preferences on freight rate, cost, and time into account. Jiang et al. (2020) consider preferences on the weekly ship arrival times of big customers (freight forwarders and shippers) in near-sea container shipping. Duan et al. (2019) solve a railway service network design problem with heterogeneous preferences for transport time and reliability, and the Value of Time (VOT) and Value of Reliability (VOR) are taken into account in the objective. Zhang et al. (2020c) optimize the China Railway express network and homogeneous and heterogeneous preferences of shippers are considered. Their results show that the sustainability and service level of the network is improved by recognizing the heterogeneous preferences of shippers. Duan et al. (2019) and Zhang et al. (2020c) consider heterogeneous preferences, which is similar to this study. However, there are three main differences between this study and their studies: (a) Duan et al. (2019) and Zhang et al. (2020c) solve the service network design problem at the tactical level and the routing optimization model in this chapter is at the operational level; (b) Duan et al. (2019) and Zhang et al. (2020c) do not consider vague preferences, while our study proposes approaches to model them; (c) although Zhang et al. (2020c) consider road transport, Duan et al. (2019) and Zhang et al. (2020c) focus on rail transport, and this chapter studies synchromodal transport with three modes (waterway, railway, and road). Shao et al. (2022) also consider preferences at the operational level. The context of their study is intermodal transport, while this study is in the context of synchromodal transport. Shippers express preferences in different ways in intermodal and synchromodal transport. The shippers in Shao et al. (2022) express their preferences during the optimization by accepting or rejecting solutions. However, in synchromodal transport, shippers hand over modal control to the freight forwarder, which allows flexible selection and real-time switching of modalities for the freight forwarder. Therefore, it's a mode-free booking and shippers usually express vague preferences to the freight forwarder in synchromodal transport. Our study uses fuzzy set theory to capture vague preferences of shippers, which is not considered in their study. In addition, the maximum number of requests in their case study is five, while our study considers instances with 100 requests.

In the decision-making domain, preferences are often considered in Multiple Criteria Decision Making (MCDM), which can be divided into Multiple Objective Decision Making (MODM) and Multiple Attribute Decision Making (MADM) (Kahraman 2008). The MADM is associated with problems where alternatives have been predetermined and the decision-maker is to select/prioritize/rank a finite number of courses of action. On the other hand, in MODM the alternatives have not been predetermined and the decision maker's primary concern is to design the "most" promising alternative with respect to limited resources (Chen and Hwang 1992). In synchromodal transport, most studies build MODM models considering the freight forwarder/carrier's preferences rather than shippers' preferences (Baykasoğlu and Subulan 2016, Zhang et al. 2020a, 2022a). The decision-making process considering shippers' preferences belongs to MADM because the freight forwarder needs to evaluate predetermined alternatives provided by the optimization model. Therefore, this study is a combination of routing optimization and MADM.

6.3 Problem description

The main research problem of this study is Synchromodal Transport Planning Problem with Heterogeneous and Vague Preferences (STPP-HVP) for the freight forwarder. The STPP-HVP is an optimization problem for synchromodal transport considering time windows, capacity, multiple modes, transshipments, and preferences. As shown in Figure 6.2, the STPP is formulated as a mathematical model and HVP is modeled by the MADM integrating fuzzy set theory. To reduce the computation time, the STPP-HVP is solved by a customized ALNS. For each shipper, a number of alternatives could be obtained by the ALNS. The satisfaction values of alternatives are calculated by the MADM integrating fuzzy set theory according to shippers' preferences. Alternatives with low satisfaction will be filtered and rejected by the ALNS. The chosen alternatives will constitute the overall transport plan.

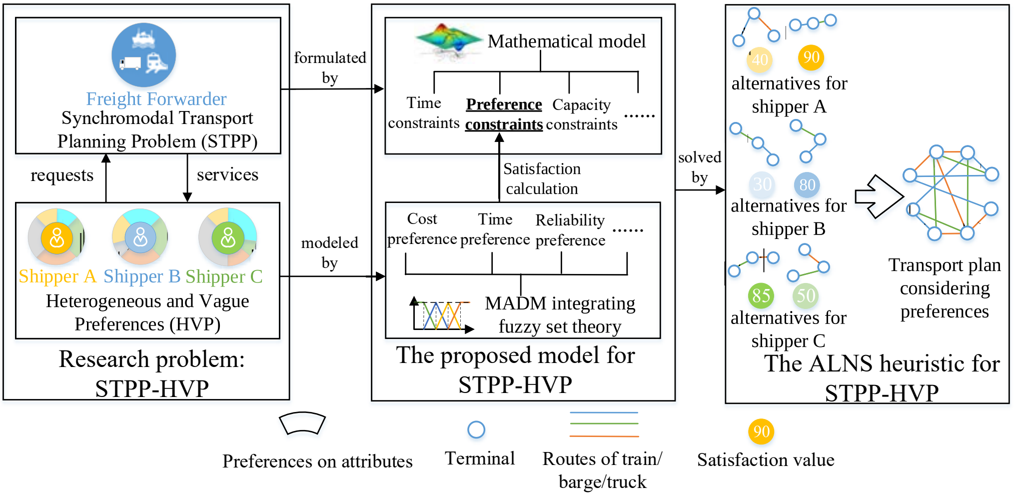


Figure 6.2: The research problem and proposed methodology.

Figure 6.3 gives an example of such an STPP-HVP problem. Requests 1 and 2 of shippers 1 and 2 are transported by two and three vehicles, respectively. Besides transports with transshipments, using only one vehicle to transport containers from origination to destination is also possible.

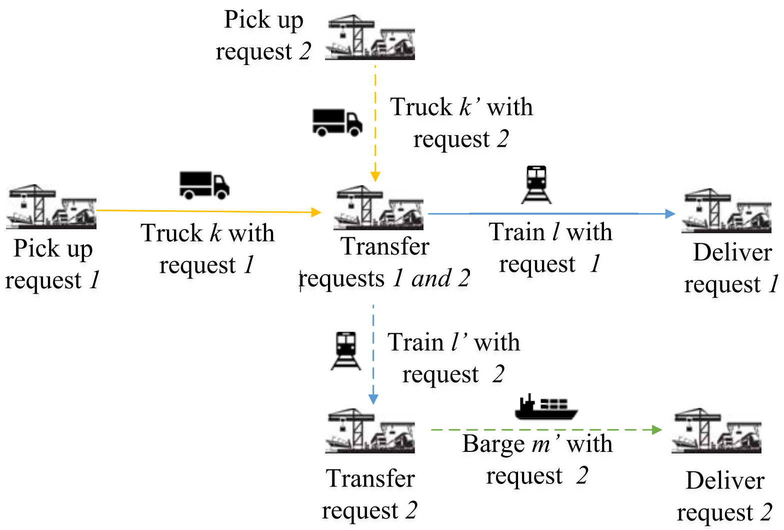


Figure 6.3: An example of the STPP-HVP.

The solution also needs to respect preferences of shippers. For example, in Figure 6.3, the solution is only accepted by the freight forwarder if the preferences of both shippers are respected after satisfaction calculation. In synchromodal transport, the preferences of shippers are usually expressed linguistically and vaguely. For example, the importance level of attribute 1 is "very high", while attribute 2 has a "low" level of importance. Assume that there are n shippers served by the freight forwarder and that there are m attributes that characterize the services provided by the freight forwarder. Each shipper r expresses vague preferences $\tilde{w}_i^r$ towards attribute i. The value of attribute i for shipper r is f_i^r. Whether preference $\tilde{w}_i^r$ is satisfied or not is judged according to the value f_i^r. Take the cost attribute as an example, if $\tilde{w}_i^r$ is level 2, which means the shipper thinks the cost is important, and f_i^r is 0.3, which means the unit cost is 0.3 euro/km/TEU and is very low, then the shipper will be satisfied with a high probability. The attribute values and heterogeneous preferences are represented by the following matrices:

$$\begin{bmatrix} f_1^1 & f_2^1 & \cdots & f_m^1 \\ \tilde{w}_1^1 & \tilde{w}_2^1 & \cdots & \tilde{w}_m^1 \end{bmatrix} \begin{bmatrix} f_1^2 & f_2^2 & \cdots & f_m^2 \\ \tilde{w}_1^2 & \tilde{w}_2^2 & \cdots & \tilde{w}_m^2 \end{bmatrix} \begin{bmatrix} f_1^n & f_2^n & \cdots & f_m^n \\ \tilde{w}_1^n & \tilde{w}_2^n & \cdots & \tilde{w}_m^n \end{bmatrix}$$

Vague preferences are linguistic terms provided by shippers, such as "I would like to transport cargoes timely" or "I think the transport time is important", and quantifying the vague preferences is the first challenge for the freight forwarder. Shipper's satisfaction towards an alternative for a request r need to be calculated. When the satisfaction is less than a predefined satisfaction benchmark, this alternative will not be chosen. Another challenge is considering heterogeneous preferences on multiple attributes of shippers as well as the freight forwarder itself. The term "attributes" may be referred to as "goals" or "criteria", which could be cost, time, reliability, etc. Among attributes, there may be conflicts because of the inherent interdependence, e.g., reducing transport time usually means choosing an expensive mode. Conflicts also exist among shippers because the resources owned by the freight forwarder are limited. Considering shippers' preferences, e.g., low-risk transport, may increase the transport cost of the freight forwarder. Therefore, there are also conflicts between the freight forwarder and shippers. An appropriate approach needs to be developed to solve these conflicts.

6.4 The proposed model for the STPP-HVP

To optimize the transport plan considering preferences, the STPP is formulated as a mixed-integer programming problem and HVP is modeled by the MADM integrating fuzzy set theory.

6.4.1 The mathematical model for the STPP-HVP

There are two objectives. One objective (F_1) is to maximize the number of served requests, and another objective (F_2) is minimizing cost, which consists of transport cost, transfer cost, storage cost, carbon tax, waiting cost, and delay penalty, as illustrated in Chapter 3. The emissions are calculated using an activity-based method by Demir et al. (2016) and the amount of emissions is related to vehicle type, distance, and amount of containers. The model will choose the solution with a higher objective value of F_1, and the solution with a lower objective value of F_2 will be chosen if objective values of F_1 are the same. In this way, the model will try to serve as many as requests in the first place and choose the solution with minimum costs thereafter.

Objective:

$$\max\ F_1 = \sum_{r\in R}\sum_{k\in K}\sum_{j\in N} y^{kr}_{p(r)j} \tag{6.1}$$

$$\begin{aligned}
\min\ F_2 = &\sum_{k\in K}\sum_{(i,j)\in A}\sum_{r\in R}(c^1_k \tau^k_{ij} + c^{1'}_k d^k_{ij})q_r y^{kr}_{ij} + \sum_{k,l\in K,k\neq l}\sum_{r\in R}\sum_{i\in T}(c^2_k + c^2_l)q_r s^{kl}_{ir} \\
&+ \sum_{k\in K}\sum_{(i,j)\in A_p}\sum_{r\in R} c^2_k q_r y^{kr}_{ij} + \sum_{k\in K}\sum_{(i,j)\in A_d}\sum_{r\in R} c^2_k q_r y^{kr}_{ij} \\
&+ \sum_{k,l\in K,k\neq l}\sum_{r\in R}\sum_{i\in T} c^3_k q_r s^{kl}_{ir}({t'}^{lr}_i - \bar{t}^{kr}_i) + \sum_{k\in K}\sum_{(i,j)\in A_p}\sum_{r\in R} c^3_k q_r y^{kr}_{ij}({t'}^{kr}_i - a_{p(r)}) \\
&+ \sum_{k\in K}\sum_{(i,j)\in A}\sum_{r\in R} c^4_k e_k q_r d^k_{ij} y^{kr}_{ij} + \sum_{k\in K_{\text{b\&t}}}\sum_{i\in N} c^5_k t^{\text{wait}}_{ki} + \sum_{r\in R} c^{\text{delay}}_r q_r t^{\text{delay}}_r
\end{aligned} \tag{6.2}$$

Constraints (6.3)/(6.4) ensure that absolute/relative preferences are respected (the meanings of absolute/relative preferences will be introduced in Section 6.4.2). $\overline{S_i}$ and $\overline{S}$ are the predefined satisfaction benchmarks of attribute i and overall satisfaction benchmark, and they are set as 50 and 8.1, respectively.

$$S^r_i \geqslant \overline{S_i} \quad \forall r\in R,\ \forall i\in I \tag{6.3}$$

$$S^r \geqslant \overline{S} \quad \forall r\in R \tag{6.4}$$

Because this chapter allows unserved requests if the preference cannot be respected, the Constraints 3.13 and 3.14 in Chapter 3 are replaced by the Constraints 6.5 and 6.6 to ensure that containers for each served request must be picked and delivered at its pickup and delivery terminal, respectively.

$$\sum_{k \in K} \sum_{j \in N} y_{p(r)j}^{kr} \leqslant 1 \quad \forall r \in R \tag{6.5}$$

$$\sum_{k \in K} \sum_{j \in N} y_{jd(r)}^{kr} \leqslant 1 \quad \forall r \in R \tag{6.6}$$

Other constraints in Chapter 3, except for Constraints (3.41) to (3.48) that take care of time-dependent travel time, are also considered in this chapter and not repeated.

6.4.2 Satisfaction calculation for HVP

This section aims to obtain the satisfaction S_i^r/S^r in Constraints (6.3)/(6.4) according to preferences of shippers. The fuzzy set theory can be used to handle linguistic preferences. Fuzzy set theory captures the subjectivity of human behavior and model imprecision arising from mental phenomena which are neither random nor stochastic (Chen and Hwang 1992). Compared with simple value ranges, which obtain results following crisp "true"/"false" logic, fuzzy set theory expresses the "truthiness" as partially true or partially false.

Different shippers may express their preferences over attributes by means of different linguistic terms. The given preference information could typically be of two types: absolute and relative preferences. The absolute preferences mean that shippers give concrete preferences on attributes, e.g., they need containers to be transported in a "low-cost" (Cost attribute) and "very reliable" (Reliability attribute) way. Relative preferences mean that shippers express the importance of different attributes, e.g., they may say minimizing cost and emissions are "very important" and reducing risk is "not important" for them. The ranking of attributes is one type of relative preferences, for example, the first-ranked and second-ranked attributes can be regarded as "very important" and "important", respectively. This section presents the steps to calculate satisfaction under absolute and relative preferences.

Multiple attributes and fuzzy variables

Figure 6.4 shows the multiple attributes and fuzzy variables with linguistic terms and fuzzy sets. Shipper r has vague preferences $\tilde{w}_i^r$ towards attribute i. We obtain attribute value f_i^r for each attribute, then calculate satisfaction value S_i^r/S^r through MADM approaches.

An attribute i can be defined as a fuzzy variable, such as Cost or Time. The fuzzy variable has a predefined value range and several linguistic terms that are used to describe the variable. We use l_i^j to represent the j-th linguistic term of attribute i. Take the cost attribute as an example, its value range could be [0, 1.8], and linguistic terms are adjectives like "low-cost", "medium", and "expensive". The value in the value range is called *crisp value*, which is how we think of the variable numerically, e.g., 1 euro/km/TEU for the cost attribute. A linguistic term l_i^j corresponds to a fuzzy set A_i^j, which is a pair (U, μ), where U is referred to as the universe of discourse and μ is a membership function. For each $x \in U$, the value $\mu(x)$ is called the grade of membership of x, which means the degree of truth to the

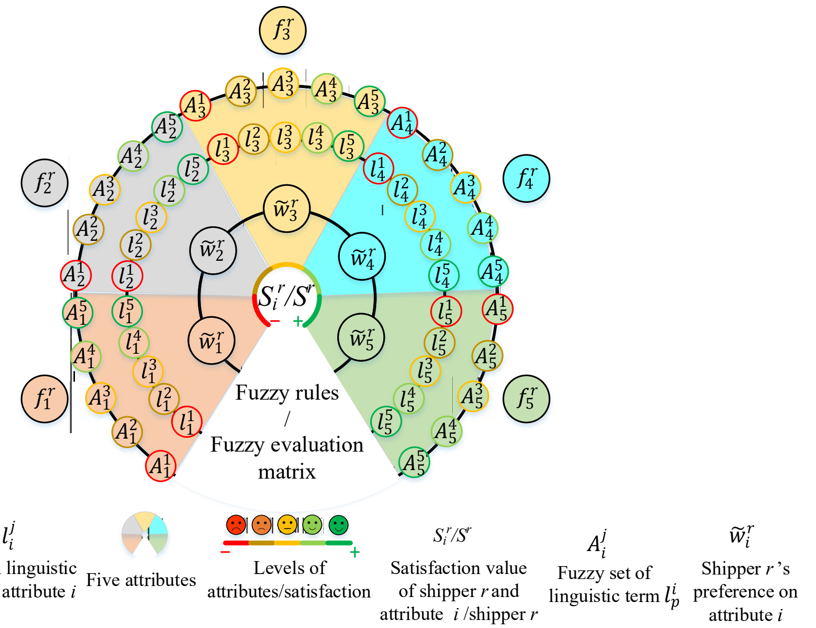


Figure 6.4: Multiple attributes and fuzzy variables.

term. For example, 1 euro/km/TEU's grades to "expensive" and "very expensive" could be 0.8 and 0.2, respectively. The trapezoidal and triangular membership functions are used in this chapter, where the triangular membership function is a special trapezoidal membership function. The trapezoidal membership function is given in Equation (6.7) with a trapezoidal fuzzy number (a,b,c,d), whereby $a \leq b \leq c \leq d$ and $b = c$ for the triangular membership function:

$$\mu(x) = \begin{cases} 0, & x < a \\ \dfrac{(x-a)}{(b-a)}, & a \leq x \leq b \\ 1, & b \leq x \leq c \\ \dfrac{(d-x)}{(d-c)}, & c \leq x \leq d \\ 0, & x > d \end{cases} \tag{6.7}$$

In this research, important attributes in synchromodal transport are selected according to two surveys and an interview, as shown in Table 6.2. In the interview and surveys, we receive a total of 13 responses from shippers, freight forwarders, and carriers in different intermodal/synchromodal transport companies, and the results are shown in Table 6.2. Cost and Reliability are the two most important attributes, followed by the Time attribute. Compared with passenger transportation, the probability of damage on the cargoes is quite higher because of multiple handling operations during freight transportation, especially at transshipment terminals. Therefore, Risk of damage is also an important attribute, and the "number of transferred containers" is used here to represent it because more transshipments may cause more cargo damage. For the Emission attribute, respondents agree that it is important if there is a sustainability policy from the government, especially for large companies. Both Europe and China have such policies (European Commission 2011, State Council of China 2021a). The proposed model can be extended to work with other attributes (such as flexibility and frequency) when needed.

Table 6.2: The chosen attributes in this study.

Attribute	Definition	Unit	Importance⋆	Sources
1: Cost	The cost of shipping one TEU (20-foot container)one km from origin to destination	euro	71% L_1, 29% L_2	survey 2, interview
2: Time	The ratio of actual time between the origin and destination to expected time	percentage	46% L_1, 31% L_2, 23% L_3	survey 1&2, interview
3: Reliability	The ratio of the delay time to total travel time	percentage	77% L_1, 23% L_2	survey 1&2, interview
4: Emissions	CO_2 emitted per container per km	kg	23% L_2, 39% L_3, 15% L_4, 23% L_5	survey 1&2, interview
5: Risk of damage	The number of containers transferred from one vehicle to another vehicle	TEU	29% L_1, 57% L_3, 14% L_4	survey 2, interview

⋆: the importance evaluation is from respondents in all related sources.
L_1, L_2, L_3, L_4, and L_5: importance levels representing extremely, very, moderately, slightly, and not at all important, respectively.
survey 1: in the "Novel inland waterway transport concepts for moving freight effectively" (NOVIMOVE) project, we designed the first survey and received six reactions from shippers/freight forwarders (Ramos et al. 2020).
survey 2: we designed the second survey (https://freeonlinesurveys.com/s/DZS7QlrE) and received three responses from a shipper in FAW-Volkswagen Automotive Co. Ltd, a shipper in China Railway Materials Trade company, and a carrier in China International Marine Containers (Group) Co. Ltd.
interview: we interviewed three freight forwarders in China Railway Container Transport Co. Ltd. and one shipper in China National Fisheries Corporation.

For request r, the actual travel time is:

$$t_r = \max\{\bar{t}_i^{kr} y_{ij}^{kr} : \forall (i,j) \in A, \ \forall k \in K\} - \min\{t'^{kr}_i y_{ij}^{kr} : \forall (i,j) \in A, \forall k \in K\} \tag{6.8}$$

The values of five attributes are calculated according to Equations (6.9) to (6.13).

$$f_1^r = F_2^r / (q_r \sum_{k \in K} \sum_{(i,j) \in A} d_{ij}^k y_{ij}^{kr}) \tag{6.9}$$

$$f_2^r = t_r / (d_{p(r)d(r)}^{\text{average}} / v_{\text{average}}) \tag{6.10}$$

$$f_3^r = \max\{0, (t_r^{\text{delay}} - \max\{\bar{t}_i^{kr} y_{ij}^{kr} : \forall (i,j) \in A, \forall k \in K\})\} / t_r \tag{6.11}$$

$$f_4^r = \sum_{k \in K} \sum_{(i,j) \in A} e_k y_{ij}^{kr} q_r d_{ij}^k / (q_r \sum_{k \in K} \sum_{(i,j) \in A} d_{ij}^k y_{ij}^{kr}) \tag{6.12}$$

$$f_5^r = \sum_{k,l \in K, k \neq l} \sum_{i \in T} s_{ir}^{kl} q_r \tag{6.13}$$

where F_2^r is the overall cost of request r and the calculation of F_2^r is similar to Equation (6.2). The expected travel time is calculated by the average travel distance of all vehicles $d_{p(r)d(r)}^{\text{average}}$ divided by the average speed of all vehicles v_{average}.

Satisfaction calculation under absolute preferences

The satisfaction value of each attribute S_i^r is calculated when shippers express absolute preferences:

$$S_i^r = Fuzzy(f_i^r, \tilde{w}_i^r) \tag{6.14}$$

where $Fuzzy()$ represents the MADM approach for absolute preferences. The satisfaction value S_i^r is obtained according to the following steps.

Step 1: handle the shipper's vague preferences toward attributes. We define five levels for linguistic terms l_i^j of absolute preferences, as shown in Figure 6.5(a). For example, Level 1 for Cost/Reliability attribute means "very low cost"/"very reliable", and Level 4 for Time/Risk of damage attribute means "slow"/"high risk". Figure 6.5(a) also shows the membership function μ for five levels. The membership functions of attributes are different because the value ranges U of attributes are different.

Step 2: obtain the actual attribute value's level. After obtaining the attribute value f_i^r, the memberships to levels are determined. Specific fuzzy numbers of levels used in this chapter are shown in Table 6.4 in Section 6.6.

Step 3: link the preference, attribute value, and satisfaction. The satisfaction is also set as a fuzzy variable, as shown in Figure 6.5(b). Fuzzy variables for attributes and satisfaction are linked by a set of fuzzy rules, which are IF-THEN statements. The same attribute value may lead to different satisfaction because shippers have different preferred levels. For example, if shipper 1 prefers "low" cost and shipper 2 prefers "medium" cost, shipper 2 will be more satisfied than shipper 1 when the actual cost is "low".

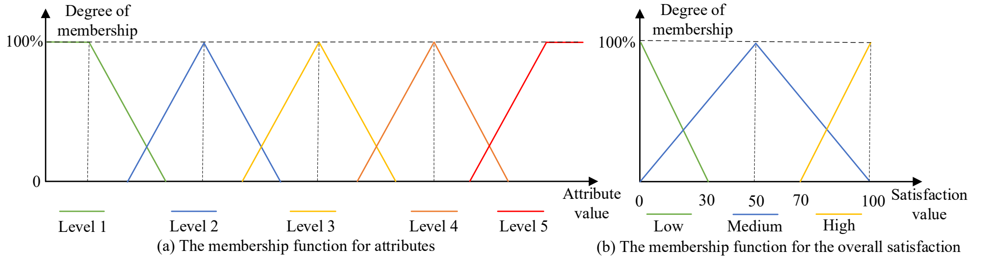


Figure 6.5: The membership functions for attributes and overall satisfaction.

When the preferred level is the highest level, the fuzzy rule is:

IF the level of the attribute i *equals/is lower than* the highest level $\tilde{w}_i^r$, THEN the satisfaction will be *high/low*.

When the preferred level is the lowest level, the fuzzy rule is:

IF the level of the attribute i *is higher than/equals* the lowest level $\tilde{w}_i^r$, THEN the satisfaction will be *high/medium*.

When calculating the satisfaction value for a specific attribute and the preferred level is neither the highest nor lowest level, the fuzzy rule is:

IF the level of the attribute i *is higher than/equals/is lower than* the preferred level $\tilde{w}_i^r$, THEN the satisfaction will be *high/medium/low*.

For the preference constraints, the satisfaction value of each attribute S_i^r is calculated by Equation (6.14) through fuzzy rules for one attribute. When calculating the satisfaction value of h attributes, a set of rules for these attributes will be used, as shown in Equation (6.15).

$$S^r = Fuzzy(f_1^r, \tilde{w}_1^r, \cdots, f_n^r, \tilde{w}_h^r) \tag{6.15}$$

Step 4: calculate the satisfaction value by defuzzification. After defining fuzzy variables and fuzzy rules, the satisfaction value can be obtained using a defuzzification method, such as Center of Gravity used in this chapter (Van Leekwijck and Kerre 1999).

Satisfaction calculation under relative preferences

When shippers express the relative importance of attributes, the linguistic terms represent relative preferences among attributes. In this case, the overall satisfaction value of all attributes S^r is:

$$S^r = Fuzzy'(f_1^r, f_2^r, f_3^r, f_4^r, f_5^r, \tilde{w}_1^r, \tilde{w}_2^r, \tilde{w}_3^r, \tilde{w}_4^r, \tilde{w}_5^r) \tag{6.16}$$

where $Fuzzy'()$ represents the MADM approach for relative preferences. The overall satisfaction value S^r is obtained according to the following steps.

Step 1: handle the shipper's vague preferences toward attributes. Five levels of linguistic terms are used to describe the importance of each attribute. Table 6.3 presents the attribute i's j-th linguistics term l_i^j and the corresponding fuzzy importance number $\tilde{w'}_i^j$, where $\tilde{w'}_i^j = (a_i^j, b_i^j, c_i^j, d_i^j)$, $1 \leq j \leq 5$. The membership grades $\mu(x)$ are represented by real number ranging from [0,1]. For request r and attribute i, the fuzzy importance number $\tilde{w}_i^r$ is obtained based on the linguistic preference expressed by the shipper.

Table 6.3: Linguistic terms and trapezoidal fuzzy numbers on attributes and satisfaction.

Linguistic terms	Fuzzy importance number $\tilde{w'}_i^j$	Linguistic terms	Fuzzy satisfaction number $\tilde{s'}_i^j$
Very low importance	[0, 0, 0.1,0.3]	Very low satisfaction	[0, 0, 1, 3]
Low importance	[0.1, 0.3, 0.3, 0.5]	Low satisfaction	[1, 3, 3, 5]
Medium importance	[0.3, 0.5, 0.5, 0.7]	Medium satisfaction	[3, 5, 5, 7]
High importance	[0.5, 0.7, 0.7, 0.9]	High satisfaction	[5, 7, 7, 9]
Very high importance	[0.7, 0.9, 1.0, 1.0]	Very high satisfaction	[7, 9, 10, 10]

Step 2: obtain the actual attribute value's level. According to the actual attribute value f_i^r, the j-th level's fuzzy satisfaction number $\tilde{s'}_i^j$ is given, where $\tilde{s'}_i^j = (\omega_i^j, \beta_i^j, \sigma_i^j, \theta_i^j)$, $1 \leq j \leq 5$. When the attribute value f_i^r is less than the expected value, it meets the relevant satisfaction level, and the actual level $\tilde{s}_i^r$ is the highest level reached. The membership grades $\mu(x)$ are represented by real numbers ranging from [0,10]. Table 6.3 also shows the linguistic terms for satisfaction and their corresponding fuzzy number.

Step 3: link the preference, attribute value, and satisfaction. After Steps 1 and 2, the fuzzy importance number $\tilde{w}_i^r$ and the actual satisfaction level $\tilde{s}_i^r$ for request r and attribute i are obtained. Using these fuzzy numbers, the fuzzy evaluation matrix can be constructed:

$$\begin{aligned} S^r &= \tilde{w}_1^r \otimes \tilde{s}_1^r \oplus \tilde{w}_2^r \otimes \tilde{s}_2^r \oplus \tilde{w}_3^r \otimes \tilde{s}_3^r \oplus \tilde{w}_4^r \otimes \tilde{s}_4^r \oplus \tilde{w}_5^r \otimes \tilde{s}_5^r \varnothing (\tilde{w}_1^r \oplus \tilde{w}_2^r \oplus \tilde{w}_3^r \oplus \tilde{w}_4^r \oplus \tilde{w}_5^r) \\ &= (z_1, z_2, z_3, z_4) \end{aligned} \tag{6.17}$$

The operations $\otimes$, $\oplus$, and $\varnothing$ are defined by Chen and Niou (2011). Let $\tilde{u} = (u_1, u_2, u_3, u_4)$ and $\tilde{v} = (v_1, v_2, v_3, v_4)$ be two trapezoidal fuzzy number, where $0 \leq u_1 \leq u_2 \leq u_3 \leq u_4$ and $0 \leq v_1 \leq v_2 \leq v_3 \leq v_4$. The operations between $\tilde{u}$ and $\tilde{v}$ are defined as:

$$\tilde{u} \oplus \tilde{v} = (u_1 + v_1, u_2 + v_2, u_3 + v_3, u_4 + v_4) \tag{6.18}$$

$$\tilde{u} \otimes \tilde{v} = (u_1 \times v_1, u_2 \times v_2, u_3 \times v_3, u_4 \times v_4) \tag{6.19}$$

$$\tilde{u} \varnothing \tilde{v} = (\frac{u_1}{v_4}, \frac{u_2}{v_3}, \frac{u_3}{v_2}, \frac{u_4}{v_1}) \tag{6.20}$$

Step 4: calculate the satisfaction value by defuzzification. The satisfaction value S^r is calculated by defuzzifying (z_1, z_2, z_3, z_4):

$$S^r = (z_1, z_2, z_3, z_4) = \frac{z_1 + z_2 + z_3 + z_4}{4} \tag{6.21}$$

6.5 The ALNS heuristic for the STPP-HVP

The pseudocode of the ALNS that is developed for the research problem in this chapter is extended from Algorithm 1. Compared with Algorithm 1, the ALNS in this chapter is customized as follows: (a) requests are allowed not to be served if preferences can not be met; (b) the synchronization methods considering time and preferences constraints are added in the removal and insertion operators; (c) the best solution is judged according to objectives F_1 and F_2 with a priority on F_1.

The Algorithm 2 in Chapter 3 is also modified to consider preference constraints in the synchronization, as shown in Algorithm 10.

6.6 Case study

This section evaluates the proposed model in various scenarios by comparing it with different benchmarks. Section 6.6.1 describes the settings in case studies and Section 6.6.2 analyzes results.

6.6.1 The transport network and instances

The same EGS transport network in Chapter 4 is used in this chapter. All instances and detailed results are available at a research data website[2].

According to the average attribute values of all modes in the EGS network, the fuzzy numbers are set as in Table 6.4. For Cost, Time, and Emissions attributes, the values of Levels 1, 3, and 5 are calculated according to the minimum, average, and maximum values using any mode/mode combination, respectively. The values of Levels 2 and 4 are obtained

[2]https://figshare.com/s/e1631bc804deed885d43

Algorithm 10: Synchronization considering time and preference constraints

```
Input: relevant_routes; Output: feasibility;
for route k ∈ relevant_routes do
    update pickup/delivery time and extend/shorten the waiting or storage time of
      influenced requests;
    if route k does not satisfy time constraints then
        return infeasible
    else
        for request r served by route k do
            obtain the vehicles that serve request r;
            calculate the satisfaction value of request r;
            if request r does not satisfy the preference constraints then
                return infeasible
            end
        end
        obtain relevant_routes of route k;
        Synchronization(relevant_routes)
    end
end
return feasible;
```

based on other levels with a value interval of 0.3. For the Reliability attribute, a maximum 15% delay (Level 5) is allowed, and other Levels are obtained with a value interval of 3%. Depending on the maximum number of containers in instances, we define the maximum value (Level 5) of the Risk attribute as 150 and values at other Levels are obtained with a value interval of 30. Experiments of using varying fuzzy numbers are also performed. Since similar insights are obtained, this section only presents results using fuzzy numbers in Table 6.4 to avoid repetition.

Table 6.4: Trapezoidal fuzzy numbers $\tilde{w'}_i^j$ on specific levels.

Level	Cost	Time	Reliability	Emissions	Risk of damage
Level 1	[0.0,0.0,0.3,0.5]	[0.0,0.0,0.5,0.7]	[0.00,0.00,0.01,0.03]	[0.0,0.3,0.3,0.5]	[0,0,10,30]
Level 2	[0.4,0.6,0.6,0.8]	[0.6,0.8,0.8,1.0]	[0.02,0.04,0.04,0.06]	[0.4,0.6,0.6,0.8]	[20,40,40,60]
Level 3	[0.7,0.9,0.9,1.1]	[0.9,1.1,1.1,1.3]	[0.05,0.07,0.07,0.09]	[0.7,0.9,0.9,1.1]	[50,70,70,90]
Level 4	[1.0,1.2,1.2,1.4]	[1.2,1.4,1.4,1.6]	[0.08,0.10,0.10,0.12]	[1.0,1.2,1.2,1.4]	[80,100,100,120]
Level 5	[1.3,1.5,1.8,1.8]	[1.5,1.7,2.2,2.2]	[0.11,0.13,0.15,0.15]	[1.3,1.5,1.8,1.8]	[110,130,150,150]

Several scenarios are designed to analyze the impact of considering shippers' preferences in the freight forwarder's transport planning, including a benchmark where preferences are ignored, five scenarios of homogeneous preferences on five attributes, and six scenarios of heterogeneous preferences. In the benchmark scenario, Constraints (6.3)/(6.4) are not applied. In each scenario, results under hard constraints, fuzzy constraints, and the satisfaction objective are compared. Under hard constraints, if the attribute value of an alternative is lower than the middle value in the fuzzy number, the alternative is accepted by the ALNS, otherwise is rejected. Take the Cost attribute in Table 6.4 as an example, the middle values for Level 1 to Level 5 are 0.3, 0.6, 0.9, 1.2, and 1.5, respectively. In the literature, besides studies like our study that improve service levels by setting preferences as constraints (Dumez et al. 2021, Zhang et al. 2013), some studies consider preferences in the objective by minimizing the sum of costs and dissatisfaction (Baniamerian et al. 2018, Los et al. 2018). It is interesting to compare these two ways of handling preferences. Therefore, we have compared the proposed method with the method in Los et al. (2018) and Baniamerian et al. (2018) (it is called the satisfaction objective method hereinafter). When considering preferences in the objective, Constraints (6.3)/(6.4) are not considered and the objective F_2 is replaced by the objective F_3:

$$F_3 = normal(F_2) - normal(\sum_{r \in R} S^r) \tag{6.22}$$

where $normal()$ is the min-max normalization function that transforms costs and satisfaction values to be on a similar scale.

The preference data are randomly generated according to the proportion of different types of shippers, such as cost-sensitive and reliability-sensitive shippers. In the scenario with homogeneous preferences, it is as if there is only one type of shipper, which means all shippers have similar preferences, such as low-cost or fast transport. However, their preferences are not totally the same because some shippers have higher requirements than others. In the scenario with heterogeneous preferences, there are different proportions of shippers with heterogeneous preferences depending on their cargo types or company features. Cargoes requiring low-cost, fast, reliable, low-risk, and sustainable transport are mixed in all requests. We consider six scenarios, i.e., heter. 1/2/3/4/5/6, which means the proportions of shippers that prefer attributes are: [Cost, Time, Reliability, Risk of damage, Emissions] = [0.2,0.2,0.2,0.2,0.2] / [0.5,0.1,0.1,0.1,0.2] / [0.2,0.5,0.1,0.1,0.1] / [0.2,0.1,0.5,0.1,0.1] / [0.2,0.1,0.1,0.5,0.1] / [0.2,0.1,0.1,0.1,0.5]. The results in this section are obtained under a setting that all vehicles have fixed services, i.e., all vehicles follow predefined routes and schedules.

6.6.2 Results under absolute preferences

Table 6.5 shows the average computation time for different instances. There is a trend that the computation time increases when the number of requests increases. The computation time when using fuzzy constraints or satisfaction objective is usually higher than others because handling vague preferences needs more time. However, there is no obvious difference between the computation time of experiments considering homogeneous and heterogeneous preferences.

Based on the results in Figure 6.6, relationships between preferences and attributes (Cost, Time, Reliability, Emissions, and Risk) are analyzed. The attribute value is improved when the shipper has a higher requirement on this attribute. For example, in Figure 6.6(a), when a shipper wants fast transport because the product is perishable, more trucks are used and the transport time decreases compared with the benchmark which ignores preferences. Under heterogeneous preferences in Figure 6.6(b), the freight forwarder needs to trade-off the different preferences of shippers. Therefore, the results do not have as significant as an improvement on a specific attribute compared with results under homogeneous preferences.

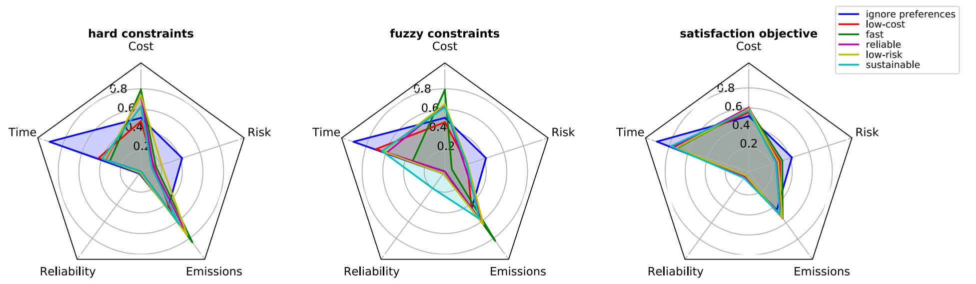
Table 6.5: Average computation time (seconds).

Number of requests	Homogeneous preferences ignore	hard	fuzzy	obj	Heterogeneous preferences ignore	hard	fuzzy	obj
5	0.2	0.3	1.7	3.3	0.3	0.2	2.2	3.3
10	0.7	2.9	72.7	45.4	0.7	1.2	28.8	31.3
20	1.7	1.4	13.1	70.7	1.6	1.5	12.7	82.8
30	4.0	25.0	16.7	194.6	3.3	7.7	785.4	243.1
50	10.2	26.2	29.2	463.0	5.5	78.3	594.4	509.2
100	51.8	200.0	4332.5	638.8	15.8	247.5	2076.5	388.9

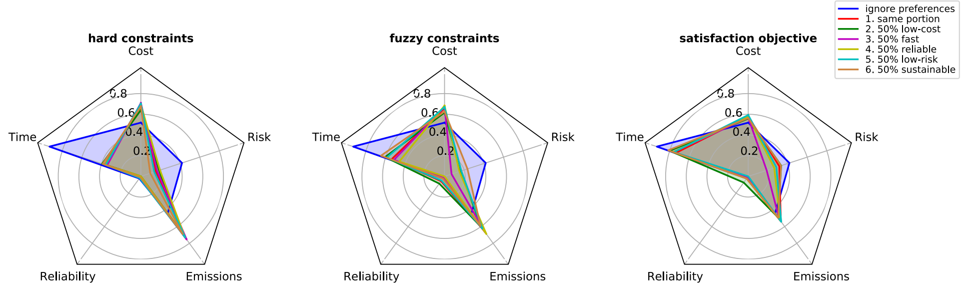
ignore: experiments that ignore preferences; hard/fuzzy: experiments considering hard/fuzzy constraints; obj: experiments with the satisfaction objective.

When shippers have requirements on conflicting attributes, the freight forwarder will find a trade-off between these attributes by making each attribute better without making any other attribute worse than the expectation of shippers. Attributes may reinforce each other. Both low-cost and fast transport needs unimodal transport (barge or truck), so there are fewer transshipments and lower risk of damage, and their risks are even lower than the case when shippers prefer low-risk transport, as shown in both Figures 6.6(a) and 6.6(b). The costs under fuzzy attributes are higher than costs under the satisfaction objective except for the case that all shippers prefer low-cost transport. However, the values of preferred attributes are lower under fuzzy attributes and shippers are more satisfied.

Figure 6.7 shows mode shares (Barge, Train, Truck) across different preferences. In Figure 6.7(a), compared with other preferences, the mode shares of barges and trains are larger when shippers prefer low-cost and sustainable transport. When all shippers prefer fast transport in Figure 6.7(a), the mode shares of trains and trucks, especially trucks, increase substantially compared with the benchmark. When shippers prefer reliable transport in Figure 6.7(a), the mode share of trucks increases compared with low-cost and sustainable transport, but the increase is not as significant as the fast transport, because reliable transport focuses on delay rather than total time. When considering preferences, the mode share of barges is smaller than the benchmark because barges not only have advantages (low-cost and low-emissions) but also disadvantages (slow), which make barges unsuitable to resolve conflicts. Under fuzzy constraints, the freight forwarder has more room to reduce costs when satisfying the preferences of shippers, therefore the mode share of barges is usually higher than under hard constraints. Satisfaction is no longer the constraint under the satisfaction objective method. Solutions that have lower costs and higher dissatisfaction rather than higher cost and lower satisfaction are chosen, therefore the mode share of barges under the satisfaction objective method is always higher than other methods. When 50% of shippers prefer low-cost (heter. 2) or sustainable transport (heter. 6) in Figure 6.7(b), more trucks are used compared with the mode share under homogeneous preferences in Figure 6.7(a), because there are the remaining 50% of shippers with other preferences under the heterogeneous case. The fast transport scenarios in Figures 6.7(a) and 6.7(b) show the opposite phenomenon. In summary, based on our parameter settings, using more trucks benefits fast, reliable, and low-risk transport, whereas low-cost and sustainable transports need more



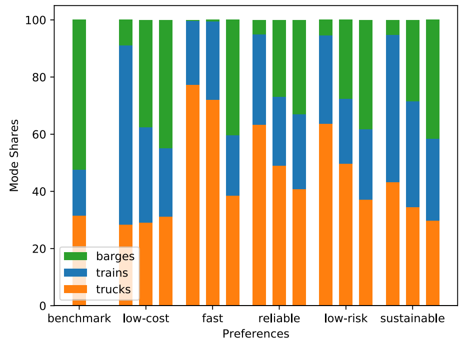
(a) Homogeneous preferences



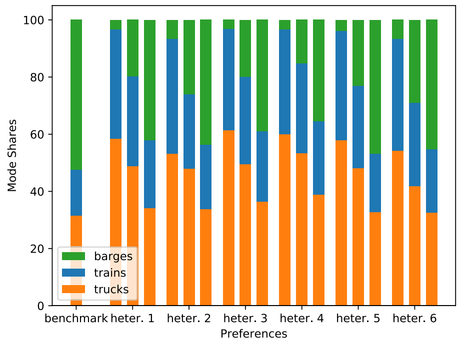
(b) Heterogeneous preferences

Figure 6.6: Radar charts of five attributes across homogeneous and heterogeneous preferences.

barges, and trains are preferred when considering conflicting attributes or preferences.



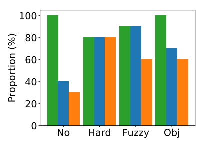
(a) Homogeneous preferences



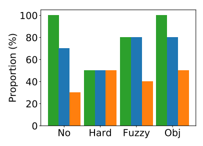
(b) Heterogeneous preferences

Figure 6.7: Mode shares under homogeneous and heterogeneous preferences. The three bars from left to right of each instance are results under hard constraints, fuzzy constraints, and the satisfaction objective, respectively.

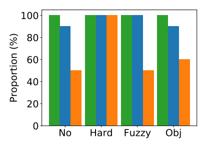
Figure 6.8 shows the number of served requests (N), the number of requests that satisfy fuzzy constraints (F), and those that satisfy hard constraints (H) across different preferences. All requests can be served when preferences are not considered. This is not the case under hard preferences and N is in between the two under fuzzy constraints. When using fuzzy constraints, the proportion of satisfied shippers is the largest. Both F and H increase after considering preferences except Figure 6.8(b), where N decreases because of hard constraints. H under fuzzy constraints is usually less than H under hard constraints due to two reasons: (i) more requests are served under fuzzy constraints, but the used resources are the same with hard constraints, therefore service quality for each request is not as high as before; (ii) the freight forwarder has more room to minimize cost under fuzzy constraints, which deteriorates service quality a bit. Compared with considering preferences in constraints, the number of served requests (N) is higher under the satisfaction objective, while the number of requests that respect shippers' preferences (F and H) is lower.



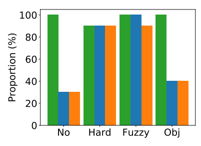
(a) each attribute is preferred by 20% of shippers



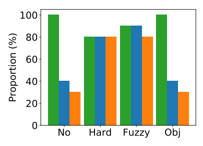
(b) all shippers prefer low-cost



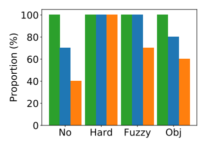
(c) 50% shippers prefer low-cost



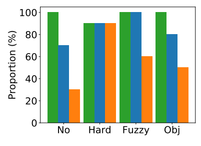
(d) all shippers prefer fast



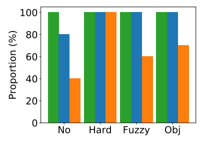
(e) 50% shippers prefer fast



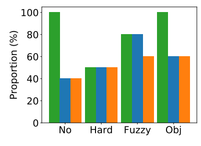
(f) all shippers prefer reliable



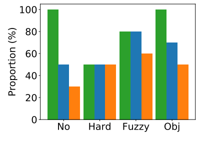
(g) 50% shippers prefer reliable



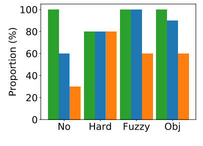
(h) all shippers prefer low-risk



(i) 50% shippers prefer low-risk



(j) all shippers prefer sustainable



(k) 50% shippers prefer sustainable

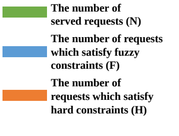


Figure 6.8: Proportion (%) of served requests across different preferences. "No", "Hard", "Fuzzy", and "Obj" mean results under no preference constraints, hard constraints, fuzzy constraints, and the satisfaction objective, respectively.

The average satisfaction values (S) are shown in Figure 6.9. Under hard constraints, only those requests that can be fully satisfied are served, therefore S is always 100 and is not shown in Figure 6.9. When considering preferences, satisfaction values of shippers increase significantly compared with the cases that ignore preferences (N). S under fuzzy constraints (F) is less than 90 because the freight forwarder wants to minimize transport costs when the shippers' vague preferences are satisfied, which usually reduces the quality of services. Therefore, the freight forwarder's objective of minimizing cost is not ignored in the proposed model, especially when using fuzzy constraints. The satisfaction values under the satisfaction objective (O) are usually lower than the ones under fuzzy constraints (F) because satisfaction is sacrificed to obtain a lower cost when satisfaction is considered in the objective instead of constraints. Therefore, when the freight forwarder wants to ensure shippers' satisfaction, it is better to consider preferences in constraints.

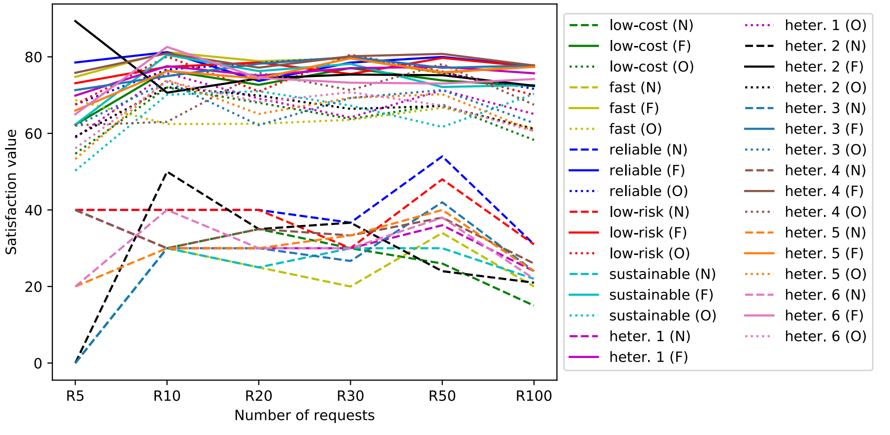


Figure 6.9: Satisfaction values under no preference constraints (N), fuzzy constraints (F), and the satisfaction objective (O) across different preferences.

6.6.3 Results under relative preferences

Similar to Section 6.6.2, scenarios for shippers with homogeneous and heterogeneous preferences are designed. In the homogeneous preferences scenario (A), five sub-scenarios, i.e., the most important attribute is Cost (A-1), Time (A-2), Reliability (A-3), Risk of damage (A-4), and Emissions (A-5), are considered. For the heterogeneous preferences scenario (B), different preferences will be assigned to each request randomly. For the three sub-scenarios with heterogeneous preferences (B-1, B-2 & B-3), the preference proportions of five attributes, i.e., [Cost, Time. Reliability, Risk of damage, and Sustainability], are [30, 0, 20, 10, 40], [20, 20, 10, 30, 20], and [30, 40, 10, 10, 10] for cases B-1, B-2, B-3, respectively. For the ease of writing, in this section, we use a similar expression with Section 6.6.2, e.g., "low-cost preference" means "the most important attribute is Cost". Since the proportion of served requests is not high in some cases in Section 6.6.2, this section tries a setting with more flexibility, i.e., barges and trucks with flexible services, and trains with fixed services. Based on the studied transport network, the expected value of each linguistic term of satisfaction is given in Table 6.6.

Table 6.6: Expected values of each attribute.

Linguistic terms of satisfaction	Expected value				
	Cost	Time	Reliability	Emissions	Risk of damage
Very high	[0, 0.8]	[0, 0.8]	[0, 0.05]	[0, 0.5]	[0, 10]
High	(0.8, 1.2]	(0.8, 1.2]	(0.05, 0.1]	(0.5, 0.9]	(10, 20]
Medium	(1.2, 1.6]	(1.2, 1.6]	(0.1, 0.15]	(0.9, 1.3]	(20, 30]
Low	(1.6, 2.0]	(1.6, 2.0]	(0.15, 0.20]	(1.3, 1.7]	(30, 40]
Very low	(2.0, +∞]	(2.0, +∞]	(0.20, +∞]	(1.7, +∞]	(40, +∞]

Results with an instance with 100 requests are shown in Table 6.7. The satisfaction and attribute values are improved by incorporating preferences. In low-cost transport (A-1), the unit cost reduces by 10% from 0.51 to 0.46. In the fast transport scenario (A-2), the reduction of time ratio is 59%. Risk of damage increases in the low-emission transport scenario (A-5) because more sustainable transport modes are selected and more transshipments are needed. As for scenario B, because of the heterogeneous preferences of shippers, the improvement on certain attributes is not significant. Mode shares of the barge, train, and truck are presented in Figure 6.10. In the homogeneous preferences scenario, the usage of vehicles can reflect their corresponding preferences. In low-cost, reliable and low-emissions transport cases, truck shares a low percentage compared with the other two modes. In the fast transport case, the barge is not the preferred mode. For the heterogeneous preferences scenario, the mode shares vary among cases.

Table 6.7: Experiment results under relative preferences (100 requests).

Scenario	R	#r	S	Total cost	Cost	Time	Reliability	Emission	Risk	t(s)
benchmark	100	100	–	196130.69	0.51	1.51	0	0.35	1.59	-
A-1	100	82	9.60 (6.77∗)	174637.14	0.46	1.38	0	0.34	1.09	1333.15
A-2	100	66	9.93 (5.96∗)	168207.16	0.70	0.62	0	0.59	0.76	4098.90
A-3	100	100	9.43 (9.43∗)	196130.69	0.51	1.51	0	0.35	1.59	3582.21
A-4	100	100	9.38 (8.20∗)	196299.25	0.50	1.41	0	0.38	0.1	4740.46
A-5	100	89	9.38 (6.84∗)	181896.14	0.45	1.66	0	0.28	1.89	240.62
B-1	100	95	9.38 (7.62∗)	198095.42	0.52	1.55	0	0.33	2.14	280.98
B-2	100	98	9.43 (7.38∗)	198090.03	0.54	1.45	0	0.38	1.49	412.35
B-3	100	98	9.49 (7.69∗)	209791.81	0.54	1.23	0	0.40	1.77	473.68

R: number of total requests; #r: number of served requests; S: satisfaction value; Cost: unit cost(/km/TEU); Time: time ratio (%); Reliability: delay ratio (%); Emission: unit emission cost (/km/TEU); Risk: number of transferred containers (TEU); t(s): computation time (seconds). The value with ∗ means satisfaction of the benchmark when considering relevant preferences.

6.7 Conclusions

To address research question Q3, in this chapter, an optimization model is established for the Synchromodal Transport Planning Problem with Heterogeneous and Vague Preferences

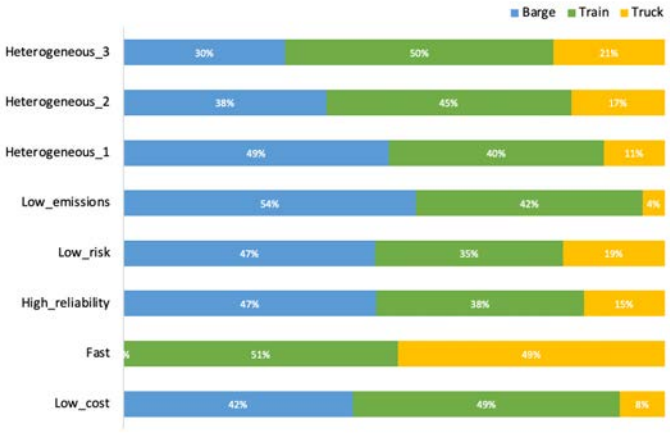


Figure 6.10: Mode share under relative preferences (100 requests).

(STPP-HVP). Two typical types of linguistic terms, i.e., absolute and relative preferences are considered. The mathematical model is proposed to formulate the STPP-HVP and Multiple Attribute Decision Making integrating fuzzy set theory is used to model heterogeneous and vague preferences. A customized Adaptive Large Neighborhood Search is developed to solve the STPP-HVP. We address conflicts between the freight forwarder and shippers by setting the preferences of the freight forwarder and shippers as objectives and constraints, respectively. The objectives of the freight forwarder are to maximize the number of served requests and minimize the transport cost. Shippers' satisfaction is calculated by fuzzy set theory according to attribute values, and satisfaction values are limited to be higher or equal to a predefined value. In this way, the freight forwarder will try to find the solution with the lowest cost while ensuring service quality. Moreover, compared with using hard constraints, using fuzzy constraints gives more room to resolve conflicts between the freight forwarder and shippers. Compared with setting the objective as the sum of costs and dissatisfaction, the satisfaction values are higher when using fuzzy constraints. In the results, when the freight forwarder considers shippers' preferences that have conflicts with minimizing overall transport cost, the freight forwarder satisfies shippers with minimal cost by choosing more suitable modes and routes. The results also show that the proposed model improves shippers' satisfaction significantly by utilizing multiple transport modes and addresses conflicts between shippers by balancing the satisfaction levels.

Based on the experimental results, the following managerial insights are obtained:

1. In synchromodal transport planning, considering preferences is conducive to providing customized services by using the advantages of different modes. The shippers are more satisfied when their preferences are considered because corresponding attribute values are improved.

2. The conflicts between the freight forwarder and shippers are resolved by improving the service quality at the minimum cost. The transport reaches a trade-off between conflicting preferences of shippers by allocating appropriate services to specific requests without compromising any other's preferences.

In practice, freight forwarders in synchromodal transport can use the proposed model to improve their service quality and competitiveness by providing customer-oriented services. In the meantime, the cost, time, emissions, delay, and risk of damage could be reduced when considering related preferences using the proposed model. In this chapter, we work with container shippers in the context of synchromodal transport. Nevertheless, the proposed methodologies are applicable in the case of other shippers as well if the importance of attributes is given. The proposed model can also be used to solve similar problems, such as pickup and delivery problems with transshipment and preferences, by simplifying the objectives and constraints related to multiple modes.

Chapter 7

Collaborative planning with eco-label preferences

The previous chapters focused on transport planning for a single carrier. However, in reality, multiple carriers may collaborate to allocate shipment requests to the most appropriate carrier by sharing requests and services. This type of collaboration can help reduce emissions and consider sustainability preferences. This chapter addresses research question Q4: What types of collaborative planning should be adopted and what is their effect on the consideration of preferences?

This chapter is structured as follows. Section 7.1 introduces collaborative planning in synchromodal transport. Section 7.2 presents a review of the relevant literature. Section 7.3 describes the studied problem. Section 7.4 provides the approach for handling vague preferences, the mathematical model and heuristic algorithm for transport planning of each carrier, and the collaborative planning approach for multiple carriers. Section 7.5 describes the experimental settings and the results from the case study. Section 7.6 concludes this chapter.

Parts of this chapter have been published in Zhang et al. (2022c)[1].

7.1 Introduction

While synchromodal routings are often triggered by potential cost reductions, they are also considered as a means for more sustainable transport solutions. For example, Heinold and Meisel (2018) show in a comprehensive simulation study for Europe that 90% of the shipments have a lower environmental impact if they are routed in a rail-road connection instead of using a road-only connection. For shippers, such considerations play an increasing role as transportation contributes to "almost a quarter of Europe's greenhouse gas emissions and is the main cause of air pollution in cities" (European Commission 2020). According to surveys and expert interviews conducted in Zhang et al. (2022d), reducing emissions is im-

[1]Zhang, Y., Heinold, A., Meisel, F., Negenborn, R. R., & Atasoy, B. (2022). Collaborative planning for intermodal transport with eco-label preferences. Transportation Research Part D: Transport and Environment, 112, 103470.

portant for carriers and shippers when the government releases policies or sets emission reduction goals. Shippers and transport companies will need to comply with regulations and they will become motivated to keep track of their footprint. Moreover, with the raising awareness of global warming, more and more carriers and shippers will want to contribute to sustainable transportation. Therefore, several approaches and policies have been proposed to reduce the environmental impact of logistics, such as low-emission zones for heavy vehicles (Fensterer et al. 2014), emission reduction targets (Chen and Wang 2016), or emission trading systems (Demailly and Quirion 2008). Recently, the concept of eco-labels has been proposed to achieve a more sustainable freight transportation (Heinold and Meisel 2020, Kirschstein et al. 2022). Thereby, eco-labels use a traffic light-colored preset scheme to indicate a shipment's relative environmental impact. For example, an eco-label "A" indicates that emissions caused in a transport process are very low whereas somewhat higher emissions lead to eco-label "B", and so on. Eco-labels can then be used as an indicator for a shipper's environmental preference, e.g., by requesting for a shipment that it is transported in accordance to a certain label.

The services of each transport carrier (operators of transport modes) are limited and may not be sufficient to achieve sustainable transport, especially when emission reduction requirements are high. Collaborative planning may then help in reducing emissions. Collaborative planning is becoming more and more prevalent due to the intensive competition in the transport market (Li et al. 2015a). There are different types of collaborative planning and collaboration partners can be shippers, receivers, or carriers (Pan et al. 2019). This study focuses on collaborative planning among carriers by exchanging shipment requests from shippers. Figure 7.1 shows an example of non-collaborative and collaborative planning. In this example, there are three synchromodal transport carriers and each carrier has two requests with high requirements on sustainability. When carriers do not collaborate, requests are served by their own services and the environmental requirements of some requests are not reached. For example, request a is served by carrier 1's truck service, and request f is served by carrier 3's train and truck services with transshipment. In collaborative planning, carriers decide which requests they are willing to share or serve. After collaboration, carrier 1's request a is shared with carrier 2 and carrier 2/3's requests d/f are shared with carrier 1. Thus, the capacity of low-cost and low-emission vehicles is better utilized and all carriers improve service levels and avoid unnecessary trips.

In its essence, collaboration enables the aggregated consideration of each carrier's demand, which is placed by shippers who own or supply shipments that can then be transported in a more efficient and sustainable way through a larger and more diverse logistics network. Large vehicles in synchromodal transport, such as trains or barges, benefit from economies of scale by increasing capacity which reduces costs and emissions per container. Therefore, they are more profitable and sustainable if there is sufficient demand, which can be achieved through collaboration among carriers (e.g., Groothedde et al. 2005). Collaborating carriers can make better use of their vehicles' capacity and avoid empty trips, which then leads to cost and emission reductions, service improvements, and market share increases (e.g., Cruijssen et al. 2007, Krajewska and Kopfer 2006, Schmoltzi and Wallenburg 2011).

To achieve a more sustainable synchromodal transport, we present a collaborative planning model with eco-labels. The considered carriers each operate networks on their own that differ in structure. For example, the predominant mode might be trains in one network and barges in another network. We consider shippers with different expectations regarding a

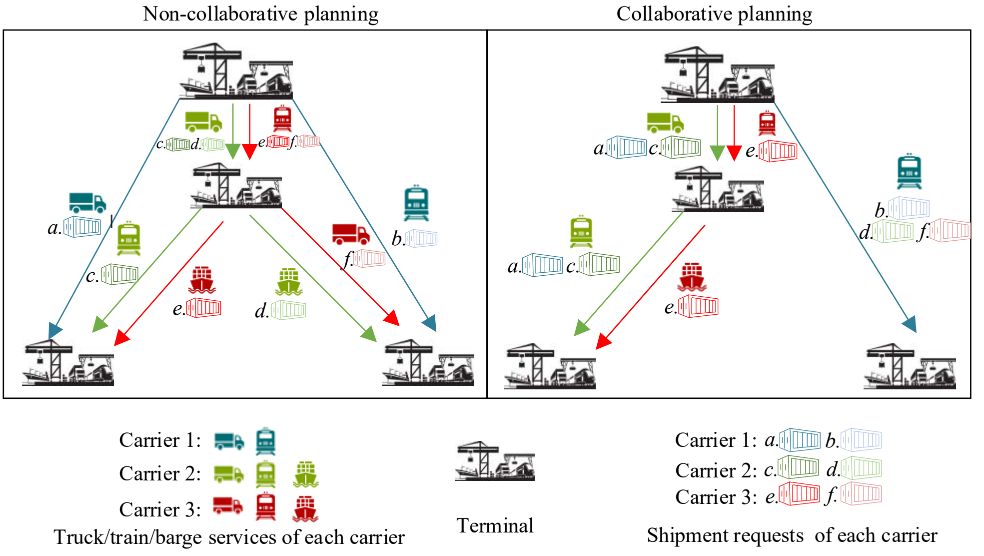


Figure 7.1: Example of non-collaborative and collaborative planning.

shipment request's eco-label. However, integrating environmental preferences through eco-labels for each request imposes additional challenges to the underlying transport planning problem as well as to the collaborative planning model. The transport planning needs to handle vague preferences on eco-labels, such as "around eco-label B is fine". Appropriate collaborative planning approaches also need to be proposed to reach the required eco-label at the lowest cost by using different modes of service of carriers. To address these challenges, we provide a mathematical model and an ALNS heuristic for synchromodal transport planning considering vague preferences on eco-labels. We do not view eco-labels exclusively as either "fulfilled" or "not fulfilled" but calculate the degree of how much a request's routing complies with its requested eco-label using fuzzy set theory. Regarding collaboration, we consider centralized, collaborative, and non-collaborative approaches. An auction-based mechanism is adopted for exchanging requests among carriers in collaborative planning. We apply our model to a realistic case study in which we consider collaboration among unimodal or synchromodal carriers along the European Rhine-Alpine corridor. Based on obtained results, we provide insights on situations in which collaboration is beneficial out of reasons of sustainability.

The main contributions to the existing literature are as follows. First, an optimization model with eco-label preferences is developed considering characteristics of synchromodal transport and vagueness of preferences. Second, we provide a conceptual framework for horizontal collaborative planning in the context of sustainability. Finally, we perform an experimental study that investigates settings in which collaboration leads to more sustainable solutions.

7.2 Literature review

This chapter considers horizontal collaboration between synchromodal transport carriers that principally offer the same service, namely, transporting a freight shipment from its origin to its destination. Accordingly, this literature review comprises two fields: (i) collaborative planning in unimodal freight transportation and (ii) collaborative planning in synchromodal transportation. A brief review of relevant literature in these fields is provided in Sections 7.2.1 and 7.2.2, respectively. Note that the first field is very general but, in the context of this study, comprises those papers on collaboration that do not belong to synchromodal transport but are considered as relevant for our study. A summary of the reviewed literature is provided in Section 7.2.3.

7.2.1 Collaborative planning in freight transport

This section provides a review on collaborative planning in freight transportation. It starts with a general overview of how collaborations can be classified and continues with a review on collaboration in networks in which only a single mode of transportation is used. The latter review is included as it introduces general concepts of collaborative planning in freight transport. These concepts are used in Section 7.2.3 to highlight the distinct characteristics of this study.

Gansterer and Hartl (2018) identify three major streams of research for collaborative vehicle routing: centralized collaborative planning, decentralized planning without auctions, and auction-based decentralized planning. If a central coordinator has full power on carriers, it is called centralized planning, otherwise called decentralized planning. Further divided by the means of exchanging requests, decentralized planning can be non-auction or auction-based.

Assuming a powerful central coordinator is not necessarily practical because carriers may not be willing to give full information to such a party. Moreover, the optimization problems in centralized collaborative planning are usually hard to solve because the overall transport network is of a large scale. Decentralized approaches without auctions typically involve various steps such as partner selection, request selection, and request exchange (Gansterer and Hartl 2018). Compared to non-auction-based systems, the auction-based approaches are more complex due to the bidding procedure. However, it is in the nature of auctions to address the reassignment of transport requests and the allocation of the profit gained by carrier collaboration simultaneously (Berger and Bierwirth 2010).

The research on collaborative freight transportation for unimodal transport often focuses on road freight transport be it for Full Truckload (FTL, size of shipment equal to vehicle capacity) or Less Than Truckload (LTL, size of shipment less than vehicle capacity) services. Collaborative planning of FTL mainly benefits from avoiding empty trips (Liu et al. 2010) and collaborative planning of LTL mainly benefits from making better use of vehicle capacity (Dai and Chen 2012a, Wang and Kopfer 2014). Berger and Bierwirth (2010) propose two solution approaches for the LTL request reassignment problem involving decentralized control and auction-based selection and exchange of requests. Dai and Chen (2011) propose a multi-agent and auction-based framework for carrier collaboration in LTL transport. Lai et al. (2017) propose an iterative auction approach in FTL transport, which enables carriers to collaborate by exchanging their shipping requests iteratively.

Wang et al. (2014) extend the pickup and delivery problem with time windows to collaborative transport planning, where both subcontracting and collaborative request exchange are taken into account. There is also some research on collaborative planning in maritime transport and inter-terminal transport. For example, Agarwal and Ergun (2010) study collaboration among carriers in liner shipping. Both tactical problems such as the design of large-scale networks and operational problems such as the allocation of limited capacity on a transport network among the carriers are discussed. Vojdani et al. (2013) focus on collaborative approaches in the empty container management. They demonstrate the potential for cost savings through the use of container pooling in comparison to non-cooperative solutions. For inter-terminal transports, Kopfer et al. (2016) evaluate by experiment scenarios for isolated planning, central planning, and collaborative planning. Their results show there are discrepancies in the collaboration profits of individual carriers.

7.2.2 Collaborative planning in synchromodal transport

Compared to the literature on collaboration in single-mode networks, there is a lack of research on collaborative planning for synchromodal transport (Gumuskaya et al. 2020, Pan 2017). In the last decade, some scholars researched cooperation in synchromodal transport at a strategical level from a business model perspective (Lin et al. 2017, Saeed 2013). Nevertheless, very few research effort has been spent on the collaborative planning of independent players in a synchromodal transport chain at the tactical and operational level, see the survey of Gansterer and Hartl (2018). The recent study of Gumuskaya et al. (2020) presents a framework for such collaboration but no decision support model. An example of a more decision-oriented study is Puettmann and Stadtler (2010), who investigate the coordination of a long-haul carrier and a drayage carrier in an intermodal transport chain. The carriers are allowed to keep their private planning information and critical data. The focus of this chapter is on analyzing the impact of stochastic demand. Di Febbraro et al. (2016) propose a multi-actor system for cooperation in intermodal freight transport. They decompose the optimization problem into a set of sub-problems, each of them representing the operations of one actor. A Lagrangian-based Network Communication Coordinator is employed in this approach to establish a framework for sharing information and coordinating operations among various actors. Each actor receives information from both its preceding and successive actors, allowing them to optimize their local operations accordingly. The dynamics of synchromodal transport are studied by developing a discrete event model based on the concept of a rolling horizon. Li et al. (2017) investigate cooperative planning among multiple carriers that connect deep-sea ports and inland terminals where the transport networks of these carriers are interconnected with each other. Li et al. (2017) investigate service networks that are non-overlapping and the cooperative planning is done at the tactical flow level by all operators.

Only a few papers have studied the auctioning of requests in synchromodal transport collaboration. Xu et al. (2015a) study intermodal transport auctions for B2B (Business to Business) e-commerce logistics with transaction costs. Sun et al. (2019) focus on intermodal transport service procurement problem in the context of the “Belt and Road Initiative”, where a shipper contains a bundle of requests in different lanes (origin-destination pairs) and each carrier may cover either one or multiple lanes. The results indicate that the auctioneer should decrease transaction costs, increase the numbers of shippers/carriers, control the types of shipper demand, and induce true biding prices of bidders.

7.2.3 Summary

Table 7.1 provides a summary of the reviewed papers. All papers are divided by their research domains, i.e., FTL road transport, LTL road transport, Road Freight Transport (RFT) without specifying FTL/LTL, Maritime Freight Transport (MFT), Inter Terminal Transport (ITT), Inland Waterway Transport (IWT), and Synchromodal Transport (ST). The collaboration approaches (CA) are divided by the categories proposed by Gansterer and Hartl (2018), i.e., Centralized Planning (CP), Non-auction-based Decentralized Planning (DP), Auction-based Decentralized Planning (ADP). The table furthermore reports if papers consider features such as transshipments (T), fixed timetables (FT), overlapping transport networks (OTN), or sustainability preferences (S).

Table 7.1: Summary of the literature review.

Literature	Domain	CA	T	FT	OTN	S
Liu et al. (2010)	FTL	DP				
Li et al. (2015a)	FTL	ADP				
Lai et al. (2017)	FTL	ADP				
Dai and Chen (2011)	LTL	ADP				
Dai and Chen (2012a)	LTL	CP				
Wang and Kopfer (2014)	LTL	ADP				
Berger and Bierwirth (2010)	RFT	ADP			✓	
Wang et al. (2014)	RFT	ADP				
Özener (2014)	RFT	–				carrier
Agarwal and Ergun (2010)	MFT	DP	✓	✓		
Vojdani et al. (2013)	MFT	DP			✓	
Kopfer et al. (2016)	ITT	ADP	✓			
Puettmann and Stadtler (2010)	ST	ADP	✓	✓		
Xu et al. (2015a)	ST	ADP				
Di Febbraro et al. (2016)	ST	DP	✓	✓		
Li et al. (2017)	ST	DP	✓	✓		
Sun et al. (2019)	ST	ADP				
Liotta et al. (2014)	ST	CP				carrier
This research	ST	ADP	✓	✓	✓	shipper

As shown in Table 7.1, there are many studies on collaborative vehicle routing in unimodal road freight transportation (including RFT, LTL and FTL). However, there are significant differences between unimodal and synchromodal settings. For example, in many studies on road freight transport, the carrier has only one type of vehicles (homogeneous fleet). In synchromodal transport, the carrier potentially owns vehicles of multiple modes and different characteristics. In particular, vehicles can be very large, which has various implications such as that the emissions of barges and trains are highly influenced by their actual load. Furthermore, the requests in synchromodal transport can be segmented and transported by multiple vehicles, while requests in the road mode usually just comprise one vehicle. When a request is segmented, it will be transferred between vehicles at transshipment terminals. Therefore, synchronization at transshipment terminals needs to be considered in synchromodal transport. Furthermore, synchromodal carriers often have specific terminals and operating areas where trains and ships typically follow fixed timetables and predefined routes, which is hardly the case in traditional road freight transportation.

The research in RFT/LTL/FTL, MFT, and ITT only considers one transport mode, either trucks or ships. Some research has been done in ST, however, the carriers in these papers are hardly modelled realistically. For instance, the carriers assumed by Puettmann and Stadtler (2010) and Li et al. (2017) can control different transport networks whereas in reality a transport network may be occupied by multiple carriers. When considering carriers that serve the same or at least overlapping parts of a transport network, horizontal collaboration approaches become relevant (Cleophas et al. 2019). Moreover, most papers ignore the individual sustainability preferences of carriers or shippers. Some papers regard reducing emissions as an objective from the perspective of carriers (Liotta et al. 2014, Özener 2014). However, they do not study how carriers take shippers' sustainability preferences into account.

7.3 Problem description

We consider a problem in which multiple synchromodal transport carriers are willing to achieve increased sustainability through collaboration. Eco-labels are used to evaluate the relative environmental impact of transporting a shipper's order from its origin to its destination. We measure this impact by subsuming relevant greenhouse gases, such as carbon dioxide (CO_2), methane (CH_4) or nitrous oxide (N_2O), resulting from transportation under the term 'emissions' and evaluate their impact on global warming relative to CO_2, the most important greenhouse gas (United States Environmental Protection Agency 2022). With this, we use the single measure CO_2e to state the amount of CO_2-equivalents resulting from transportation, and use those emissions (kgCO_2e) per container and per kilometer (km) as a sustainability measure and refer to it as emission rate (kgCO_2e/(TEU·km)). Thereby, we assume that each container corresponds to one twenty-foot equivalent unit (TEU) of 13 tons (Heinold and Meisel 2018). The eco-labeling scheme is derived from a large-scale simulation study in Europe's synchromodal rail/road network (Heinold and Meisel 2018) and consists of three classes A, B, and C with emission rate limits as shown in Figure 7.2.

Figure 7.3 shows a conceptional sketch of the considered problem. In this figure, there are two requests in the request pool and three carriers. Each carrier needs to solve a Synchromodal Transport Planning Problem with Sustainability Preferences (ITPP-SP) to match its offered services with the placed requests. In these services, combinations of modes and routes can be used to serve requests while distinct combinations result in distinct emissions. If the carrier cannot match the services with the preferred eco-label of request r, r

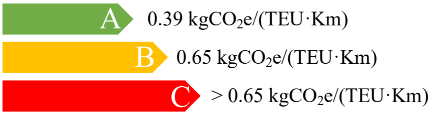


Figure 7.2: Eco-labeling scheme.

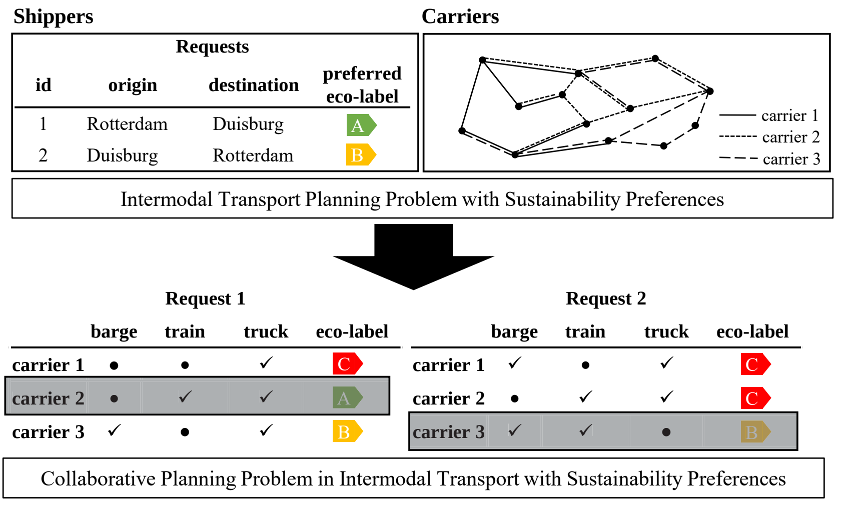


Figure 7.3: Conceptional sketch of the considered problem.

will be shared with other carriers. In this case, the Collaborative Planning Problem in Synchromodal Transport with Sustainability Preferences needs to be solved to find a suitable carrier.

Each carrier $c \in C$ owns a set of heterogeneous vehicles K^c of capacity u_k and speed v_k, and receives a set of requests R^c with preferred eco-labels from shippers. We use el_r (A, B, or C) to express the *eco-label* of request r, where emission rates per eco-label level el_r can be found in Figure 7.2. To provide more sustainable transport and better services, carriers collaborate by exchanging requests, i.e., horizontal collaboration. Carriers only share requests when they cannot match requirements by themselves because they want to serve shippers and gain additional profits. The shared requests can be served by any other carrier as long as the required eco-label is respected.

7.4 Modeling and solution approach

This section presents the modeling and heuristic algorithm to solve the ITPP-SP together with a framework for the collaborative planning approach. Firstly, we introduce how emissions are calculated and how to handle vague sustainability preferences by fuzzy logic theory in Section 7.4.1. Then, the mathematical model and an ALNS heuristic for the ITPP-SP of an individual carrier are presented in Section 7.4.2. Finally, the collaborative planning framework is described in Section 7.4.3.

7.4.1 Emissions calculation and vague preferences

To analyze whether or not a request is shipped in accordance with its eco-label we have to measure the emissions that are emitted while shipping the request from its origin to destination. For this, two kinds of transport-related emissions need to be considered for a request r: first, emissions from the vehicles that are transporting requests on the arcs (e_r^{arcs}), and, second, emissions from transshipment operations at the nodes that are required in a synchromodal transport setting (e_r^{nodes}).

Regarding emissions from vehicles, several emission estimation models have been proposed in the literature. We refer to Demir et al. (2011) and Heinold (2020) for studies comparing models for trucks and trains, respectively. Generally, the models differ in the level of detail of the required input data, with microscopic models requiring granular data inputs (e.g., speed profiles) and macroscopic models requiring only a few rough data inputs (e.g., average speed). For our purpose, we use a macroscopic methodology proposed by the EcoTransIT World Initiative (2019), the so-called ETW model. The model provides calculation procedures for all of our considered transport modes: trucks, trains, and barges. The model is further in accordance with the European norm EN 16258 (European Committee for Standardization 2012) on the calculation of freight transport related greenhouse gas emissions. Generally, the ETW method uses empirically-based functions that take the vehicle's load q_{ij}^k (in TEU) and traveled distance d_{ij}^k (in km) between terminals i and j as the main input to estimate emissions. Thereby, various sources are used to come up with realistic functions like the average annual energy consumption of rail freight transport companies or surveys among transport companies. With this, the model considers emissions from the driving of vehicles as well as from the idling of vehicles (e.g., Rahman et al. 2013). In our problem, we consider emissions that relate to a regular 40-ton truck (Euro VI norm), a typical diesel train with "sgis" cars, and a standard European barge. We refer to EcoTransIT World Initiative (2019) for details on the model's methodology and data of the parameters that are used for these vehicle types. Further emission estimation model parameters are set as follows: the empty trip factor is set to 0.2, the slope profile is set to 1, and the well-to-wheel emission factor is set to 3.90 (kgCO_2e/kg) for regular diesel and to 3.92 (kgCO_2e/kg) for marine diesel (see European Committee for Standardization (2012)). With this, the condensed formulas to calculate emissions e_w^{kij} (in kgCO_2e) of vehicle k travelling between terminals i and j in one of the three modes $w \in \{\text{truck, train, barge}\}$ are shown in Equations (7.1) to (7.3), respectively.

$$e_{truck}^{kij} = 0.7233 \cdot d_{ij}^k + 0.1872 \cdot d_{ij}^k \cdot q_{ij}^k \tag{7.1}$$

$$e_{train}^{kij} = 22.6278 \cdot d_{ij}^k \cdot q_{ij}^k \cdot (123 + 13 \cdot q_{ij}^k + 23 \cdot \lceil q_{ij}^k \cdot 13/40 \rceil)^{-0.62} \tag{7.2}$$

$$e_{barge}^{kij} = 35.9525 \cdot d_{ij}^k + 0.0819 \cdot d_{ij}^k \cdot q_{ij}^k \tag{7.3}$$

These emissions are then allocated among the requests based on each request's contribution to a service's overall load between terminals i and j:

$$e_r^{kij} = e_w^{kij} \cdot q_r / q_{ij}^k \tag{7.4}$$

The emissions of request r using vehicle k is the sum of emissions of all trips served by k:

$$e_r^k = \sum_{(i,j) \in A^c} y_{ij}^{kr} e_r^{kij} \tag{7.5}$$

The total emissions on arcs of request r is:

$$e_r^{\text{arcs}} = \sum_{k \in K_r^c} e_r^k \tag{7.6}$$

Regarding emissions from transshipment processes at ports (i.e., transshipments involving barge l), the values of e^{kl} are 6.3, 19.6, and 11.2 kgCO_2e/TEU when vehicle k is a truck, a train, and a barge, respectively, as reported in an analysis of two container terminals in the Port of Rotterdam (Geerlings and van Duin 2011). For all other transshipment operations (e.g., from truck to train and vice versa), we assume the value of e^{kl} is 2.6 kgCO_2e/TEU. This value is based on the energy consumption of such processes as reported for the European synchromodal rail/road network by Kim and van Wee (2009). The emissions of request r during transshipment between vehicles k and l can be obtained by the following equation:

$$e_r^{kl} = q_r(e^{kl} + e^{lk}) \tag{7.7}$$

The total emissions at nodes of request r are:

$$e_r^{\text{nodes}} = \sum_{k,l \in K^c, k \neq l} \sum_{i \in T^c} s_{ir}^{kl} e_r^{kl} \tag{7.8}$$

The total emissions of request r are:

$$e_r = e_r^{\text{arcs}} + e_r^{\text{nodes}} \tag{7.9}$$

The unit emissions of request r are:

$$e'_r = e_r / (q_r \sum_{k \in K} \sum_{(i,j) \in A} d_{ij}^k y_{ij}^{kr}) \tag{7.10}$$

Shippers' sustainability preferences are usually vague, such as "around eco-label B is fine" or "eco-label C is enough", i.e., a shipper's satisfaction is still relatively high when the emission value does not perfectly match the required eco-label but is very close to it. Therefore, simple rules like only accepting services with lower emissions than the eco-label are not necessarily appropriate for the evaluation of shippers' satisfaction. Instead, we use the fuzzy set theory to capture such vague preferences. Fuzzy set theory is a methodology that does not express the "truthiness" in a discrete manner as either true or false but instead also allows for partially true or partially false. Accordingly, whether an emission value belongs to a particular eco-label or not is also expressed as (partially) true or false in our study. For this, emissions can be represented by a fuzzy variable, which has a predefined value range and eco-labels are used to describe it. The value in the value range is called crisp value, which is how we think of the variable using normal mathematics, e.g., 0.4 kgCO_2e/(TEU·km). Each eco-label has a membership function that defines the degree of truth of a crisp value that belongs to the eco-label on a scale of 0 to 1. For example, 0.4 kgCO_2e/(TEU·km)'s membership to eco-label A and eco-label B could be 0.8 and 0.2, respectively.

Based on request r's actually caused unit emissions e'_r and the emission boundary el_r

of the requested eco-label, the satisfaction value S_r will be obtained by fuzzy set theory:

$$S_r = Fuzzy(e'_r, el_r) \tag{7.11}$$

where $Fuzzy()$ represents the fuzzy set theory approach used in this study as is described next.

The membership function of emissions e'_r and satisfaction S_r are shown in Figure 7.4. The trapezoidal and triangle fuzzy numbers are used in the membership function, where the triangular membership function is a special trapezoidal membership function. The trapezoidal membership function is given in Equation (7.12) for the trapezoidal fuzzy number of e'_r involving scalar parameters a, b, c, d, whereby $a \leq b \leq c \leq d$ and $b = c$ for the triangular membership function. For the fuzzy number of S_r, we use the same type of function.

$$\mu(e'_r) = \begin{cases} 0, & e'_r < a \\ \dfrac{(e'_r - a)}{(b-a)}, & a \leq e'_r \leq b \\ 1, & b \leq e'_r \leq c \\ \dfrac{(d - e'_r)}{(d-c)}, & c \leq e'_r \leq d \\ 0, & e'_r > d \end{cases} \tag{7.12}$$

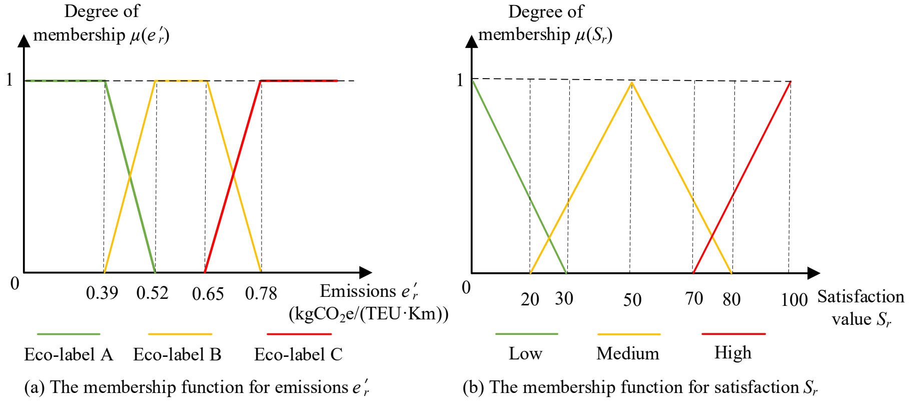


Figure 7.4: Membership functions for emissions and satisfaction.

Fuzzy variables for the emissions and satisfaction can be linked using a set of rules, which are IF-THEN statements that describe how one variable relates to another. The used fuzzy rules are as follows:

1. When the shipper prefers eco-label A, IF the obtained eco-label *equals/is worse than* A, THEN the satisfaction will be *high/low*.

2. When the shipper prefers eco-label B, IF the obtained eco-label *is better than/equals/is worse than* B, THEN the satisfaction will be *high/medium/low*.

3. When the shipper prefers eco-label C, IF the obtained eco-label *is better than/equals* C, THEN the satisfaction will be *high/medium*.

After defining fuzzy variables and fuzzy rules, the satisfaction value S_r can be obtained using a defuzzification method, such as Center of Gravity used in Van Leekwijck and Kerre (1999). The same emissions may lead to different satisfaction because preferred eco-labels are different for different shippers. For example, if shipper 1 prefers eco-label B and shipper 2 prefers eco-label C, shipper 2 will be more satisfied than shipper 1 when the actual eco-label is B.

7.4.2 Mathematical model and ALNS for ITPP-SP

This section presents the mathematical model for one carrier c. In this model, we try to ensure shippers' satisfaction while minimizing the carrier's costs. There are two levels of objectives. The upper-level objective (F_1) is to maximize the number of served requests of the considered carrier c. The lower-level objective (F_2) is minimizing the carrier's cost, which consists of transport cost, transfer cost, storage cost, carbon tax, waiting cost, and delay penalty. For the lower-level objective (F_2), we refer to Chapter 3. In practice, it is important to serve as many requests as possible for long-term trust. Shippers will not opt for a less costly service when it is not reliable. Therefore, the model will choose the solution with the highest objective value of F_1. If several solutions have the same optimal value for F_1, the solution with a lower objective value of F_2 among these is selected. There are also other ways to model the objective function, e.g., the objective (7.13) can be weighted by a penalty and added to the objective function (7.14). The results of this alternative approach are compared in Section 7.5.3.

Objective:

$$\max\ F_1 = \sum_{r\in R^c}\sum_{k\in K^c}\sum_{j\in N^c} y^{kr}_{p(r)j} \tag{7.13}$$

$$\begin{aligned}
\min\ F_2 = &\sum_{k\in K^c}\sum_{(i,j)\in A^c}\sum_{r\in R^c}(c^1_k\tau^k_{ij} + c^{1'}_k d^k_{ij})q_r y^{kr}_{ij} + \sum_{k,l\in K^c,k\neq l}\sum_{r\in R^c}\sum_{i\in T^c}(c^2_k + c^2_l)q_r s^{kl}_{ir}\\
&+\sum_{k\in K^c}\sum_{(i,j)\in A^c_p}\sum_{r\in R^c} c^2_k q_r y^{kr}_{ij} + \sum_{k\in K^c}\sum_{(i,j)\in A^c_d}\sum_{r\in R^c} c^2_k q_r y^{kr}_{ij}\\
&+\sum_{k,l\in K^c,k\neq l}\sum_{r\in R^c}\sum_{i\in T^c} c^3_k q_r s^{kl}_{ir}({t'}^{lr}_i - \bar{t}^{kr}_i) + \sum_{k\in K^c}\sum_{(i,j)\in A^c_p}\sum_{r\in R^c} c^3_k q_r y^{kr}_{ij}({t'}^{kr}_i - a_{p(r)})\\
&+\sum_{k\in K^c}\sum_{r\in R^c} c^4_k e^k_r + \sum_{k,l\in K^c,k\neq l}\sum_{r\in R^c}\sum_{i\in T^c} q_r s^{kl}_{ir}(c^4_k e^{kl} + c^4_l e^{lk})\\
&+\sum_{k\in K^c_{\text{b\&t}}}\sum_{i\in N^c} c^5_k t^{\text{wait}}_{ki} + \sum_{r\in R^c} c^{\text{delay}}_r q_r t^{\text{delay}}_r
\end{aligned} \tag{7.14}$$

Constraints (7.15) ensure that preferences are respected. $\overline{S}$ is a preset satisfaction benchmark. It is set as 50 in our experiments, which means "medium satisfaction". Only when the satisfaction value S_r reaches satisfaction benchmark $\overline{S}$, the solution for request r is considered acceptable.

$$S_r \geqslant \overline{S} \quad \forall r \in R^c \tag{7.15}$$

Other constraints are consistent with those outlined in Chapter 3.

The operators and adaptive mechanism of ALNS are illustrated in detail in Chapter 3. As these papers did not involve eco-labels, we briefly sketch here how this feature is incorporated into the ALNS. The emissions in this study are load-dependent, which means the load of barges/trains will influence the emissions allocated to a transported request. Therefore, it is difficult for ALNS to "predict" which vehicle is more suitable to reduce the emissions because the final load of the vehicle is not yet known while constructing a solution. For example, when ALNS inserts a new request to a route of an empty barge, it will obtain a very high emission. But later in the solution process, this barge may serve many requests with a high load factor, and the emissions allocated to a single request are then much lower. To alleviate the impact of the load-dependent emissions, we expect large capacity vehicles will be utilized at the end and set the load factors of trains and barges as 60% during each iteration of ALNS when computing emissions. By doing so, requests may be added to these large-capacity vehicles already when these vehicles are quite empty. After each iteration, the preference Constraints (7.15) are then rechecked using the actual load, and requests will be removed when Constraints (7.15) cannot be satisfied due to a too low load factor.

7.4.3 Collaborative planning approach

In the following, we consider three approaches of a (non-)collaboration of the carriers in set C, namely: (a) a centralized approach, (b) an auction-based collaborative approach, and (c) a non-collaborative approach. Since carriers do not want to reveal private information (such as costs) to their competitors, we assume there is a neutral coordinator in approaches (a) and (b). In reality, the coordinator could be a collaborative planning platform in synchromodal transport. In approach (a), the coordinator conducts the routing and scheduling for carriers. In approach (b), carriers make decisions by themselves and the coordinator only plays a role in connecting carriers and providing request and bid pools.

More precisely, in approach (a), shippers send requests, including lanes (origin-destination pairs), time windows, amounts of containers, and requested eco-labels, to carriers which then forward this information to the coordinator. Furthermore, carriers send their transport network information including terminals, vehicle fleets, and associated parameters to the coordinator, as shown in Figure 7.5(a). The coordinator solves a single holistic ITPP-SP and optimizes the overall synchromodal network based on this information, then assigns requests to carriers and reports costs to shippers either directly or via the carriers.

In approach (b), when a carrier has unserved requests, they will be exchanged with others via the coordinator as shown in Figure 7.5(b). This is done through an auction as is explained later in this section. In approach (c), carriers receive requests from shippers and do not share them with others. Each carrier solves an ITPP-SP and optimizes schedules only using their own services, and some requests might be rejected when their requirements cannot be met by the carrier who received these requests.

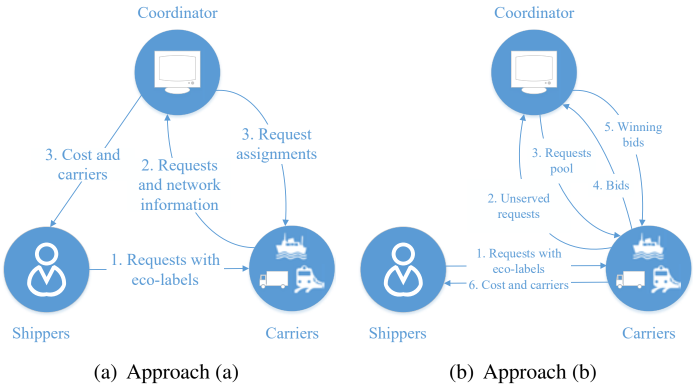


Figure 7.5: Collaboration approaches (a) and (b), which are centralized approach and auction-based collaborative approach, respectively.

In approaches (a) and (c), solutions are obtained by the ALNS directly where approach (a) optimizes schedules based on requests and resources of all carriers C, i.e., X^C_{best}, R^C_{pool} = $ALNS(K^C, R^C, N^C, A^C, X^C_{\text{best}})$ and approach (c) optimizes the operations individually for each carrier $c \in C$. For approach (b), a request exchanging mechanism is needed and an auction-based approach is adopted in this study because auctions can respect the preferences of participants by bidding (Gansterer and Hartl 2018, Li et al. 2015a). For example, consider two carriers A and B that bid for requests in an auction pool. The bidding of carrier A is based on costs and the bidding of carrier B is based on both costs and emissions. The auction will then reveal the carriers' preferences as they only place a bid if it is reasonable to add a request to the current routing with respect to their individual criteria. Specifically, we use a sealed-bid first-price iterative auction, where bidders submit sealed bids and the bidder submitting the lowest cost wins the request and charges this cost to the shipper. In an iterative auction, there are multiple rounds until a stopping criterion is reached and bidders can adapt their bids during the iterative process. The flowchart of the iterative auction procedure in collaborative planning is shown in Figure 7.6, where dashed arrows represent the exchange of information between carriers and the coordinator.

In an auction round, there are three steps for each carrier c:

1. Obtain an initial solution: Based on the K^c, N^c, A^c, and the carrier's own requests R^c, each carrier solves an ITPP-SP and the routes are optimized by the ALNS. Then, the carrier sends unserved requests R^c_{pool} to the coordinator.

2. Try and bid: The carrier obtains requests $CPR^{C\setminus c}_{\text{pool}}$ shared by other carriers from the coordinator and sets $CPR^{C\setminus c}_{\text{pool}}$ as R^c_{pool}. Then the carrier tries to insert these requests into its routes by Algorithm 11. If the carrier can serve requests $R^c_{\text{try}} = CPR^{C\setminus c}_{\text{pool}} \setminus R^c_{\text{pool}}$ and finds a better solution than before, the carrier submits bids Bid^c to the coordinator with costs of these requests R^c_{try}.

3. Insert new requests: For those bids $Bid^c_{\text{win}} \subseteq Bid^c$ that carrier c won through the

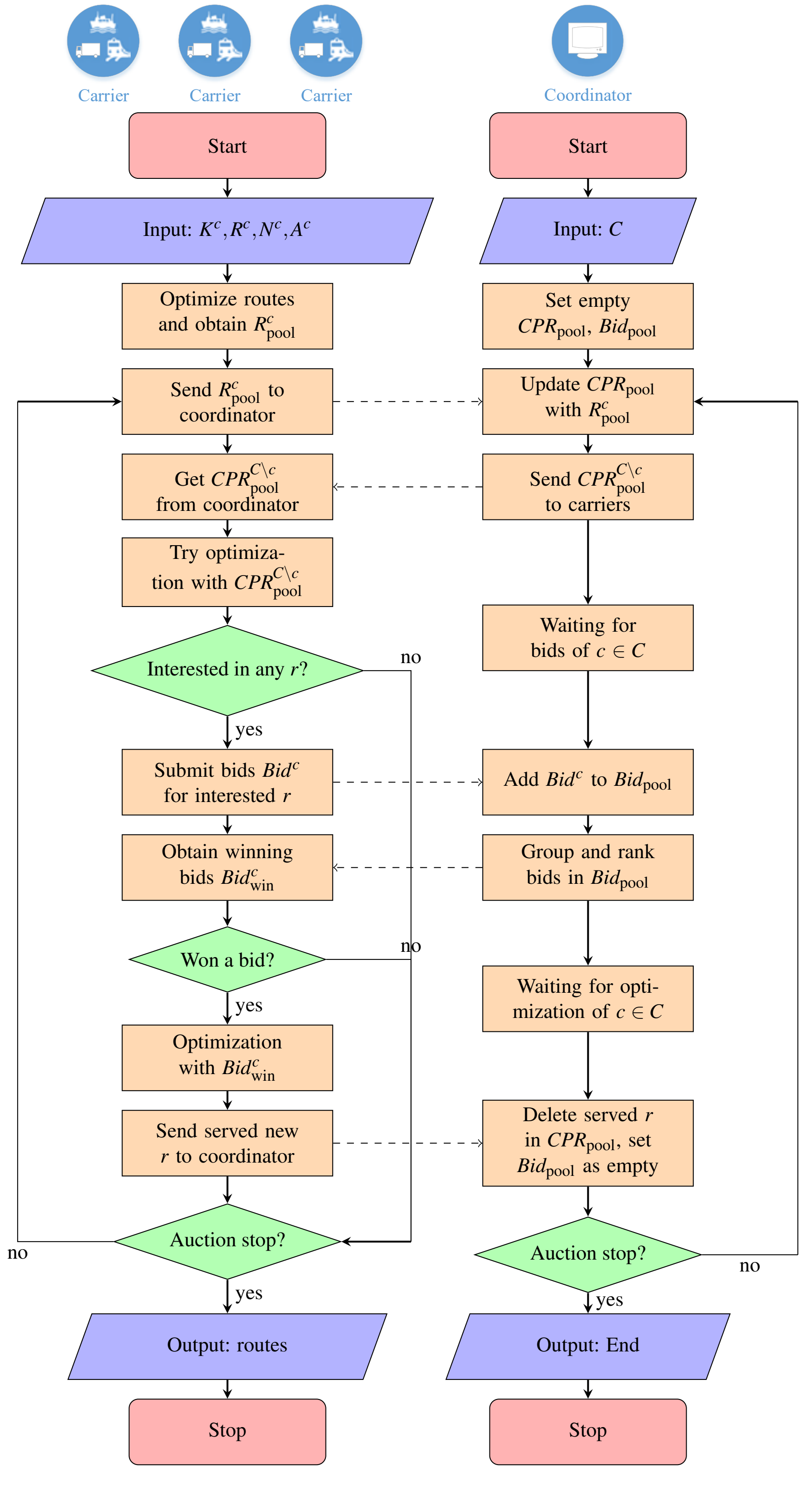


Figure 7.6: Flowchart of the iterative auction procedure in collaborative planning.

auction, requests in Bid^c_{win} are set as R^c_{pool} and the carrier inserts these requests into its routes by Algorithm 11. It is worth noting that maybe a request r that can be served in Step 2 cannot be served in Step 3, because it can only be served in combination with some other requests in the failed bids. In this case, r will be added to R^c_{pool} and considered in the next round of the auction. Finally, the carrier sends the information of served new requests R_{new} to the coordinator.

Algorithm 11: Re-planning with shared requests.

Input: K^c, R^c_{pool}, N^c, A^c, X^c_{best}; **Output**: X^c_{best};
Obtain served requests R^c_{serve} in X^c_{best};
Combine R^c_{pool} and R^c_{serve} as a set of requests R^c;
$R^c_{\text{pool}}, X^c_{\text{best}} = ALNS(K^c, R^c, N^c, A^c, X^c_{\text{best}})$
return R^c_{pool}, X^c_{best};

From the perspective of the coordinator, the procedure is as follows: The coordinator operates two pools, i.e., a collaborative planning request pool (CPR_{pool}) and a bids pool (Bid_{pool}). The coordinator adds or deletes requests in CPR_{pool} when receiving related information from carriers. Before an auction starts, the coordinator sets these two pools as empty and then receives unserved requests R^c_{pool} of each carrier $c \in C$. Request $r \in R^c_{\text{pool}}$ will be added in CPR_{pool} if $r \notin CPR_{\text{pool}}$. After receiving all carriers' R^c_{pool} and updating CPR_{pool}, the coordinator sends unserved requests of other carriers $CPR^{C\setminus c}_{\text{pool}}$ to each carrier c and waits for bids. After receiving bids from carriers, the coordinator groups bids according to requests and ranks them depending on the cost. Then, the coordinator sends winning bids to carriers and waits for the final optimization of carriers. Finally, the served requests are removed from CPR_{pool} and Bid_{pool} is set empty to prepare for the next round of the auction.

The auction will stop either when no carrier wants to exchange further requests or a predefined number of rounds is reached. This mechanism aims to provide carriers enough chances to share requests.

7.5 Case study

A network with three carriers along the European Rhine-Alpine corridor is considered as a real-world case to test the proposed model. The three carriers are European Gateway Services (EGS), Contargo, as well as Haeger & Schmidt Logistics (HSL) which are all synchromodal transport carriers that provide barge, train, and truck services from seaports (Rotterdam and Antwerp) to inland terminals. Figure 7.7 presents the transport networks of these carriers. In this case study, EGS, Contargo, and HSL provide services among 10, 20, and 15 terminals/ports, respectively. A total of 11 terminals are shared by two or three carriers (there are multiple terminals in the seaport). The three carriers can share their requests in the overlapping transport network. Services' information is obtained from schedules on their websites (Contargo 2021, EGS 2021, HSL 2021), and EGS, Contargo, and HSL operate 49/33/34, 38/23/95, and 41/8/70 barge/train/truck services, respectively, according to this data. For the distances between terminals of different modes, we use the same data sources as in Shobayo et al. (2021).

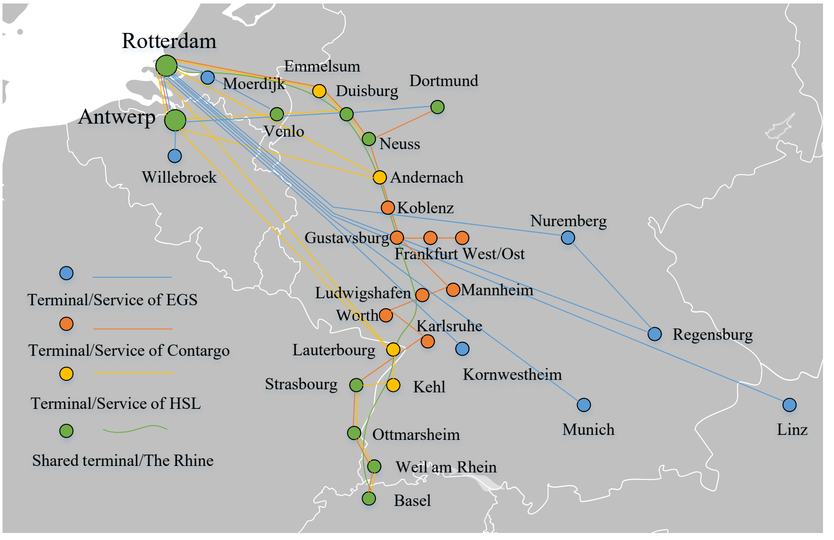


Figure 7.7: Transport networks of EGS, Contargo, and HSL.

The origins and destinations of requests are distributed randomly among deep-sea terminals and inland terminals, respectively. The container volumes of requests are drawn independently from a uniform distribution with range [10, 30] (unit: TEU). According to services of EGS/Contargo/HSL, the earliest pickup time $a_{p(r)}$ of requests is drawn independently from a uniform distribution with range [1, 120]/[1, 140]/[1, 140]; the latest delivery time $b_{d(r)} = a_{p(r)} + LD_r$, where LD_r is the lead time and it is independently and identically distributed among 24, 48, 72 (unit: hours) with probabilities 0.15, 0.6, 0.25. Moreover, to define pickup and delivery time windows, we set $b_{p(r)}$ and $a_{d(r)}$ equal to $b_{d(r)}$ and $a_{p(r)}$, respectively. Parameters for vehicles are taken from the literature and shown in Table 7.2. In the objective function (7.14), the transport cost is a linear function of the travel time τ_{ij}^k and distance d_{ij}^k. We use different unit costs c_k^1 and $c_k^{1'}$ for τ_{ij}^k and d_{ij}^k, which makes it possible to handle differences in the speed of vehicles. For trucks and trains, as reported in Li et al. (2015b), we set $c_{\text{truck}}^1/c_{\text{truck}}^{1'}$ as 30.98 euro/(TEU·h)/0.2758 euro/(TEU·km) and 7.54 euro/(TEU·h)/0.0635 euro/(TEU·km). According to the used type of barges and the database of an inland shipping community (Association of the inland shipping 2010), the parameters of the Large Rhine Vessel (Va class) are used. Considering the labor, capital, maintenance, total sailing hours in a year, and occupancy rate, the time-related cost for barges c_{barge}^1 is set as 0.6122 euro/(TEU·h). Based on the fuel consumption, the distance-related cost unit $c_{\text{barge}}^{1'}$ is set as 0.0213 euro/(TEU·km). According to Sun and Lang (2015b), the loading/unloading costs c_k^2 for trucks, trains, and barges are set as 3, 18, and 18 euro/(TEU·h). The CO_2e is converted into carbon tax using a price c_k^4 of 8 euro per ton, based on the price of the EU emission allowance (Van Riessen et al. 2015b). As reported in Guo et al. (2020) and Zhang et al. (2022b), the vehicle can wait for containers with a waiting fee, and containers can be stored in the terminal with a storage fee. We use the same storage and waiting unit costs c_k^3 and c_k^5 of 1 euro/(TEU·h).

We generate six instances for each carrier with 5, 10, 20, 30, 50, and 100 requests, re-

Table 7.2: Vehicle parameters used in this chapter (Guo et al. 2020, Li et al. 2015b, Van Riessen et al. 2015b).

parameter	value	parameter	value	parameter	value
c^1_{truck}	30.98	c^1_{train}	7.54	c^1_{barge}	0.6122
$c^{1'}_{\text{truck}}$	0.2758	$c^{1'}_{\text{train}}$	0.0635	$c^{1'}_{\text{barge}}$	0.0213
c^2_{truck}	3	c^2_{train}	18	c^2_{barge}	18
c^3_k	1	c^4_k	8	c^5_k	1

spectively. Each instance contains three sub-instances with homogeneous preferences, i.e., all shippers prefer the same eco-label (A, B, or C), and one sub-instance with heterogeneous preferences (labeled as H), i.e., shippers have different preferred eco-labels. Under heterogeneous preferences, the eco-label for each request is obtained randomly from a uniform distribution over eco-labels A, B, and C.

We consider two scenarios of collaborative planning. Scenario 1 is the collaboration among unimodal transport carriers and each carrier operates one of three modes (inland waterway, railway, and road). Scenario 2 is the collaboration among synchromodal transport carriers and each carrier offers services in all three modes. In scenario 1, services of unimodal transport carriers are based on the transport network of EGS with varying total numbers of requests [5, 10, 20, 30, 50, 100] across instances. In scenario 2, the synchromodal transport carriers are EGS, Contargo, and HSL and the total numbers of requests are [15, 30, 60, 90, 150, 300]. To ensure the accuracy of experimental results, all experiments are repeated five times and the results are averaged.

7.5.1 Results analysis

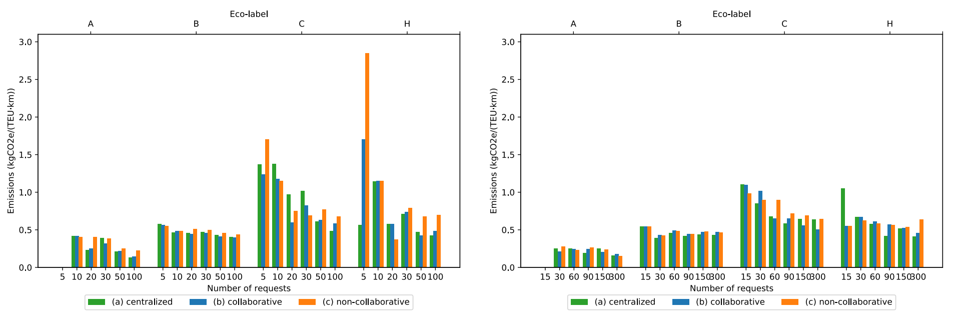
Table 7.3 shows the average computation time of instances with different numbers of requests under centralized, collaborative, and non-collaborative approaches with preferences (a, b, c) and without (a∗, b∗, c∗) preferences. The computation time in scenario 2 is shorter than the computation time in scenario 1 because scenario 2 has more requests, more vehicles, and a larger transport network. Due to the communication time used in collaboration, approach (b)/(b∗) needs more computation time than approach (a)/(a∗) in most cases. On some exceptionally large instances, such as the instance with 300 requests in scenario 2, approach (b)/(b∗) uses less computation time than approach (a)/(a∗), because the collaborative approach (b)/(b∗) saves computation time by parallel computation which compensates the communication time. The computation time with preferences is usually larger since it is harder to find feasible solutions when preferences are incorporated. In most cases, the computation time is less than 2h even in large instances.

Figure 7.8 shows the resulting emissions across different approaches, scenarios and eco-label settings. Under eco-label A, no requests are served in the instances with 5/15 requests because the sustainability requirement is high and load factors of sustainable vehicles are still too low to reach the requirement. For the instances with more requests, the average unit emissions for eco-label A, B, C, and H under scenario 1/2 are 0.29/0.24, 0.47/0.47, 0.92/0.84, 0.86/0.62 $kgCO_2e/(TEU\cdot km)$, respectively. The corresponding solutions meet the requested eco-labels and it is observed that higher requirements on eco-labels indeed

Table 7.3: Computation time (s).

	Scenario 1						Scenario 2					
Approach	5	10	20	30	50	100	15	30	60	90	150	300
a	2.3	13.6	52.4	135.5	434.8	3041.1	36.0	534.1	1824.8	3976.5	6145.3	34646.2
a∗	0.7	3.3	12.3	14.3	92.2	604.1	17.7	119.8	2299.0	4247.0	7065.0	22697.7
b	284.4	399.7	906.6	1767.5	2467.2	7667.3	801.5	1192.3	3129.9	4467.0	12309.3	13282.7
b∗	178.4	172.8	324.4	513.3	711.5	1544.7	182.4	184.6	276.6	495.3	603.3	2225.8
c	0.3	0.9	1.9	3.1	27.7	92.2	4.5	55.2	162.4	505.7	1897.0	5385.4
c∗	0.2	0.6	1.4	1.7	31.9	68.2	3.4	3.4	23.4	364.9	1004.7	3188.4

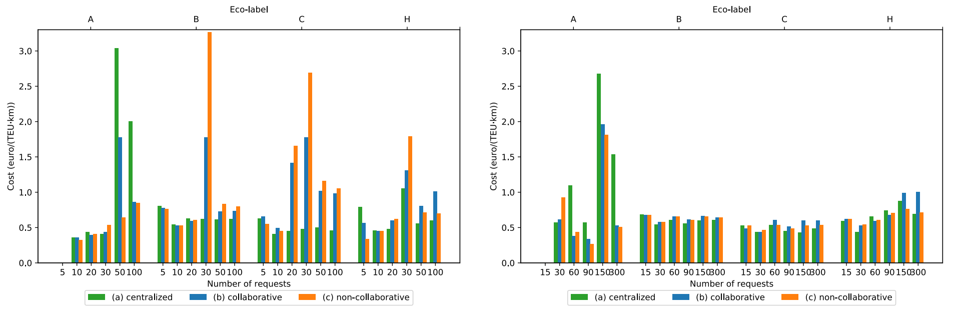
lead to lower average emissions. The emissions under eco-label A are reduced by around 70% compared with eco-label C. Under eco-label C, more requests lead to lower emissions due to the high load factor of vehicles, but they still cannot reach the same level as eco-labels B and A. Scenario 2 has a better performance compared with scenario 1 under the same eco-label due to the additional services.



(a) Scenario 1 (unimodal carriers) (b) Scenario 2 (synchromodal carriers)

Figure 7.8: Emissions comparison across approaches and eco-labels.

Figure 7.9 shows a cost comparison across approaches and eco-labels. We compare solutions based on cost per TEU·km rather than total cost as the number of served requests may differ in the solutions, which means that their total cost cannot be compared suitably with each other. In scenario 1, the average unit costs under eco-labels A, B, C, and H (heterogeneous preferences) are 0.85, 0.88, 0.93, and 0.74 euro/(TEU·km), respectively. In scenario 2, these average unit costs are 0.95, 0.62, 0.51, and 0.69 euro/(TEU·km), respectively. From eco-labels A to C, the emissions restriction decreases, while costs under scenario 1 increase. Scenario 2 shows the opposite trend. The truck carrier will keep requests when sustainability requirements are low, and requests will only be shared with train and barge unimodal carriers under high sustainability requirements. Therefore, for unimodal carriers under scenario 1, higher eco-labels could decrease costs because more low-cost vehicles are used due to emissions constraints. However, for synchromodal carriers with all three modes, costs will be minimized and barges will be used as much as possible when they do not consider sustainability preferences, therefore cost under eco-label C is the lowest. When sustainability requirements are high, more requests will be served by trains, which are more expensive than barges, hence costs increase. In some cases, the cost under the centralized approach is higher than the collaborative approach because the served requests are different under these two approaches, and the transshipment and storage costs vary for different requests. In some other cases, the collaborative approach has higher costs which happen more in scenario 1. The reason behind this is that truck carriers in scenario 1 serve requests by themselves with a high cost when the eco-label requirement is not high, such as the instance with 30 requests under eco-label B and instances with 20, 30, 50, and 100 requests under eco-label C. Therefore, unimodal carriers, especially truck carriers, need to share more requests in collaborative planning to reduce the overall cost and achieve a similar performance as centralized planning.

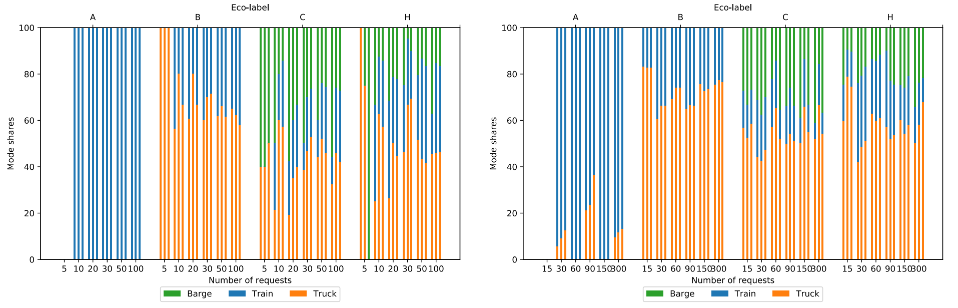


(a) Scenario 1 (unimodal carriers) (b) Scenario 2 (synchromodal carriers)

Figure 7.9: Costs comparison across approaches and eco-labels.

Figure 7.10 shows the share of transport modes under both scenarios. Under eco-label A, trains dominate, especially in scenario 1, because using unimodal truck transport cannot reach the requirement of eco-label A and barges are sustainable only when the load factor is high. Under eco-label B, trucks serve more requests than trains and the reason behind is different for scenarios 1 and 2. In scenario 1, emissions of trucks with full truckload reach the requirement of eco-label B, hence part of the requests are served by trucks from which the load factors of trains become low. Then, trains are used less due to higher emissions than trucks. In scenario 2, trucks can not only transport containers by unimodal transport but also be combined with trains in synchromodal transport to reach a lower cost. Therefore, the share of trucks is also higher than trains in scenario 2 under eco-label B. Under eco-labels C and H, more barges are used to serve requests because barges are sustainable and have a lower cost when the load factor is high. Furthermore, Figure 7.11 shows the proportions of served requests by carriers in scenario 2. Compared with HSL, EGS, and Contargo serve more requests under eco-label A, because they operate more trains than HSL. Under eco-labels B, C, and H, the proportions are similar.

Figure 7.12 shows proportions of served requests, requests that satisfy fuzzy constraints, and requests that satisfy hard constraints under approaches with environmental preferences (a, b, c) and without preferences (a$*$, b$*$, c$*$). For the results without preferences, the eco-labels are ignored, i.e., Constraints (7.15) are not considered. The higher the sustainability requirement is, the less the proportion of served requests is. Almost all requests can be served when sustainability preferences are not considered. The proportion of requests that satisfy fuzzy or hard constraints is in most cases higher when considering preferences compared to the approaches that ignore preferences. In some others, e.g., in scenario 2 under eco-label A, more requests satisfy fuzzy or hard constraints when preferences are



(a) Scenario 1 (unimodal carriers)

(b) Scenario 2 (synchromodal carriers)

Figure 7.10: Mode share comparison across approaches and eco-labels. There are three bars (left, middle, and right) for each instance, which represent mode shares under approaches (a), (b) and (c), respectively.

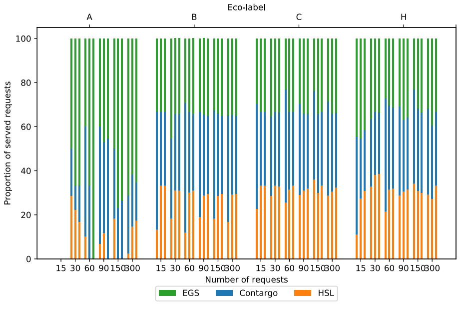
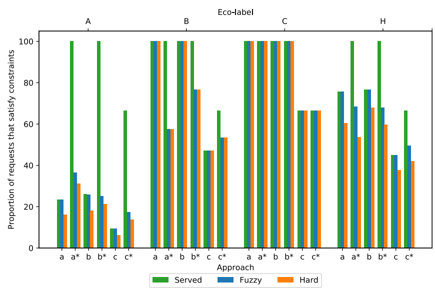


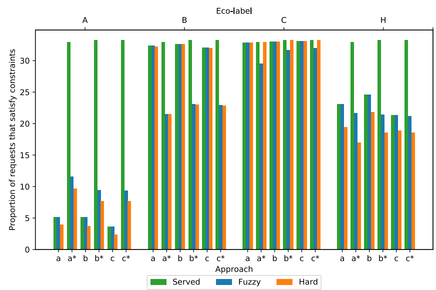
Figure 7.11: Proportions of served requests by carriers in scenario 2. There are three bars (left, middle, and right) for each instance, which represent mode shares under approaches (a), (b), and (c), respectively.

not considered because more requests are served and load factors of sustainable vehicles are high. However, this relies on the sacrifice of requests that have high emissions. Using fuzzy constraints, the number of served requests is increased by an average of 10% compared with using hard constraints since the fuzzy constraints give the model flexibility to find a more suitable solution. For unimodal carriers (scenario 1), centralized and collaborative approaches increase the number of served requests significantly compared with non-collaboration, because unimodal carriers need the services of others to satisfy emission preferences, especially under high sustainability requirements. Compared with the non-collaborative approach, the proportion in the collaborative approach is increased by an average of 65%, 53%, 33%, and 41% under eco-labels A, B, C, and H, respectively. For synchromodal carriers (scenario 2), such an increase is not significant under eco-labels B, C, and H, because carriers own enough services. However, the increase is still significant under eco-label A (29%). In both scenarios, the proportions of served requests of centralized and collaborative approaches are similar.

Figure 7.13 shows satisfaction values S_r across approaches with and without respecting preferences, i.e. with and without Constraint (7.15) for the satisfaction benchmark. As expected, considering preferences in the planning improves satisfaction significantly, especially under eco-label A. However, under eco-label C, satisfaction is slightly better when preferences are ignored since more requests can be served, which increases the load factors and in turn reduces the emissions. In Figures 7.13(b) and (d), the satisfaction under eco-label B is lower than under eco-label A because more trucks are used due to reasons mentioned in the analyses of Figure 7.10.

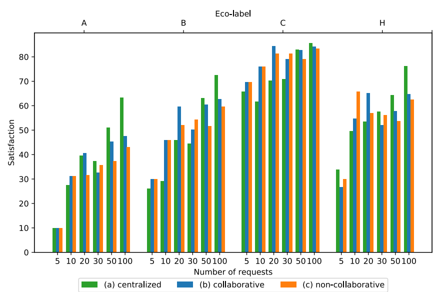


(a) Scenario 1 (unimodal carriers)

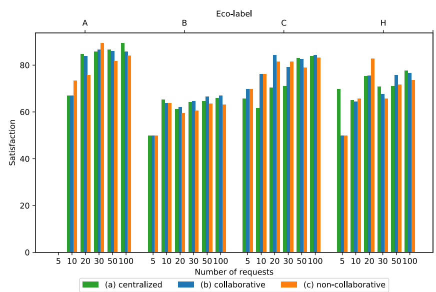


(b) Scenario 2 (synchromodal carriers)

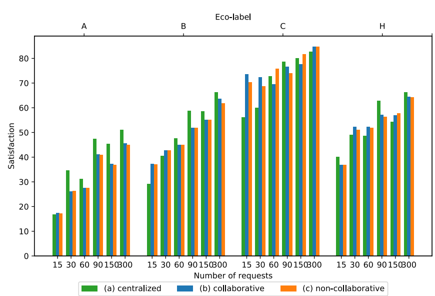
Figure 7.12: Proportions of served requests and requests that meet fuzzy/hard constraints.



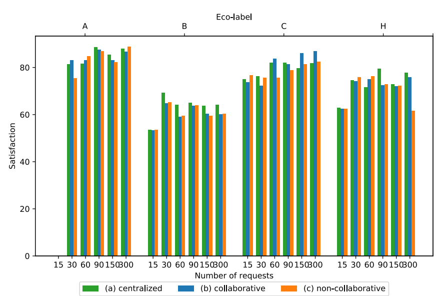
(a) Unimodal carriers without preferences



(b) Unimodal carriers with preferences



(c) Synchromodal carriers without preferences



(d) Synchromodal carriers with preferences

Figure 7.13: Satisfaction S_r comparison across approaches with and without preferences.

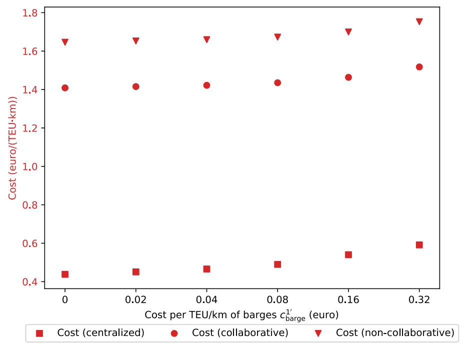
7.5.2 Sensitivity analysis and convergence of the ALNS

Due to the different infrastructure in terminals and types of vehicles, the costs may be different. Advances in technology may also change the structure of the costs across different modes. Therefore, a sensitivity analysis is needed for the parameters presented in Table 7.2 to evaluate the influence of potential changes on the benefit of our proposed approach. We conduct sensitivity analysis comparing centralized, collaborative, and non-collaborative approaches to check whether the obtained insights still hold when the parameter values vary. The costs per km may be different for vehicles with different loads and types and the carbon tax may differ in different countries/regions, therefore distance cost $c^{1'}_{\text{barge}}$ and carbon tax c^4_k are interesting parameters to conduct the sensitivity analysis. The worst case of $c^{1'}_{\text{barge}}$ relates to the possibility of having a higher cost than the truck distance cost with a very low load on the barge. When it comes to c^4_k, according to (Yan et al. 2021), the carbon tax will increase to 80 euro per ton by 2030 and this could be higher to reach net zero emissions by 2050. Considering the best- and worst-case scenarios, we vary $c^{1'}_{\text{barge}}$ and c^4_k in [0, 0.32] and [0, 128], respectively. The results are displayed in Figure 7.14 and as expected, when $c^{1'}_{\text{barge}}$ or c^4_k increases, the costs under all approaches rise. However, the cost gaps between different approaches stay similar due to the nature of approaches. The centralized approach obtains the lowest cost and the collaborative approach has a better cost than the non-collaborative approach. The emission gaps of these approaches are similar in most cases, while they change in extreme cases, e.g., the carbon tax is 128 euro per ton, where all approaches have to reduce emissions as much as possible to minimize the total cost. The number of served requests does not change for all approaches. The centralized and collaborative approaches can serve all requests, while one-quarter of requests cannot be served in the non-collaborative approach. Therefore, the proposed model is robust and the obtained insights still hold under reasonable changes in parameters.

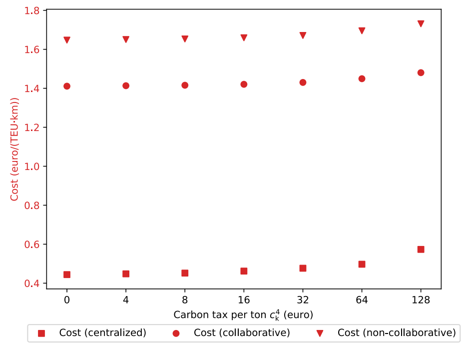
We use instances with different numbers of requests to illustrate the convergence of the ALNS heuristic. Figure 7.15 shows the costs and emissions of the best solution over 200 iterations. The cost could increase when there are more served requests and the cost is minimized when the number of served requests is stable. Figure 7.15 shows that ALNS clearly converges before terminating it on all instances. For small instances (R = 5, 10, and 20), ALNS converges rapidly in early iterations. For large instances (R = 30, 50, and 100), no better solutions are found in the final 90 iterations.

7.5.3 Results under different objectives and preferences

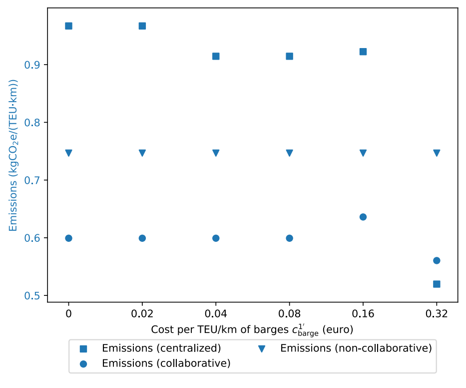
In practice, the transportation cost and time are important for shippers, and there are two methods to consider preferences on cost and time, i.e., (a) incorporate them as part of the objective function together with the number of served requests, (b) consider these preferences in a similar way as eco-labels.



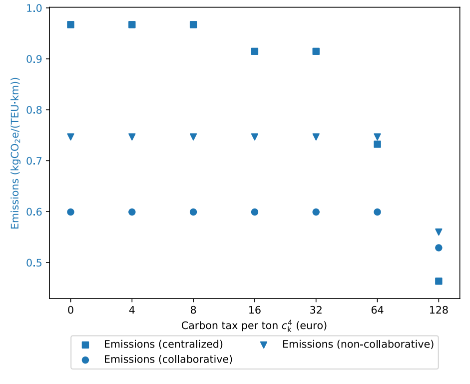
(a) Cost under varying $c^{1'}_{\text{barge}}$



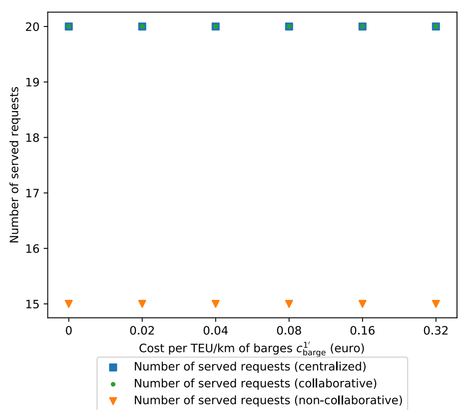
(b) Cost under varying c^4_k



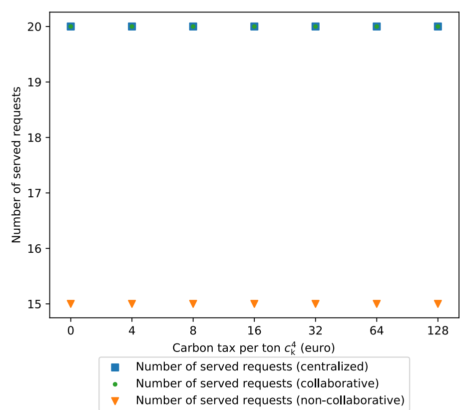
(c) Emissions under varying $c^{1'}_{\text{barge}}$



(d) Emissions under varying c^4_k



(e) Number of served requests under varying $c^{1'}_{\text{barge}}$



(f) Number of served requests under varying c^4_k

Figure 7.14: Sensitivity analysis on distance cost $c^{1'}_{barge}$ and carbon tax c^4_k under different approaches.

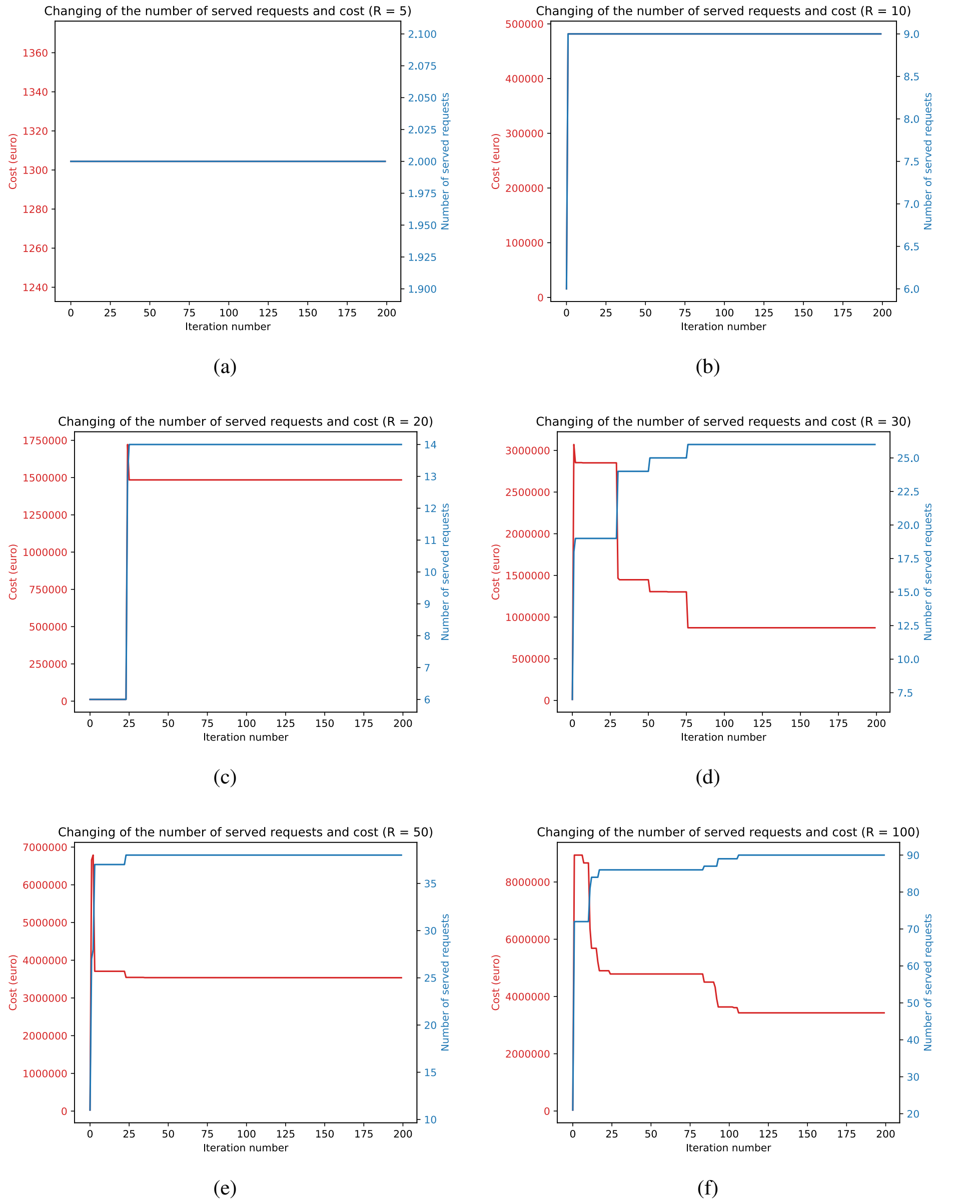


Figure 7.15: Convergence of ALNS on instances with preferences.

In method (a), we minimize F_3, which is the sum of the costs F_2 and the penalty for unserved requests:

$$\min F_3 = F_2 + \sum_{r \in R^c} g_r \lambda_r F^r_{\text{truck}}, \tag{7.16}$$

where g_r is a binary variable indicating whether request r is served or not and λ_r is a parameter that controls the size of the penalty for each unserved request r. The variable g_r respects the following constraints:

$$g_r \geqslant \sum_{(i,j)\in A^c} y_{ij}^{kr} \quad \forall k \in K^c,\ \forall r \in R^c, \tag{7.17}$$

$$g_r \in \{0,1\} \quad \forall r \in R^c. \tag{7.18}$$

When a request cannot be served by available vehicles, spot-market trucks can usually be used. Therefore, the penalty is calculated by F_{truck}^r, which is the cost of transporting request r using trucks:

$$F_{\text{truck}}^r = (c_{\text{truck}}^1 \tau_{p(r)d(r)}^{\text{truck}} + c_{\text{truck}}^{1'} d_{p(r)d(r)}^{\text{truck}})q_r + 2c_{\text{truck}}^2 q_r + c_{\text{truck}}^4 e_r^{\text{truck}}. \tag{7.19}$$

Figure 7.16 shows results for the instance with 30 requests. Similar insights are obtained from results of other instances and therefore not presented. The size of the penalty needs to be set according to the importance of requests. We vary it from 0 to 100 to evaluate the performance of method (a) in different scenarios. In the extreme case of $\lambda_r = 0$, serving requests is not important and the carrier only cares about minimizing cost F_2. The number of served requests is then significantly less than in other cases. Compared to using objectives F_1 and F_2 hierarchically as proposed in this chapter, minimizing F_3 could obtain solutions with lower unit cost or emissions by not serving requests with high cost/emissions in some scenarios, such as results when $\lambda_r = 0.5$, $\lambda_r = 1$, and $\lambda_r = 2$ in Figure 7.16(b). Nevertheless, in order to reach those results, one needs to tune the penalty term thoroughly for each instance with different numbers of requests, problem parameters, etc. When the penalty λ_r is large, i.e., $\lambda_r = 5$, $\lambda_r = 10$, and $\lambda_r = 100$, the number of served requests is the same as the proposed approach with similar costs and emissions. Except for the scenario in which $\lambda_r = 0$, these two ways of modeling the objective function have similar performance when eco-label preferences are ignored, because all requests can be served and the objective is essentially translated into the minimization of costs (F_2).

For method (b), the proposed model can be extended easily to consider cost-label and time-label. For the cost-label, the unit cost of shipping one TEU for request r is calculated by:

$$c'_r = F_2^r / (q_r \sum_{k\in K} \sum_{(i,j)\in A} d_{ij}^k y_{ij}^{kr}) \tag{7.20}$$

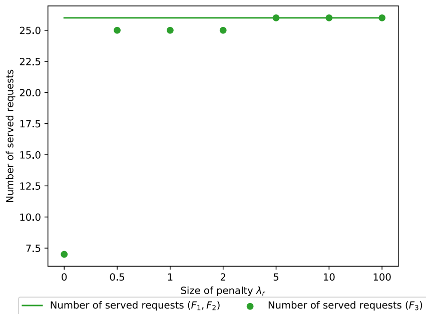
where F_2^r is the overall cost of request r and the calculation of F_2^r is similar to objective (7.14).

For the time-label, we use the ratio of actual time to expected time to evaluate how fast the transportation is, calculated by:

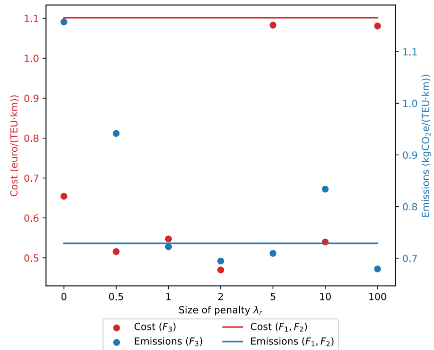
$$t'_r = t_r / (d_{p(r)d(r)}^{\text{average}} / v_{\text{average}}), \tag{7.21}$$

where $d_{p(r)d(r)}^{\text{average}} / v_{\text{average}}$ is the average travel distance/speed of all vehicles and t_r is the actual travel time:

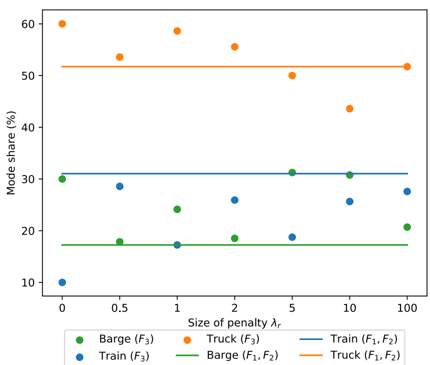
$$t_r = \max\{\bar{t}_i^{kr} y_{ij}^{kr} :\ \forall (i,j) \in A,\ \forall k \in K\} - \min\{t'^{kr}_i y_{ij}^{kr} :\ \forall (i,j) \in A,\ \forall k \in K\}. \tag{7.22}$$



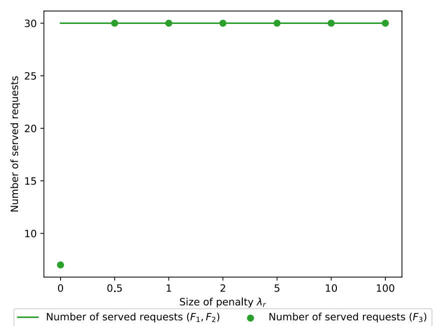
(a) Number of served requests under varying sizes of penalty (R = 30, considering preferences)



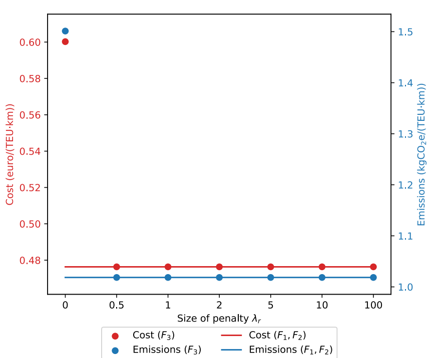
(b) Cost and emissions under varying sizes of penalty (R = 30, considering preferences)



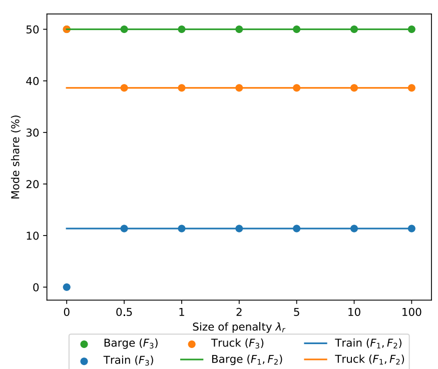
(c) Mode shares under varying sizes of penalty (R = 30, considering preferences)



(d) Number of served requests under varying sizes of penalty (R = 30, ignoring preferences)



(e) Cost and emissions under varying sizes of penalty (R = 30, ignoring preferences)



(f) Mode shares under varying sizes of penalty (R = 30, ignoring preferences)

Figure 7.16: Comparison of results with different objectives (R = 30)

The rates of cost-label/time-label A, B, and C are set as 0.6/0.8, 0.9/1.1, and 1.2/1.4, respectively. Then, we can adopt a similar method as in Section 7.4.1 to obtain the satisfaction value S_r and set constraints for S_r to ensure that the solutions are in line with cost or time preferences of shippers.

Table 7.4 shows the results under different preferences on the instance with 30 requests, where the related cost, time, or emission of the obtained solution is reduced according to the required labels. For example, when shippers prefer low-cost transport, the cost is the lowest and the mode shares of low-cost modes (barges and trains) are the largest compared with other solutions. Column T shows the frequency of using the objective function F_2, and it is used on average in 47% iterations out of 200 iterations when both objective functions F_1 and F_2 are considered. Therefore, F_2 plays an important role in the optimization and the model finds solutions with the same number of served requests frequently.

Table 7.4: Results under different preferences.

Objective	N	Cost	Time	Emissions	Barge	Train	Truck	S	T
low-cost transport (cost-label A)									
F_1, F_2	16	0.48	1.18	0.43	28.57	38.10	33.33	77	70
fast transport (time-label A)									
F_1, F_2	28	0.83	0.53	0.78	0.00	21.62	78.38	80	126
sustainable transport (eco-label A)									
F_1, F_2	18	0.52	1.33	0.44	20.00	44.00	36.00	78	85

N: number of served requests; Cost: average cost of shipping one TEU one km; Time: average time ratio; Emissions: average emissions per TEU per km; Barge/Train/Truck: mode share of used barges/trains/trucks; S: average satisfaction value; T: Times of using objective function F_2 in total 200 iterations.

7.6 Conclusions

In this chapter, we have proposed a collaborative planning model for carriers in synchromodal transport. It addresses the research question Q4: What types of collaborative planning should be adopted and what is their effect on the consideration of preferences? An auction mechanism is proposed for collaborative planning. Three approaches are compared using realistic transport networks and schedules. It opens up a way to route more shipments in accordance with their requested eco-label and, ultimately, to achieve a more sustainable overall transport solution. The eco-labels requested by shippers are considered in the optimization of carriers, and carriers exchange requests that cannot be served by themselves. The experimental results show that collaboration can lead to 48%/11% increases in proportions of served requests for unimodal/synchromodal carriers, and the highest/mixed eco-labels reduce 70%/15% emissions compared with ignoring preferences. Based on the experimental results, the following managerial insights are obtained: (a) Considering eco-label preferences reduces emissions significantly. (b) Compared with the scheme without eco-label preferences, considering eco-labels reduces the emissions at the expense of decreasing the number of served requests. (c) For collaboration among unimodal carriers, high eco-labels reduce more costs than schemes with low eco-labels or ignoring eco-labels because requests of the truck carrier will be served by train and barge carriers, who can provide both low-emissions and low-cost services. For collaboration among synchromodal carriers, satisfying high eco-labels requires more trains, and ignoring eco-labels increases barge use. Therefore, higher eco-labels cause more costs as using trains is more expensive than barges. (d) When minimizing the sum of costs and penalty of unserved requests, high-cost/-emissions requests cannot be served with a low penalty. Whereas, the solutions under high penalty are similar to those obtained with the proposed approach. (e) Compared with non-collaborative planning, collaborative planning supports both synchromodal and unimodal carriers to provide more sustainable services and serve more requests, especially under high eco-label requirements. (f) Compared with synchromodal carriers, unimodal carriers can benefit more from collaborative planning and need a higher degree of collaboration (i.e., sharing more requests) to reduce both emissions and costs. (g) Using fuzzy set theory gives carriers more room to find a more suitable solution and the number of served requests is increased compared with using hard constraints. Therefore, from the policy-making perspective to develop synchromodal transport, the policy makers can set incentives for collaborative planning and use eco-labels to achieve sustainable synchromodal transport. The proposed model provides a basis for further research analysis in policy making implications. Using the proposed model with transport networks to be analyzed, the policy maker can simulate scenarios with different carriers, different degrees of collaboration, and different levels of eco-labels to determine the degree of collaboration for each carrier and the needed eco-label to achieve emission reduction goals.

The proposed model has some limitations. To gain more profits, carriers may compete in the auction and have strategic behaviors in the bidding. The proposed model only assumes that carriers share unserved requests; it does not consider further competition among carriers. The methodology proposed in this study relies on eco-label preferences provided by each shipper. The preferences might not be easy to obtain in real life and even so shipper's stated preferences may differ from actual preferences. Therefore, the behavior of shippers needs to be observed and preferences can be learned from their behavior.

Chapter 8

Conclusions and future research

This thesis is dedicated to achieving synchromodal transport planning by filling gaps in current literature, including flexibility in static planning, handling service time uncertainty in real-time planning, preference-based planning, and horizontal collaborative planning. From static and centralized planning to dynamic and collaborative planning, this thesis proposes a series of approaches to improve the efficiency, reliability, sustainability, and attractiveness of synchromodal transport.

This last chapter concludes the thesis. The answers to research questions and managerial insights are summarized in Section 8.1. Subsequently, directions for future research are recommended in Section 8.2.

8.1 Conclusions

The main objective of this thesis is to answer the main research question:

How can flexible, real-time, and collaborative transport planning approaches be developed considering the heterogeneous and vague preferences of carriers and shippers?

This thesis answers the main research question by proposing a mathematical model and a heuristic algorithm for flexible synchromodal transport planning, developing a model-assisted Reinforcement Learning (RL) approach to handle service time uncertainty, introducing multi-objective optimization and multi-attribute decision making for capturing heterogeneous and vague preferences, and proposing a conceptual framework for horizontal collaborative planning. The proposed approaches and models are validated using real-world data and computational experiments. The results indicate the benefits of introducing flexibility, reliability, preference, and collaboration in synchromodal transport. This research has implications for shippers, freight forwarders, carriers, and policymakers in the logistics industry, as it provides practical and innovative solutions for more efficient, reliable, flexible, and sustainable transport operations.

8.1.1 Key research questions

Under the main research question, four subquestions were defined which are answered through Chapters 3, 4, 5, 6, and 7.

1. *Q1: How can routes be optimized for the carrier to provide flexible services?*

   In Chapter 3, a mixed-integer linear programming model was developed for synchromodal transport planning with flexible services. Both routing of shipments and vehicles are modeled, which allows flexible services depending on demand and specific situations. In order to solve the optimization problem efficiently, an Adaptive Large Neighborhood Search (ALNS) heuristic algorithm is adopted. The proposed model is compared to existing models in the literature using real transport networks. Case studies on small instances verified that the proposed model with flexibility performs better in all scenarios, including scenarios with different weights for the individual objectives and scenarios under congestion. On large instances (up to 1600 shipment requests), the proposed model with flexibility reduces the cost by 14% on average compared with the existing models in the literature.

2. *Q2: How can a real-time planning approach be developed for carriers to provide reliable services while taking into account uncertainties in service time?*

   In Chapter 4, an online model-assisted RL is proposed to handle the service time uncertainty. It learns from real-time information in a synchromodal transport replanning framework. The performance of the proposed planning approach is evaluated in the European Rhine-Alpine corridor under various scenarios with different types and severities of unexpected events. The results demonstrate that the RL approach consistently outperforms the other strategies by effectively handling service time uncertainty, leading to reduced costs, emissions, waiting time, and delays as well as improved rewards through accurate decision-making and agile transport replanning. For example, compared to the waiting strategy, the RL strategy reduces costs, delay, and waiting time by 44.0%, 60.1%, and 24.5% on the tested instances, respectively. This study also found that incorporating event severity information improves the average reward obtained by the RL approach in scenarios involving multiple types of events.

3. *Q3: How can heterogeneous and vague preferences of carriers and shippers be incorporated into the planning approach?*

   In Chapters 5 and 6, carriers' and shippers' preferences are incorporated into the transport planning, respectively.

   Carriers' preferences are considered in a multi-objective optimization model. The preferences of carriers are usually expressed as linguistic terms, hence weight intervals, i.e., minimum and maximum weights, are assigned to objectives to represent such vague preferences. A preference-based ALNS is used to obtain non-dominated solutions in the Pareto frontier. For instance, when a carrier prefers minimizing the time for transporting perishable goods, solutions that utilize faster vehicles are offered. The results show that the proposed approach provides non-dominated solutions which are in line with preferences. Moreover, the mode share under different preferences is analyzed, which signals that different sustainability policies in transportation will influence the mode share.

   Shippers' heterogeneous and vague preferences are modeled by multiple attribute decision-making approaches that integrate fuzzy set theory. The proposed model has an upper-level objective, i.e., maximizing the number of served requests, and a lower-level objective, i.e., minimizing the transportation cost. Shippers' preferences are set as constraints such that preferred levels for each attribute need to be respected. The case studies in the Rhine-Alpine corridor demonstrate that the proposed model can provide solutions that are more attractive to shippers compared with optimization which ignores preferences. Under various scenarios, the attributes, such as cost, time, emissions, reliability, and risk of damage, are analyzed and the (near) optimal modes and routes are suggested according to preferences. Moreover, the results show that the conflicts among attributes, conflicts among shippers, and conflicts between the freight forwarder and shippers are balanced by improving the benefit for one actor without compromising any other actor's preferences.

4. *Q4: What types of collaborative planning should be adopted and what is their effect on the consideration of preferences?*

   Chapter 7 establishes a collaborative planning model for synchromodal transport and uses eco-labels (a series of different levels of emission ranges) to reflect shippers' sustainability preferences. The fuzzy set theory is used to model the preferences towards eco-labels. For multiple carriers, an auction-based collaborative planning approach is proposed and compared with non-collaborative and centralized planning. Real data from barge, train, and truck carriers in the European Rhine-Alpine corridor is used for extensive experiments where both unimodal carrier collaboration and synchromodal carrier collaboration are analyzed. Compared with non-collaborative planning without eco-labels, the number of served requests increases and emissions decrease significantly in collaborative planning with eco-labels as transport capacity is better utilized. Collaboration between carriers leads to significant increases in served requests (up to 48% for synchromodal and 11% for unimodal). Considering eco-label preferences also leads to emissions reductions of up to 70% for the highest eco-label and 15% for mixed eco-labels. For example, when a truck carrier is unable to accommodate shippers with high eco-label requirements, the truck carrier can collaborate with a barge carrier to fulfill these requests. This results in higher utilization of capacity and additional emission reductions due to the barge carrier being able to transport the goods with a higher load factor.

8.1.2 Managerial insights

This thesis provides managerial insights for managers and policy-makers to improve operations in synchromodal transport in practice, as listed below:

1. Flexible services:

   (a) The utilization of service flexibility can bring about cost savings (14% on average for large instances) and increased competitiveness for transport operators.

   (b) Flexible services can facilitate modal shifts in synchromodal transport, reducing emissions and providing more alternatives.

   (c) In case of congestions, a higher level of flexibility can provide more options and alleviate the impacts.

    (d) Adjusting existing transport plans with predefined schedules is the best way to adopt flexible services.

2. Dynamic planning under service time uncertainty:
    (a) The efficient handling of service time uncertainty by RL leads to cost savings (44%), delay reduction (60.1%), and reduced waiting time (24.5%). RL strategy proves to be a superior approach compared to waiting and average duration strategies in handling unexpected events.
    (b) Incorporating knowledge of event severity into the decision-making process can further improve the performance of RL, although imperfect information is inevitable.
    (c) Adequate training time and computational resources are crucial for maximizing the performance of reinforcement learning. However, once the reinforcement learning model has matured, it can be deployed in real-time transport operations.
3. Preference-based planning:
    (a) By considering preferences, freight forwarders in synchromodal transport can improve their service quality and competitiveness by providing customized services.
    (b) Trucks benefit fast, reliable, and low-risk transport, while low-cost and sustainable transport requires more barges, and trains are preferred when considering conflicting attributes or preferences.
    (c) Freight forwarders strive to balance cost minimization with shipper satisfaction in transportation planning. The approach taken depends on the priority: cost or satisfaction. If cost reduction is the priority, the satisfaction objective method may result in lower costs, but also lower satisfaction for part of shippers. To prioritize shipper satisfaction, using constraints can guarantee a minimum service level for shippers, while using fuzzy constraints serves more shippers but the quality of services is lower compared to hard constraints.
    (d) Conflicts between the freight forwarder and shippers can be resolved by finding an optimal balance between cost efficiency and improved service quality. Conflicts between shippers' heterogeneous preferences can be balanced by allocating appropriate services to specific requests without negatively impacting other shippers' preferences.
4. Collaborative planning:
    (a) Considering eco-label preferences leads to significant emissions reduction. The highest eco-label can lead to a reduction of up to 70%, while mixed eco-labels can contribute to a reduction of 15%. However, this comes at the cost of a reduced number of served requests.
    (b) Collaborative planning among carriers results in more sustainable services and an increased number of served requests (up to 48% for synchromodal carriers and 11% for unimodal carriers), especially under high eco-label requirements.

(c) Policy-makers can use incentives for collaboration and eco-labels to achieve sustainable transport goals.

(d) Unimodal carriers benefit more from collaborative planning but require a higher degree of collaboration compared to synchromodal carriers.

8.1.3 Limitations

This thesis has the following limitations:

1. In the static planning approach, this thesis focuses on transport operators and shippers. However, it does not explicitly consider terminal operators, who also have influence over routing and scheduling. The open time windows of terminals are considered, but in reality, the terminal operators may play a more significant role in transport planning. For example, flexible services need the collaboration of terminal operators.

2. The proposed dynamic planning approach in this thesis is reactive in nature, meaning that re-planning actions are triggered in response to unexpected events in the transport network. While combining predictive and reactive strategies can effectively address dynamic transportation planning under uncertainty, this thesis does not consider such integration.

3. We assume eco-label preferences are provided by each shipper. The preferences might not be easy to obtain in real life and shippers' stated preferences may differ from actual preferences. Therefore, the behavior of shippers needs to be observed and preferences can be learned from their behavior.

4. This thesis focuses on collaborative planning among carriers that exchange requests, known as horizontal collaboration. However, it does not consider collaboration among carriers that serve the same requests in different sections of the transport chain, which is referred to as vertical collaboration.

5. To gain more profits, carriers may compete in the auction and have strategic behaviors in the bidding. The proposed collaboration approach considers that carriers share unserved requests, without taking into account additional competition among carriers.

8.2 Future research directions

With respect to the proposed methodological framework and its applications addressed in this thesis, challenging issues that require future research are:

1. Developing a multi-agent system that considers the preferences and objectives of multiple stakeholders (Rădulescu et al. 2020), including government agencies, freight forwarders, carriers, and shippers. These stakeholders may have both cooperative and competitive relationships, and game theory (Owen 2013) could be used to model and analyze these interactions. Such a system could provide a more comprehensive view of the synchromodal transport ecosystem, and could help to identify more efficient and sustainable solutions that take into account the needs and preferences of all involved parties.

2. Investigating ways to more accurately capture and incorporate the preferences of shippers in the planning process. Currently, many approaches rely on either stated preferences, which are explicit declarations of preference made by the shipper, or revealed preferences, which are inferred from historical data on the shipper's past transport decisions. However, both of these methods have limitations and may not accurately reflect the shipper's true preferences in real time. A promising avenue for future research would be to explore ways to incorporate real-time data on the shipper's transport decisions into the planning process, potentially through the use of machine learning techniques (Fürnkranz and Hüllermeier 2010), in order to more accurately reflect the shipper's evolving preferences and make more informed transport planning decisions.

3. Integrating big data or data-driven technology with synchromodal transport planning (Barua et al. 2020). There are the following sub-research directions: (a) Predictive modeling for demand forecasting: Using large data sets collected from various sources (e.g., GPS tracking, social media, and e-commerce platforms), machine learning algorithms can be utilized to build predictive models for demand forecasting and allocate resources accordingly. (b) Real-time monitoring and optimization: The integration of real-time data from devices and sensors can be used to monitor the performance of the transport network in real-time. (c) Network analysis and visualization: Big data analytics tools can be utilized to visualize and analyze the transport network, providing insights into the flow of goods, bottlenecks, and potential inefficiencies. (d) Dynamic pricing and pricing optimization: With the help of big data, dynamic pricing algorithms can be used to set the optimal prices for different services offered by the transport network, taking into account real-time demand, costs, and other relevant factors.

4. Designing the profit-sharing mechanism in collaborative planning. The profit margins resulting from collaboration need to be fairly shared among carriers (Dai and Chen 2012b). Determining a fair allocation mechanism will attract more carriers to join such a collaboration.

In addition to these topics, more general, fundamental future research directions are:

1. Examining the impact of different regulatory and policy frameworks on the ability to achieve synchromodal transport planning.

2. Examining the impacts of external factors, such as market conditions, regulations, and societal values, on synchromodal transport planning.

3. Investigating the role of new technologies, such as autonomous vehicles or blockchain, in enabling more efficient and collaborative synchromodal transport.

4. Investigating the role of human behavior and cognition in preference formation and decision-making in synchromodal transport planning. This could involve studying how individuals and groups perceive and evaluate different transport options, and how these perceptions and evaluations change over time.

Appendix A

Performance improvements for mathematical model and ALNS

A.1 Valid inequalities for mathematical model

The valid inequalities are divided into three categories and the reduced variables are indicated in brackets.

1. Valid inequalities related to requests (y_{ij}^{kr}):

   (a) Terminal i or j cannot be dummy depot.

$$y_{ij}^{kr} = 0 \quad \forall k \in K,\ \forall r \in R,\ \forall i \in \overline{O},\ \forall j \in N \tag{A.1}$$

$$y_{ij}^{kr} = 0 \quad \forall k \in K,\ \forall r \in R,\ \forall i \in N,\ \forall j \in \overline{O} \tag{A.2}$$

   (b) $K_{\text{small}}^{r} \subseteq K$ represents set of vehicles with a capacity that cannot accommodate request r, i.e., violate capacity constraints (3.15).

$$y_{ij}^{kr} = 0 \quad \forall k \in K_{\text{small}}^{r},\ \forall r \in R,\ \forall (i,j) \in A \tag{A.3}$$

   (c) $K_{\text{early}}^{r} \subseteq K_{\text{fix}}$ represents set of fixed vehicles whose latest departure time b_i^k is earlier than request r's earliest pickup time $a_{p(r)}$, i.e., violate Constraints (3.36).

$$y_{ij}^{kr} = 0 \quad \forall k \in K_{\text{early}}^{r},\ \forall r \in R,\ \forall (i,j) \in A \tag{A.4}$$

   (d) $K_{\text{late}}^{r} \subseteq K$ represents set of vehicles whose earliest departure time at pickup terminal, i.e., the time from begin depot to pickup terminal plus loading time, later than request r's latest pickup time $b_{p(r)}$. K_{late}^{r} will be removed due to Constraints (3.36).

$$y_{ij}^{kr} = 0 \quad \forall k \in K_{\text{late}}^{r},\ \forall r \in R,\ \forall (i,j) \in A \tag{A.5}$$

2. Valid inequalities related to vehicles (x_{ij}^{k}):

   (a) A vehicle $k \in K$ cannot go to other vehicles' dummy depots.

$$x_{ij}^{k} = 0 \quad \forall k \in K,\ \forall i \in \overline{O} \setminus \overline{o}(k), \forall j \in N \tag{A.6}$$
$$x_{ij}^{k} = 0 \quad \forall k \in K,\ \forall i \in N, \forall j \in \overline{O} \setminus \overline{o'}(k) \tag{A.7}$$

   (b) If there is a dummy depot in x_{ij}^{k}, it must be together with a depot.

$$x_{\overline{o}(k)j}^{k} = 0 \quad \forall k \in K,\ \forall j \in N \setminus o(k) \tag{A.8}$$
$$x_{i\overline{o'}(k)}^{k} = 0 \quad \forall k \in K,\ \forall i \in N \setminus o'(k) \tag{A.9}$$

   (c) Begin depot cannot be j when i is not dummy begin depot; end depot cannot be i when j is not dummy end depot.

$$x_{io(k)}^{k} = 0 \quad \forall k \in K,\ \forall i \in N \setminus \overline{o}(k) \tag{A.10}$$
$$x_{o'(k)j}^{k} = 0 \quad \forall k \in K,\ \forall j \in N \setminus \overline{o'}(k) \tag{A.11}$$

   (d) Dummy begin depot cannot be j in x_{ij}^{k}; dummy end depot cannot be i in x_{ij}^{k}.

$$x_{i\overline{o}(k)}^{k} = 0 \quad \forall k \in K,\ \forall i \in N \tag{A.12}$$
$$x_{\overline{o'}(k)j}^{k} = 0 \quad \forall k \in K,\ \forall j \in N \tag{A.13}$$

   (e) Remove x_{ij}^{k} when there is no compatible y_{ij}^{kr}.

$$x_{ij}^{k} \leqslant \sum_{r \in R} y_{ij}^{kr} \quad \forall k \in K,\ \forall (i,j) \in A \tag{A.14}$$

3. Valid inequalities related to transshipment (s_{ir}^{kl}):

   (a) A transshipment only happens when request r can be transported by both vehicles k and l at transshipment terminal i.

$$s_{ir}^{kl} \leqslant \sum_{j \in N} y_{ji}^{kr} \quad \forall r \in R,\ \forall i \in T,\ \forall k,l \in K \tag{A.15}$$
$$s_{ir}^{kl} \leqslant \sum_{j \in N} y_{ij}^{lr} \quad \forall r \in R,\ \forall i \in T,\ \forall k,l \in K \tag{A.16}$$

   (b) Request r's pickup/delivery terminal cannot be transshipment terminal i.

$$s_{p(r)r}^{kl} = 0 \quad \forall r \in R,\ \forall k,l \in K \tag{A.17}$$
$$s_{d(r)r}^{kl} = 0 \quad \forall r \in R,\ \forall k,l \in K \tag{A.18}$$

   (c) For a fixed vehicle k, the terminals in the predefined route should contain transshipment terminal i when k is used to transfer a request. K_{noT}^{r} represents set in which vehicles cannot meet the mentioned requirements.

$$s_{ir}^{kl} = 0 \quad \forall r \in R,\ \forall k \in K_{\text{noT}}^{r},\ \forall l \in K,\ \forall i \in T \tag{A.19}$$

$$s_{ir}^{kl} = 0 \quad \forall r \in R,\ \forall k \in K,\ \forall l \in K_{\text{noT}}^{r},\ \forall i \in T \tag{A.20}$$

(d) When request r is transferred from vehicle k to vehicle l trough transshipment terminal i, vehicle k's begin depot and l's end depot cannot be i.

$$s_{o(k)r}^{kl} = 0 \quad \forall r \in R,\ \forall k,l \in K \tag{A.21}$$

$$s_{o'(l)r}^{kl} = 0 \quad \forall r \in R,\ \forall k,l \in K \tag{A.22}$$

(e) When request r is transferred from vehicles k to vehicle l trough transshipment terminal i and both vehicles k and l have fixed time schedules, l's departure time cannot be earlier than k's arrival time at i. K_{earlyT} represents set in which vehicle combinations violate this rule.

$$s_{ir}^{kl} = 0 \quad \forall r \in R,\ \forall (k,l) \in K_{\text{earlyT}}^{i},\ \forall i \in T \tag{A.23}$$

Moreover, the other variables, such as z_{ij}^{k} and t_{i}^{kr}, are reduced when there is no compatible variables x_{ij}^{k}, y_{ij}^{kr}, or s_{ir}^{kl}.

A.2 Feasibility checking on time constraints

Before calculating times, the vehicle's start time needs to be defined. If the vehicle is a fixed vehicle and not a truck, its start time at begin depot is $a_{o(k)}^{k}$. Otherwise, there are two situations: (a) if $o(k)$ is pickup terminal p_{r_1}, assign $a_{p(r_1)}$ to $t_{o(k)}^{k}$; (b) if $o(k)$ is transshipment terminal T_{r_1} of the first served request, assign delivery time at transshipment terminal $Td_{o(k)}^{r_1}$ to $t_{o(k)}^{k}$. If it does not belong to any above situations, the vehicle will start from begin depot at time 0.

Flow Chart A.1 shows the flexibility check for the barge (or train) k when it is at terminal j. The different situations of fixed/flexible vehicles and transshipments are also distinguished. Flow Chart A.2 shows how to assign time to the truck fleet. *useT* means the request is transferred before and Tp_{i}^{r} means request r's pickup time at transshipment terminal i. There are no waiting times and infeasible situations when using trucks because trucks can serve requests immediately and delay is allowed.

A.3 Performance improvements for ALNS

Although the ALNS is a powerful heuristic, it is still hard to solve the proposed problem efficiently in real-life instances due to the complexity brought by characteristics mentioned in Section 3.3. Therefore, several methods are used to improve the performance of ALNS, in which preprocessing heuristics are used to reduce the solution space before the optimization and both hash table and bundle insertion are used to speed up the search process during the optimization.

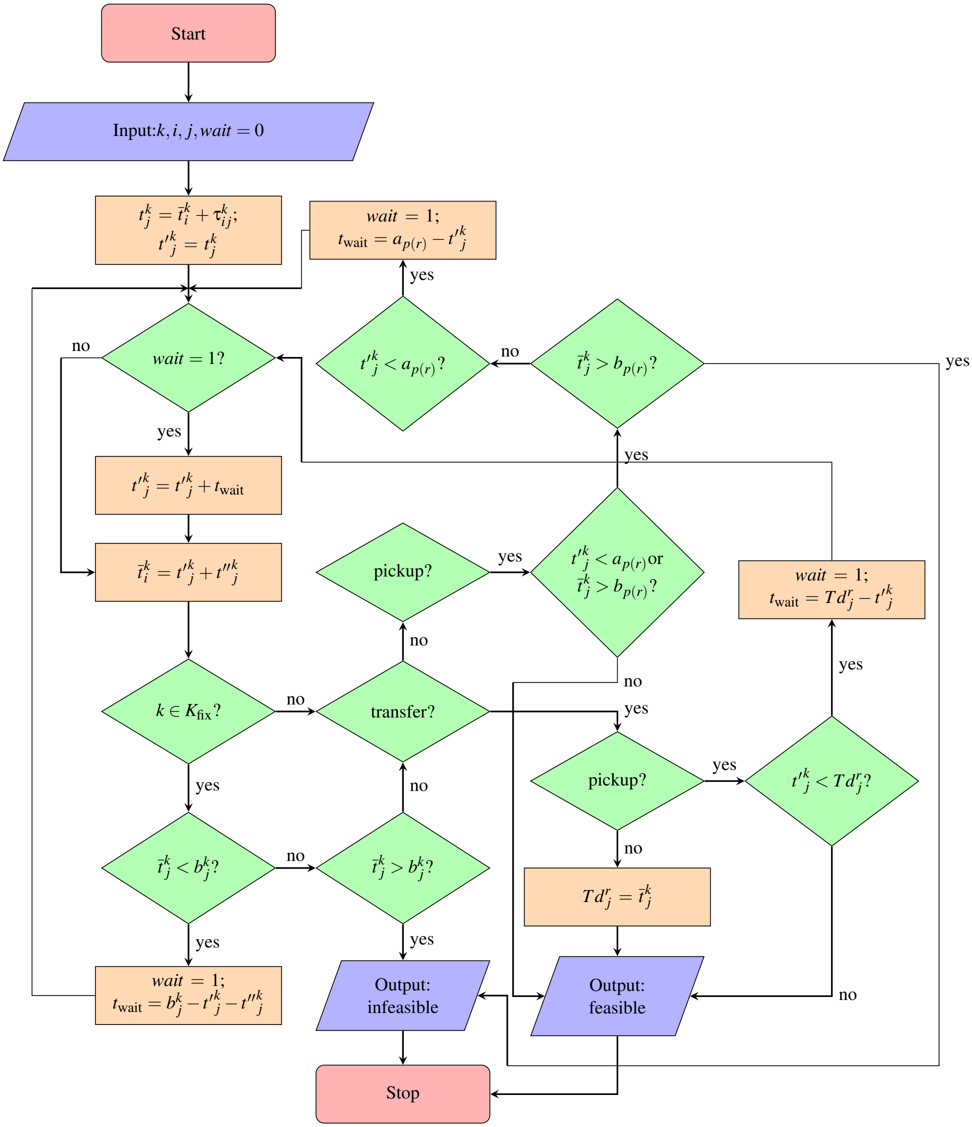


Figure A.1: Barge and train's time at pickup/delivery/transshipment terminal in ALNS

A.3.1 Preprocessing heuristics

Similar to the valid inequalities in Appendix A.1, we designed some preprocessing heuristics to reduce the solution space of ALNS. Some new sets are used in ALNS. K_r^{nk} represents vehicle combinations that can serve the same request r. The K_r^{1k} is the set of vehicles that can serve request r by itself. K_r^p represents vehicles that can pick up request r. K_r^i $(i \in T)$ represents vehicles that serve request r with specific transshipment terminal i. In ALNS, these sets are used when the related type of vehicle is needed to serve requests. The

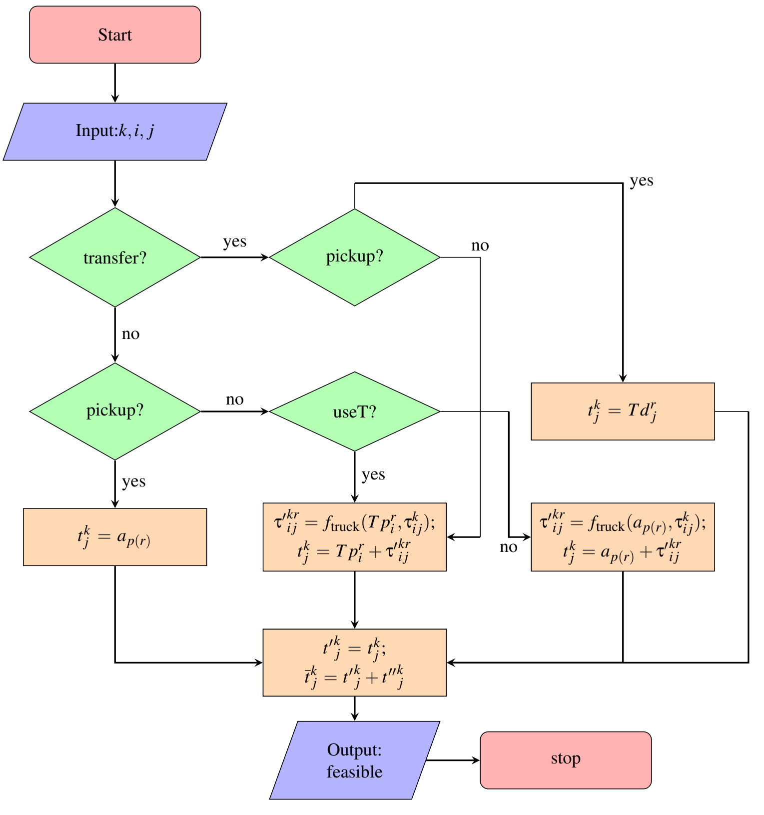


Figure A.2: Truck's time at pickup/delivery/transshipment terminal in ALNS

preprocessing heuristics are divided into two categories and the reduced sets in ALNS are indicated in brackets. The reference to valid inequalities in Appendix A.1 will be given if the meaning of the preprocessing heuristic is as same as the valid inequalities.

1. Preprocessing heuristics related to requests (K_r^{1k}, K_r^{nk} and K_r^p):

   (a) k in Appendix A.1 1b, 1c, and 1d will be removed from related K_r^{1k}, K_r^{nk}, and K_r^p.

   (b) For $k \in K_{\text{fix}} \cap K_r^{1k} \cap K_r^p$, its route should contain arc $(p(r), d(r))$. For $k \in K_{\text{fix}} \cap K_r^{nk} \cap K_r^p$, its route should contain $p(r)/d(r)$ if it is used to pick up/deliver r. Moreover, when two fixed vehicles serve the same request r in succession, their routes should contain the same transshipment terminal. Vehicles that violate the above rules will be removed from related K_r^{1k}, K_r^{nk}, and K_r^p.

2. Preprocessing heuristics related to transshipment (K_r^i):

   (a) k in Appendix A.1 3b, 3c, 3d, and 3e will be removed from K_r^i.

   (b) Vehicles that use transshipment terminal i will be removed from K_r^i when using terminal i increases too much distance, i.e., $d^k_{p(r)i} + d^k_{id(r)} > \varphi d^k_{p(r)d(r)}$, where φ

is a coefficient set according to the specific transportation network. As shown in Figure A.3 (a), three transshipment terminals are considered for request 1, and vehicles that use transshipment terminal C will be removed from K_r^i. However, vehicles that use transshipment terminal C will be added to K_r^i during the optimization of ALNS if the vehicle goes to nearby terminals, which is illustrated in Figure A.3 (b) with request 2 that is nearby transshipment terminal C.

(c) The vehicle combinations which are not in K_r^{nk} will be removed from K_r^i.

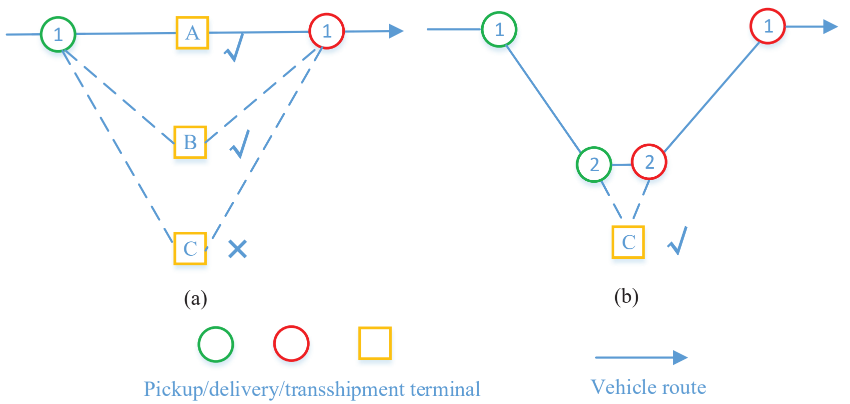


Figure A.3: Reducing transshipment terminals

A.3.2 Hash table

When using insertion operators, it is typically necessary to evaluate the same move repeatedly during the optimization. Avoiding these repetitive computations can significantly reduce computation time, especially for large instances. Inspired by the idea proposed in Qu and Bard (2012), a cache structure that uses hash tables is implemented. Specifically, the hash table holds the best insertion positions and infeasible insertion positions for a given request and route.

Tables A.1 and A.2 give an example and illustrate how to establish hash tables with and without transshipment. The keys and values of hash tables of successful insertion are shown in Table A.1. Table A.2 shows the components in keys and values. The first two hash tables are for insertions without transshipment, which includes all possible positions (All_{1k}) and the best position ($Best_{1k}$) during the search separately. Both of them have two keys and therefore have three layers. The first layer is key $(r, route)$, which includes the inserted request and route. r includes all information of the request except the index to avoid unnecessary storage when there is the same request in the hash table. $route$ includes all visited terminals $i \in N_k$, speed, capacity, time, and the label $label_i$ of the visited terminal, e.g., delivery request 1. The second layer is key $position_{1k}$, which is the inserted position (m,n)

of pickup and delivery. The third layer is the value, which includes the route after insertion and the cost of the inserted request. The other two hash tables are for insertion with transshipment and they have four layers due to a new key T, which is the transshipment terminal. T divides the request into two sub-requests, therefore $position_{2k}$ has two position tuples at two routes. Correspondingly, $value_{2k}$ also has two routes and names of two vehicles. $cost_r$ in $value_{2k}$ is the cost of inserted request at both routes.

Similarly, the hash tables for failed insertion include the same keys but they don't have values because the solution is infeasible.

Table A.1: The keys and values in hash tables of successful insertion

name	keys	value
All_{1k}	$(r, route)$, $position_{1k}$	$value_{1k}$
$Best_{1k}$	$(r, route)$, $position_{1k}^{\text{best}}$	$value_{1k}^{\text{best}}$
All_{2k}	$(r, route_1, route_2)$, T, $position_{2k}^{\text{best}}$	$value_{2k}$
$Best_{2k}$	$(r, route_1, route_2)$, T^{best}, $position_{2k}^{\text{best}}$	$value_{2k}^{\text{best}}$

Table A.2: The components in keys and values

name	components
r	$(p(r), d(r), a_{p(r)}, b_{p(r)}, a_{d(r)}, b_{d(r)}, q_r)$
$route$	$(i, v_k, u_k, t_i^k, t'^k_i, \bar{t}_i^k, label_i), i \in N_k$
$position$	(m, n)
$position_{2k}^{\text{best}}$	$((m_1, n_1), (m_2, n_2))$
$value_{1k}$	$(route^{inserted}, cost_r)$
$value_{2k}$	$(route_1^{inserted}, route_2^{inserted}, cost_r, k_1, k_2)$

A.3.3 Bundle insertion

The requests with the same pickup and delivery terminals are called bundle requests. The basic cost of request r includes request cost, loading/unloading cost and carbon tax, which are not dependent on time, as the following equation shows:

$$F_{basic} = \sum_{k\in K}\sum_{(i,j)\in A}(c_k^1\tau_{ij} + c_k^{1'}d_{ij}^k)q_r y_{ij}^{kr} + \sum_{k,l\in K, k\neq l}\sum_{i\in T}(c_k^2 + c_l^2)q_r s_{ir}^{kl} + \sum_{k\in K}\sum_{(i,j)\in A_p} c_k^2 q_r y_{ij}^{kr} + \sum_{k\in K}\sum_{(i,j)\in A_d} c_k^2 q_r y_{ij}^{kr} + \sum_{k\in K}\sum_{(i,j)\in A} c_k^4 e_k q_r d_{ij}^k y_{ij}^{kr} \tag{A.24}$$

If there are no other costs, such as delay penalty, storage cost, and waiting cost, the insertion cost of bundle requests will be the same for the same route(s). If the best position of a request is found greedily, then it's also the best position for bundle requests when there is only the basic cost. After each insertion, the bundle requests will be inserted into the same positions when it passes the feasibility check and there is only a basic cost. In this way, the computation time can be saved by not considering other possible positions. However, maybe there are other requests more suitable for this vehicle. Therefore, not all bundle requests will be inserted, which will avoid occupying too much capacity of this vehicle. The number of inserted requests in the bundle is randomly chosen based on distribution $[x_1, x_2, ..., x_3]$ for $[1, 2, ..., m]$, where m is the number of requests in the bundle, $x_1 = 1/\varsigma$ and $x_i = x_{i-1}/\varsigma$ when $i > 1$, where ς is a parameter for adjusting the distribution.

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Glossary

List of symbols and notations

Below follows a list of the most frequently used symbols and notations in this thesis.

Sets:	
W	Set of modes indexed by w.
R	Set of requests indexed by r.
N	Set of terminals indexed by i and j.
$O \subseteq N$	Set of depots indexed by o and $\overline{o}$.
$P/D/T \subseteq N$	Set of pickup/delivery/transshipment terminals.
$T_{w_1}^{w_2}$	Set of terminals that allows transshipment between mode w_1 and mode w_2.
K	Set of vehicles indexed by k and l.
$K_{\text{b\&t}} \subseteq K$	Set of barges and trains.
$K_{\text{truck}} \subseteq K$	Set of truck fleets.
$K_w \subseteq K$	Set of vehicles of mode w.
$K_{\text{fix}} \subseteq K$	Set of vehicles that have predefined routes and schedules.
$K_{ue} \subseteq K$	Set of vehicles that affected by unexpected event ue.
A	Set of arcs. For $i, j \in N$, the arc from i to j is denoted by $(i, j) \in A$.
$A_p/A_d \subseteq A$	Set of pickup/delivery arcs. For $(i, j) \in A_p$, $i \in P$. For $(i, j) \in A_d$, $j \in D$.
$A_w \subseteq A$	Set of arcs for mode w.
$A_{\text{fix}}^k \subseteq A$	Set of arcs for a fixed vehicle $k \in K_{\text{fix}}$.
I	Set of attributes.
C	Set of carriers indexed by c.
Parameters:	
u_k	Capacity (TEU) of vehicle k.
q_r	Quantity (TEU) of request r.
τ_{ij}^k	The travel time (in hours) on arc (i, j) for vehicle k.
$[a_{p(r)}, b_{p(r)}]$	The pickup time window for request r.
$[a_{d(r)}, b_{d(r)}]$	The delivery time window for request r.
$[a_i^k, b_i^k]$	The open time window for fixed vehicle k at terminal i.
t''^k_i	The loading (or unloading) time (in hours) for vehicle k at terminal i.
$t_{ue}/\overline{t}_{ue}$	The beginning/ending time of unexpected event ue.
v_k	Speed (km/h) of vehicle k.
d_{ij}^k	Distance (km) between terminals i and j for vehicle k.

e_k	CO_2 emissions (kg) per container per km of vehicle k.
e_r^{kij}	The CO_2e emissions (kg) of request r transported by vehicle k between terminals i and j.
e_r^k	The CO_2e emissions (kg) of request r transported by vehicle k.
e_r^{kl}	The CO_2e emissions (kg) of request r during the transshipment between vehicles k and l.
${e'}_r$	The unit CO_2e emissions (kg) of request r per TEU per km.
$c_k^1/c_k^{1'}$	The transport cost (euro) per hour/km per container using vehicle k.
c_k^2	The loading (or unloading) cost per container.
c_k^3	The storage cost per container per hour.
c_k^4	The carbon tax coefficient per ton.
c_k^5	The cost per hour of waiting time.
c_k^6	The fuel cost per km of vehicle k.
c_r^{delay}	The delay penalty per container per hour of request r.
t_b	The b_{th} breakpoint of time-dependent travel time functions of trucks, $b \in \{1,2,...,B\}$, B is the number of breakpoints.
T_m	The m_{th} time period within a day, $T_m = [t_m, t_{m+1}]$, $m \in \{1,2,...,B-1\}$.
θ_m	The slope of the travel time function for time period T_m.
η_m	The intersection of the travel time function for time period T_m.
$\overline{S}$	Overall satisfaction benchmark.
$\overline{S_i}$	Satisfaction benchmark of attribute i.
M	A large enough positive number.
Variables:	
x_{ij}^k	Binary variable; 1 if vehicle k uses the arc (i,j), 0 otherwise.
y_{ij}^{kr}	Binary variable; 1 if request r transported by vehicle k uses arc (i,j), 0 otherwise.
z_{ij}^k	Binary variable; 1 if terminal i precedes (not necessarily immediately) terminal j in the route of vehicle k, 0 otherwise.
s_{ir}^{kl}	Binary variable; 1 if request r is transferred from vehicle k to vehicle $l \neq k$ at transshipment terminal i, 0 otherwise.
$t_i^{kr}/{t'}_i^{kr}/\bar{t}_i^{kr}$	The arrival time/service start time/service finish time of request r served by vehicle k at terminal i.
$t_i^k/{t'}_i^k/\bar{t}_i^k$	The arrival time/last service start time/departure time of vehicle k at terminal i.
t_{ki}^{wait}	The waiting time of vehicle k at terminal i.
t_r^{delay}	The delay time of request r at delivery terminal.
$\tilde{t}_i^{kr}$	Normalized departure time of truck $k \in K_{\text{truck}}$ with request r at terminal i, $0 \leqslant \tilde{t}_i^{kr} \leqslant 24$.
${\tau'}_{ij}^{kr}$	The time-dependent travel time (in hours) on arc (i,j) for truck $k \in K_{\text{truck}}$ with request r.
n_i^{kr}	An integer variable used for normalizing departure time of truck $k \in K_{\text{truck}}$ with request r at terminal i.
ζ_{irk}^b	A continuous variable used for linearizing the time-dependent travel time function of truck $k \in K_{\text{truck}}$, $0 \leqslant \zeta_{irk}^b \leqslant 1$, $r \in R$, $i \in N$, and b means the b_{th} breakpoint of time-dependent trave time

	function.
ξ_{irk}^{m}	A binary variable used for linearizing the time-dependent travel time function of truck $k \in K_{\text{truck}}$, $r \in R$, $i \in N$, and m means the m_{th} time period within a day.
S_i^r	Satisfaction value of request r and attribute i.
S^r	Overall satisfaction value of request r.

List of abbreviations

The following abbreviations are used in this thesis:

ADP	Auction-based Decentralized Planning
ALNS	Adaptive Large Neighborhood Search
CA	Collaboration Approach
CP	Centralized Planning
DP	Non-auction-based Decentralized Planning
DQN	Deep Q-network
DRL	Deep Reinforcement Learning
FTL	Full Truckload
GA	Genetic Algorithm
HVP	Heterogeneous and Vague Preferences
ITT	Inter Terminal Transport
IWT	Inland Waterway Transport
LNS	Large Neighborhood Search
LP	Linear programming model
LTL	Less Than Truckload
MADM	Multiple Attribute Decision Making
MCDM	Multi-criteria Decision Making
MCNF	Minimum Cost Network Flow
MFL	Maritime Freight Transport
MOO	Multi-objective Optimization
PDP	Pickup and Delivery Problems
PBND	Path-based Network Design
PDPT	PDP with Transshipment
PMOO	Preference-based Multi-objective Optimization
RFT	Road Freight Transport
RL	Reinforcement Learning
RO	Route Optimization
SNDP	Service Network Design Problem
ST	Synchromodal Transport
STP	Synchromodal Transport Planning
STPP	Synchromodal Transport Planning Problem
STPP-FS	STPP with Flexible Services
STPP-HVP	STPP with Heterogeneous and Vague Preferences
TEU	Twenty-foot Equivalent Unit
VRP	Vehicle Routing Problem

Samenvatting

Vrachttransport heeft te maken met gelimiteerde beschikbaarheid van voertuigen, toenemende eisen voor efficiëntie in verplaatsing van goederen en de noodzaak om emissies te reduceren in een steeds korter tijdspad. Om deze uitdagingen op te lossen, moet de transportindustrie innoveren en nieuwe technieken en logistieke systemen in gebruik nemen, wat onze huidige manier van goederentransport ingrijpend zal veranderen. Intermodaal transport helpt om goederen efficiënt, kosteneffectief en duurzaam te vervoeren. Momenteel zijn er echter nog een aantal drempels die grootschalig gebruik belemmeren. Dit zijn onder meer gebrek aan flexibiliteit, vertragingen veroorzaakt door onzekerheid en een gebrek aan samenwerking tussen vervoersactoren. Synchromodaal vervoer zou deze barrières weg kunnen nemen. Deze geavanceerde vorm van intermodaal transport past routes en modi dynamisch aan terwijl grondstof gebruik geoptimaliseerd wordt door middel van synchronisatie en samenwerking. Ondanks dat synchromodaal transport als veelbelovend gezien wordt, zijn er nog steeds belangrijke onderzoeksvragen op het gebied van transportplanning. Voorbeelden zijn hoe we planning zowel flexibel als dynamisch, gebaseerd op voorkeuren en collaboratief kunnen maken. Dit proefschrift heeft tot doel op deze onderzoeksvragen in te gaan door de ontwikkeling en evaluatie van een reeks innovatieve benaderingen, die worden getest en gevalideerd met behulp van bestaande transportnetwerken. Het doel is om vooruitgang te boeken op het gebied van synchromodale transportplanning, waardoor flexibele, betrouwbare en duurzame diensten kunnen worden geleverd die voldoen aan de behoeften van belanghebbenden.

Om de mate van flexibiliteit te onderzoeken, bevat dit proefschrift een wiskundig model en een heuristisch algoritme ("Adaptive Large Neighborhood Search", ALNS) voor gelijktijdige planning van scheeps- en voertuigroutes. De voorgestelde aanpak maakt flexibele routering en planning van voertuigen mogelijk, waarmee de algehele efficiëntie van een transportsysteem, in een statische omgeving als proof-of-concept, kan worden verbeterd. De resultaten van numerieke experimenten tonen aan dat het implementeren van de voorgestelde aanpak met flexibele diensten kan leiden tot 14% kostenreductie in vergelijking met bestaande methoden die geen rekening houden met flexibiliteit.

Binnen dynamische planning richt dit proefschrift zich op de onzekerheid over de verblijfsduur in terminals in synchromodaal transport. We maken gebruik van een online Reinforcement Learning (RL)-benadering, ondersteund door het ALNS-algoritme. Deze benadering integreert RL en ALNS om zo de kracht van data-gedreven RL en ALNS domeinkennis te benutten. Zo omzeilt onze model-ondersteunde RL de "vloek van dimensionaliteit", die wordt veroorzaakt door de large state space and complex actions in synchromodaal transport. De RL-benadering past zich dynamisch aan onverwachte gebeurtenissen bijbehorende onzekerheid aan door te leren van real-time data. Het model heeft geen initiërende distributies nodig en de real-time data is afkomstig van vervoerders, terminaloperators en sensoren. De ALNS-RL aanpak is getest in verschillende scenario's, waaronder verstoringen, disrupties en een combinatie van verschillende gebeurtenissen. Vergeleken met traditionele strategieën presteert de voorgestelde aanpak beter bij het verminderen van vertraging, wachttijd, kosten en emissies.

Bij planning gebaseerd op voorkeuren, gaat dit proefschrift in op de uitdaging om rekening te houden met de heterogene en onduidelijke voorkeuren van verladers en vervoerders. Om rekening te houden met de voorkeuren van vervoerders, wordt een multi-objectieve optimalisatie model voorgesteld dat rekening houdt met onduidelijke voorkeuren door middel van gewicht intervallen. Het model genereert een Pareto-grens van oplossingen die het best passen bij de voorkeuren van de vervoerders, waardoor ze weloverwogen beslissingen kunnen nemen. Voor de voorkeuren van verladers maakt het proefschrift gebruik van multicriteria analyse en vage verzamelingentheorie om om te kunnen gaan met respectievelijk de heterogeniteit en vaagheid van voorkeuren. De resultaten tonen aan dat het meewegen van voorkeuren resulteert in een grotere tevredenheid onder verladers door oplossingen te bieden die rekening houden met kosten, tijd, emissies, risico's en vertragingen. Door de tevredenheid van de verladers te verbeteren, kunnen vervoerders profiteren van meer klantloyaliteit en -behoud, wat leidt tot een concurrentievoordeel in de markt. Bovendien kan het model, door rekening te houden met verschillende criteria, zoals kosten, tijd, emissies, risico's en vertragingen, vervoerders helpen beter geïnformeerde en duurzame beslissingen te nemen, wat leidt tot betere milieuprestaties en naleving van regelgeving. Over het algemeen kan het opnemen van voorkeuren in de planning resulteren in een win-winsituatie voor zowel verladers als vervoerders, wat leidt tot verbeterde prestaties en een duurzaam concurrentievoordeel.

Binnen het veld van collaboratieve planning onderzoekt dit proefschrift de voordelen van horizontale samenwerking tussen vervoerders door het delen van verzoeken en door het overwegen van ECO-labels. Het proefschrift bevat een op veilingen gebaseerd mechanisme om samenwerking te faciliteren en decentrale planning mogelijk te maken. De resultaten geven aan dat deze aanpak leidt tot een betere afhandeling van verzoeken, verbeterde duurzaamheid en lagere kosten in vergelijking met gecentraliseerde en niet-collaboratieve planningsbenaderingen. In de geteste cases kan samenwerking tussen vervoerders resulteren in een aanzienlijke toename van het aantal afgehandelde verzoeken, met winsten van respectievelijk 48% en 11% voor synchromodale en unimodale vervoerders. Bovendien kan, door rekening te houden met voorkeuren voor ECO-labels, het gebruik van het hoogste label of een mix van labels leiden tot emissiereducties van respectievelijk 70% en 15% ten opzichte van benaderingen waarbij ECO-labels niet meewegen. In vergelijking met synchromodale vervoerders moeten unimodale vervoerders, met name vrachtwagenvervoerders, meer verzoeken delen in de gezamenlijke planning om de totale kosten te verlagen. Beleidsmakers kunnen stappen ondernemen om de ontwikkeling van synchromodaal vervoer te bevorderen door gezamenlijke planning en het gebruik van ECO-labels te stimuleren en zo tot duurzame synchromodale vervoersoplossingen te komen.

Samenvattend biedt dit proefschrift antwoorden op onderzoeksvragen rond synchromodale transportplanning door gebruik van innovatieve wiskundige modellen en algoritmen. Deze benaderingen zijn bedoeld om de flexibiliteit, betrouwbaarheid en duurzaamheid van vervoersdiensten te vergroten en tegelijkertijd kosten, tijd, emissies en vertragingen te verminderen. Bovendien houden de voorgestelde methodes rekening met de voorkeuren van zowel verladers als vervoerders, waardoor een collaboratieve en milieuvriendelijke benadering van transportplanning wordt bevorderd. De numerieke experimenten en casestudies tonen de effectiviteit en superioriteit aan van de voorgestelde benaderingen in vergelijking met bestaande methodes aan.

Summary

Freight transport faces a threefold challenge of limited resources, increasing demand for efficient goods movement, and the pressing need to meet ambitious emissions reduction targets in ever shorter timelines. To address these challenges, the industry requires urgent innovation and the adoption of new technologies and logistics systems to change the way goods are transported. The use of intermodal transport has been developed due to the need for efficient, cost-effective, and sustainable freight transport. However, the current state of intermodal transport still faces various barriers to its utilization, such as a lack of flexibility, delays caused by uncertainty, and a lack of cooperation among transport actors. The proposal of synchromodal transport aims to address these barriers. Synchromodal transport represents an advanced form of intermodal transport that dynamically adapts routes and modes while optimizing resource utilization through synchronization and collaboration. Despite the recognition of synchromodal transport as a promising solution, there are still unaddressed gaps in the transport planning field, including the need for flexible, dynamic, preference-based, and collaborative planning. This thesis aims to fill these gaps through the development and evaluation of a series of innovative approaches, which are tested and validated using real-world transport networks. The goal is to advance the field of synchromodal transport planning, enabling the provision of flexible, reliable, and sustainable services that meet the needs of stakeholders.

In order to investigate the potential of flexibility, this thesis presents a mathematical model and a heuristic algorithm (Adaptive Large Neighborhood Search, ALNS) for the simultaneous routing of shipments and vehicles. The proposed approach enables flexible routing and scheduling of vehicles, improving the overall efficiency of the transport system in a static setting as a proof of concept. The results of numerical experiments demonstrate that implementing the proposed approach with flexible services can result in 14% reduction in costs compared to existing methods that do not consider flexibility.

In dynamic planning, this thesis tackles the issue of service time uncertainty in synchromodal transport by using an online Reinforcement Learning (RL) approach, assisted by the ALNS algorithm. The proposed model-assisted RL integrates RL and ALNS to leverage the data-driven strengths of RL and the domain knowledge of ALNS. In this way, the model-assisted RL addresses the "curse of dimensionality" caused by the large state space and complex actions in synchromodal transport. The RL approach dynamically adapts to unexpected events that cause uncertainty by learning from real-time data collected from transport operators, terminal operators, and sensors, without requiring any prior information. The proposed approach was tested in various scenarios that included disturbances, disruptions, and a combination of different types of events, and was found to perform bet-

ter than traditional waiting and average duration strategies in reducing delay, waiting time, cost, and emissions.

When it comes to preference-based planning, this thesis addresses the challenge of incorporating the heterogeneous and vague preferences of shippers and carriers. To account for carriers' preferences, a multi-objective optimization model that incorporates weight intervals is proposed to handle vague preferences. The model generates a Pareto frontier of solutions that best reflects the carriers' preferences, allowing them to make informed decisions. For shippers' preferences, the thesis employs multiple attribute decision-making and fuzzy set theory to address the heterogeneity and vagueness of preferences, respectively. The results demonstrate that incorporating preferences results in improved satisfaction among shippers by providing solutions with preferred attributes on cost, time, emissions, risk, and delay. By improving shipper satisfaction, carriers can benefit from increased customer loyalty and retention, leading to a competitive advantage in the market. Moreover, by considering various attributes, such as cost, time, emissions, risk, and delay, the model can help carriers make more informed and sustainable decisions, leading to improved environmental performance and compliance with regulations. Overall, incorporating preferences in planning can result in a win-win situation for both shippers and carriers, leading to improved operational performance and a sustainable competitive advantage.

In collaborative planning, this thesis examines the benefits of horizontal collaboration among carriers through the sharing of requests and the consideration of eco-labels. The thesis presents an auction-based mechanism to facilitate collaboration and enable distributed planning. Results indicate that this approach leads to increased request fulfillment, improved sustainability, and reduced costs compared to centralized and non-collaborative planning approaches. On the tested instances, the collaboration between carriers can result in significant increases in the proportion of served requests, with gains of 48% and 11% for synchromodal and unimodal carriers, respectively. Additionally, by taking into account eco-label preferences, the use of the highest or mixed eco-labels can lead to emissions reductions of up to 70% and 15%, respectively, compared to ignoring preferences. Compared to synchromodal carriers, unimodal carriers, especially truck carriers, need to share more requests in collaborative planning to reduce the overall cost. From a policy-making perspective, policymakers can take steps to promote the development of synchromodal transport by implementing incentives for collaborative planning and utilizing eco-labels to achieve sustainable synchromodal transport solutions.

In summary, this thesis provides solutions to address the gaps in synchromodal transport planning by proposing innovative mathematical models and algorithms. These methodologies aim to increase the flexibility, reliability, and sustainability of transport services while also reducing cost, time, emissions, and delay. Additionally, the proposed methodologies consider the preferences of both shippers and carriers, promoting a collaborative and eco-friendly approach to transport planning. The numerical experiments and case studies demonstrate the effectiveness and superiority of the proposed approaches compared to existing methodologies.

Curriculum vitae

Yimeng Zhang was born on November 15, 1994, in Baoding, China. He finished high school in 2012 at Tang County No. 1 High School, Baoding, China. After this, Yimeng Zhang began his undergraduate studies in Navigation Technology at Wuhan University of Technology, Wuhan, China. After receiving his bachelor's degree in 2016, he started his study for the Master of Engineering in Traffic Information Engineering and Control at the Navigation School, Wuhan University of Technology.

Upon acquiring his master's degree in 2019, Yimeng Zhang decided to continue with his study in transportation engineering. Sponsored by the China Scholarship Council, Yimeng Zhang started his Ph.D. research in September 2019 at the Department of Maritime Technology and Transport, Delft University of Technology. In his Ph.D. project, he focused on flexible, dynamic, and collaborative synchromodal transport planning with preferences. His research interests revolve around the intersection of operations research, multi-agent systems, and machine learning, with a focus on their practical applications in transportation and logistics, particularly in the realm of multimodal transportation.

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