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# DECISION SUPPORT FOR INTEGRATED URBAN PASSENGER AND FREIGHT TRANSPORT ON RAIL

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## **Inaugural-Dissertation**

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## List of Acronyms

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**ABM** Agent-based Model

**ALNS** Adaptive Large Neighborhood Search

**DES** Discrete Event Simulation

**FCFS** First Come First Serve

**HC** Hill Climbing

**LEZ** Low Emission Zone

**LNS** Large Neighborhood Search

**LSP** Logistics Service Provider

**MILP** Mixed Integer Linear Program

**PT** Public Transport

**PTSP** Public Transport Service Provider

**RRT** Record-To-Record-Travel

**SI** Shared Infrastructure

**SV** Shared Vehicles

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# 1.

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## Synopsis

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### 1.1. Introduction

The *last mile* describes the final segment of transportation in a supply chain, delivering goods to their ultimate destination. The rise in e-commerce has led to a surge in parcel deliveries and significantly drove up associated costs (Bosona, 2020; Brabänder, 2020a). Therefore, optimizing last mile logistics has become a critical factor in ensuring the overall success of supply chains. However, the sector faces a multitude of challenges like congested streets, tight delivery time-frames, expensive failed home deliveries and the need to offer low-emission delivery options (Boysen et al., 2020; Ranieri et al., 2018). These dynamics make last mile logistics a highly competitive field and a vibrant area of research. Researchers search for and analyze transport modes as an alternative to classic vans, e.g., drones, robots, and crowd shipping (Boysen et al., 2020; Silva et al., 2023; Srinivas et al., 2022).

This dissertation proposes integrating parcel deliveries into existing urban passenger transport systems, focusing on utilizing urban light-rail networks. Systems including transportation by trains, which are typically powered by electricity, often provide a more eco-friendly alternative to a transport by diesel-powered delivery trucks (Kirschstein & Meisel, 2015). Integrating parcel deliveries into existing tram networks can reduce the number of delivery vehicles on the roads, leading to lower greenhouse gas emissions and improved air quality (Bruzzzone et al., 2021). This also eases traffic congestion and contributes to smoother traffic flow, benefiting both public and private transport users. Furthermore, this shift aligns with global environmental goals and supports local municipal initiatives, such as the establishment of low emission zones (LEZ) (Ku et al., 2020). Additionally, it provides an opportunity for public transport service providers (PTSPs) to generate additional revenue, which can be reinvested into enhancing urban transit services.

This thesis is a cumulative dissertation in which each of the following chapters constitutes a self-contained essay. Section 1.2 outlines how those essays fit into existing research. Section 1.3 further explores the interconnection between the essays and how

they contribute to the research in detail. Lastly, Section 1.4 identifies three potential streams for future research.

## 1.2. State of the art

As early as the 1830s, the UK's mail was transported by rail (Johnson, 1995). In the following years, other countries did follow this example. With the rise of private transportation, many of these rail-based services were eventually discontinued. However, due to the current climate crisis and rapid urbanization, the concept of shared passenger and freight transportation has experienced renewed interest in recent years.

Cleophas et al. (2019) review types of collaboration among various stakeholders of urban logistics. Mourad et al. (2019) examine advancements in the optimization of shared mobility systems, categorized in two streams: People sharing rides and the combination of freight and people transportation. Cavallaro and Nocera (2021) provide a comprehensive review of shared passenger and freight transport systems. Similarly, Elbert and Rentschler (2021) focus their literature review on urban transport systems. Most recently, El Amrani et al. (2024) outline recent models considering the integration in public transportation services. During the early 2010s, the field was dominated by qualitative studies. For example, Arvidsson and Browne (2013) survey existing and historical systems to identify success factors, while Cochrane et al. (2017) conduct a Delphi study to outline challenges and opportunities. Post-2015, researchers published the first quantitative works, which hold greater significance for this thesis.

Each essay of this dissertation includes a section outlining its specific contributions within existing literature. The next two paragraphs provide a concise review of the literature on planning and evaluating urban shared passenger and freight transportation systems.

**Planning:** When planning an urban shared passenger and freight system, numerous critical decisions must be addressed. Operations research offers a range of methodologies to support decision making in this context. Various studies explore operational decisions, particularly on variants of routing problems (Ghilas et al., 2016b; Masson et al., 2017; Zhao et al., 2019), and models exploring how resources such as carriages or vehicles are allocated to serve passenger or freight processes (Di et al., 2022; Li et al., 2021).

At a tactical level, researchers focus on planning an optimal timetable for passenger and freight operations (Behiri et al., 2018; Ozturk & Patrick, 2018; Yin et al., 2021). However, the existing models focus on the integration of freight processes and assume

the passenger timetable as given. This thesis fills this research gap by proposing a model that develops a demand-oriented timetable from scratch. For this purpose, this dissertation presents:

- A mixed integer linear program (MILP) that integrates the demand-based scheduling of cargo and passenger trains, and the allocation of cargo to vehicles, solved by Gurobi (Essay 1).
- An adaptive large neighborhood search (ALNS) approach to solve an extension of the proposed model (Essay 2).

Yao et al., 2024 further extend the model presented in Essay 1 with a rolling-stock problem.

At the strategic level this includes creating an infrastructure with suitable facility locations for storage and transshipment processes (Delle Donne et al., 2023; Dong et al., 2018; Ji et al., 2020; Zhao et al., 2018). This dissertation does not explicitly model a strategic planning decision. Nevertheless, it contributes to answering a strategic network design decision by analyzing the system's sensitivity to the strategic capacity decision of freight micro-depots (Essay 2).

**Evaluation:** Optimization models, as previously introduced, are inherently tied to their specified objectives and constraints. Consequently, the solutions they generate are highly dependent on the model's design. Therefore, it is essential to thoroughly analyze the available options and evaluate the quality of the proposed solutions.

Cost-benefit analyses can provide valuable insights to challenges and advantages of a shared passenger and freight transport system (De Langhe et al., 2019; Regué & Bristow, 2013; Xie et al., 2020). However, as noted by Arvidsson and Browne (2013), distributing costs and benefits among the involved parties is highly complex. After conducting an extensive literature review of past projects and interviewing participants from a failed pilot project, the authors emphasize that a successful concept must align with the objectives and motivations of all stakeholders. Similarly, Cochrane et al. (2017) conclude that technical challenges may be easier to overcome than institutional obstacles, based on interviews with 34 transportation experts. It is therefore important that possible solutions are viewed from different angles and carefully evaluated.

Computer simulations are widely used to assess the quality and performance of logistics system solutions. Among these, discrete event simulations (DESs) model only changes in the simulation environment, assuming a static state between these discrete time points (Banks, 1998). DES has been extensively applied in research to evaluate shared passenger and freight systems. For example, Motraghi and Marinov (2012)

design a DES to compare two urban freight rail systems: one with a fixed scheduled operation service and another with an improvised service prioritizing freight. Similarly, Behiri et al. (2018) employ a DES to evaluate the performance of heuristics designed for a freight-rail-transport scheduling problem. Hu et al. (2023) use DES to analyze operational decision making within a metro-based underground logistics system, offering insights into the effectiveness and efficiency of various system configurations while ensuring compatibility with passenger services. This thesis builds on such applications by proposing a DES to evaluate schedules generated by the optimization model proposed in Essay 1. Additionally, Essay 1 analyzes the system's sensitivity to changes in demand volume.

An agent-based model (ABM) simulates the interaction of multiple agents, each making independent decisions. For example, Ji et al. (2024) present a multi-agent simulation model to examine pricing strategies for a taxi service that integrates passenger and package transportation. Moreover, Bosse et al. (2023) apply an ABM approach to evaluate the effectiveness of dynamic priority rules. Soeffker et al. (2022) provide a comprehensive review of models in prescriptive analytics for stochastic dynamic vehicle routing, showing various examples for simulations to assess the performance of proposed approaches. Despite these advancements, much of the existing research focuses on the perspective of a single stakeholder. This thesis addresses this gap by conceptualizing an ABM framework that incorporates the perspectives of multiple stakeholders, as outlined in Essay 3. Furthermore, Essay 4 applies the proposed ABM to evaluate and compare two distinct business models.

### **1.3. Research contribution**

The following section provides an overview of how each of the four essays of this cumulative dissertation meets academic standards. Afterwards, Section 1.3.2 elaborates how each essay fits into the context of this thesis, and individually contributes to closing the research gap.

#### **1.3.1. Publication status**

Table 1.1 gives an overview of the four essays that are part of this thesis, contributing to the field of logistics and operations research. The VHB-Rating 2024 is a comprehensive, multidimensional quality assessment framework for the most important scientific journals in German-language business administration. It classifies scientific journals into (A+) “*outstanding and world-leading journals in business administration*“, (A) “*leading journals in business administration*“, (B) “*important and respected journals*

Essay	Title	Author(s)	Year	Publication status	VHB
1	Scheduling Shared Passenger and Freight Transport on a Fixed Infrastructure	Lena Hörsting, Catherine Cleophas	2023	<i>European Journal of Operational Research</i> , 306(3): 1158-1169.	A
2	Integrating Micro-Depot Freight Transport in Existing Public Transport Services	Lena Hörsting, Catherine Cleophas	2023	<i>Operations Research Forum</i> , 4: 54	B
3	Conceptualizing an Agent-Based Simulation for Integrated Urban Transport	Lena Hörsting	2025	<i>Operations Research Proceedings 2023</i> , Springer Cham, accepted for publication	-
4	Two sides of shared passenger and freight transport? An agent-based perspective	Lena Hörsting, Catherine Cleophas	2025	<i>Transportation Research Part E: Logistics and Transportation Review</i> , under review	B

Table 1.1.: Overview of the essays belonging to this thesis

in *business administration*“, (C) “*recognized journals in business administration*“, and (D) “*other academic journals in business administration*“. Essay 1 is published in the (A)-ranked journal *European Journal of Operational Journal* and Essay 2 is published in the (B)-ranked journal *Operations Research Forum*. Essay 3 is accepted for publication in the proceedings from the international conference *Operations Research 2023* in Hamburg, Germany, organized by the *Society for Operations Research Germany (GOR e.V.)*. The proceedings are not listed in the VHB-Rating 2024. Lastly, Essay 4 was submitted to the (B)-rated journal *Transportation Research Part E: Logistics and Transportation Review*, and is currently under review. The appendix includes a declaration that lists the contribution of each co-author and confirms compliance the with guidelines for “Safeguarding Good Research Practice“ by the German Research Foundation (Deutsche Forschungsgemeinschaft, DFG).

### 1.3.2. Key insights

Figure 1.1 illustrates the context and objectives of the individual essays. The given essays focus on the transportation of parcels via light-rail-based public transport systems. They assume that the rail network is independent from the road infrastructure. Further, the focus is on two transportation modes. The *shared vehicles* (SV) mode represents a system where passenger and parcel are transported in the same trains, where the *shared infrastructure* (SI) mode assumes dedicated cargo trains operating. The

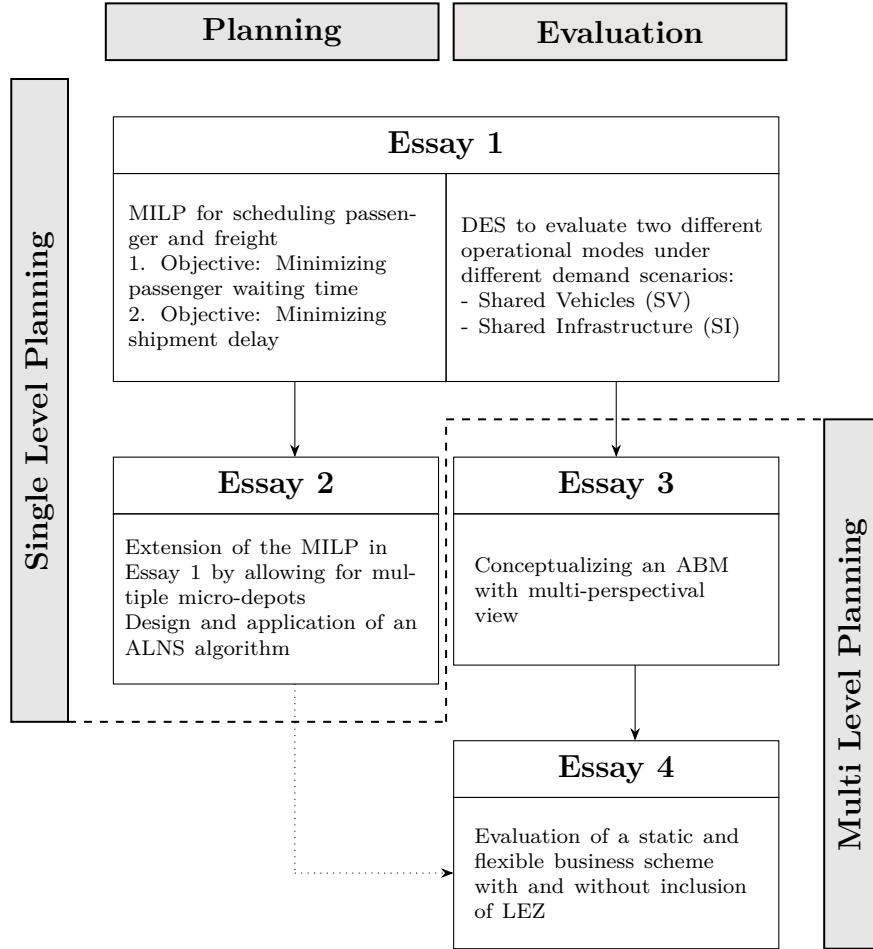


Figure 1.1.: Context and objective of essays belonging to this thesis

contribution of this thesis is two-fold: It provides analytical tools to assist in planning decisions and applies tools to evaluate potential outcomes in different scenarios.

**Planning:** Integrating freight into an existing public transport system presents significant challenges, as stakeholders must make crucial planning decisions despite the limited number of real-world examples. A key concern in freight integration is the potential disruption to passenger services (Arvidsson & Browne, 2013). Prescriptive analytics can aid in planning to minimize these disruptions. The proposed optimization approaches in this thesis focus on a single planning level, i.e., they are limited by a given set of objectives and constraints.

Essay 1 introduces mixed integer linear program (MILP) models designed to schedule both passenger and cargo trains, while also optimizing shipment allocations within the timetable. Two variations of the model support planning in both, SV and SI modes. Building on the demand-based timetabling model by Barrena et al. (2014a), which focuses on passenger transport, this essay extends the model in two key ways: The

first extension integrates parcel transportation into the scheduling process. A set of constraints enables the allocation of shipments to trains, and the objective function incorporates the goal of minimizing delivery delays alongside reducing passenger waiting times. The second extension introduces flexible dwell times, with additional constraints accounting for the necessary service times for passenger boarding, alighting, and cargo loading/unloading. This addition helps to reduce the potential impact on passenger services.

The models are solved using Gurobi, and results indicate that a well-optimized train schedule can significantly enhance service quality. However, due to the complexity of the problem, realistically-sized instances cannot be solved within acceptable times. As such, the essay focuses on small instances, with a planning horizon limited to three hours and up to 28 stops in the public transport network. The optimality gap for the largest instances ranges between 65% and 99% after a 9-hour run time, highlighting the need for more computationally efficient approaches.

To address these computational limitations, Essay 2 introduces a meta-heuristic designed to solve large-scale instances more efficiently. Inspired by the work of Yin et al. (2021), this essay extends the ALNS approach with additional destroy and repair operators to manage freight allocation and flexible dwell times. It also compares two acceptance criteria: Hill climbing (HC) and record-to-record-travel (RRT). While HC achieves improvements in earlier iterations, RRT may require more iterations for similar results. A hybrid approach, using HC for early iterations followed by an intensified search via RRT, offers a promising balance between run time efficiency and global solution quality. The results show that the meta heuristic achieves substantial runtime reductions compared to exact solvers, with a maximum gap of only 5% from the best solution found, including solutions found by Gurobi. Thus, Essay 2 shows that the proposed ALNS serves as a suitable alternative to conventional solvers.

Azcuy et al. (2021) demonstrate that substantial distance reductions can be achieved when public transport systems are utilized to deliver freight to micro-depots. Inspired by this concept, Essay 2 extends the model of Essay 1 by featuring multiple micro-depots instead of a single depot. Our findings suggest that the storage capacity of micro-depots plays a critical role in the system's effectiveness when enabling pick-ups beyond a central depot.

**Evaluation:** The proposed planning models are well suited to find a good solution with regard to a specific set of objectives and constraints. However, planning decisions should also be evaluated in a more robust sense. Thus, this thesis provides tools to account for uncertainty and evaluate the solutions performance under stochasticity.

Essay 1 uses a DES to assess the performance of the optimized schedules on the proposed operational models, SV and SV, and analyzes the solution's sensitivity to changes in demand volume for both passengers and freight. The results indicate that the rush hour in is highly prone to delays from dedicated freight trains. Conversely, low-demand periods like early mornings are less affected by delays, making dedicated trains viable. If freight transportation is unavoidable during rush hour, shared trains would be a more suitable option.

Inspired by the work of van Heeswijk et al. (2020), Essay 3 conceptualizes an ABM, including a multi-perspectival view on shared passenger and freight systems. Thus, it offers a tool for multi level decision making. The framework accounts for diverse objectives and interactions among the city administrator, the transport services providers and users. Additionally, it pioneers a multi-level modeling approach that integrates passenger and freight transport decision making over different time horizons, providing a holistic framework for urban mobility planning.

Based on this concept, Essay 4 utilizes an ABM to evaluate two business schemes for integrating passenger and freight transport. The static scheme employs the SI approach under long-term contracts, while the flexible scheme utilizes SV with a spot-market-based allocation. The findings indicate that logistics service providers (LSPs) particularly benefit from consolidation effects in the flexible scheme. In contrast, the static scheme needs accurate demand forecasting and more advanced planning approaches. Furthermore, the study examines the impact of policies like LEZs on these systems, concluding that well-implemented LEZ policies can drive the adoption of shared transport solutions.

## 1.4. Future research

This thesis comprises four essays that explore diverse approaches to planning and evaluating integrated urban passenger and freight transport systems, with a particular focus on parcel transportation by rail. Essay 1 introduced an MILP aimed at optimizing schedules for passengers and freight while minimizing passenger waiting times and shipment delays. Essay 2 builds on this model, presenting an ALNS algorithm to solve realistically-sized instances within an acceptable run time. Essay 3 and Essay 4 conceptualize and apply an ABM to incorporate perspectives from multiple stakeholders.

The concluding section of each essay features further issues for future research on the individual essay. Building on the findings of this thesis, this synopsis proposes three additional directions for further research:

1. **Support of strategic decision making.** Strategic considerations, such as de-

termining locations for transshipment points and storage facilities, are crucial for the success of logistics systems. However, most research on integrated passenger and freight transport systems focuses on operative and tactical planning (Elbert & Rentschler, 2021). This thesis contributes to strategic planning by conducting a sensitivity analysis of a micro-depot capacity problem in Essay 1, and including strategic decision making considerations within the ABM framework in Essay 4. Nevertheless, explicit modeling and optimization of strategic decisions, for example by integration with the ABM proposed in Essay 4, remains an untapped area. Future research could address the implementation and application of strategic optimization models, enhancing decision making capabilities.

2. **Consideration of multi-stakeholder perspectives.** Most of the current literature consider integrated passenger and freight transport systems from the perspective of the freight logistics company, as many problems deal with routing and freight allocation problems (cf. Section 1.2). While the freight logistics is important, the smooth transport of passengers and a sustainable business model for the public transport service is essential for the system's success. This thesis contributes by providing an ABM with a multi-stakeholder perspective in Essay 3, and considering pricing and institutional policies in Essay 4. However, optimization models from different perspectives, e.g., finding a viable pricing structure, are useful and needed. Overall, offering tools for various stakeholders would sustainably contribute to the research field.
3. **Enhanced simulations and analysis.** This thesis proposes multiple simulation models for the evaluation of model solutions and business schemes. Those could be further improved by allowing for more dynamic and realistic urban scenarios. Additionally, future approaches could further account for interactions between different stakeholders and different scenarios, e.g., varying demand levels, environmental impacts, and financial implications.

Beyond these suggestions, the growing interest in shared passenger and freight systems highlights the significance of this field and promises many compelling studies to come.

# 2.

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## Essay 1: Scheduling shared passenger and freight transport on a fixed infrastructure

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### Abstract

Increases in last-mile transport contribute to congestion and pollution in urban environments. To make deliveries more sustainable, they may be integrated with existing public transport infrastructure, e.g., metros or trams. This integration can rely on alternative operational modes: shared infrastructure lets passenger and cargo vehicles share the same rail network, whereas shared vehicles simultaneously transport cargo and passengers.

To explore the effects of integrated planning under different operational modes, we introduce a linear mixed-integer program that optimizes the train schedule and allocates cargo. It features a lexicographical objective function that prioritizes passenger transport while minimizing cargo delivery delay. We analyze the interplay of operational modes, scheduling solutions, and demand settings in a simulation study. The results show that a well-planned train schedule significantly contributes to service quality and reduces the system's sensitivity to increasing freight demand. Furthermore, a system with shared vehicles is more robust towards fluctuating demand, whereas a system with only shared infrastructure is a valid option to allow a high dwell time for freight vehicles.

**Keywords.** Transportation, Logistics, Shared Transport, Scheduling, Simulation

## 2.1. Introduction

While demand for urban deliveries continues to increase, last-mile transport drives up congestion rates and air pollution. In consequence, the challenge of realizing deliveries not just cost-efficiently and customer-friendly, but environmentally sustainable becomes more urgent. Municipal initiatives such as low emission zones add external motivation for retailers and service providers to consider new approaches to urban transport (Arvidsson et al., 2016).

One conceivable step toward reducing the footprint of freight transport is to integrate it with public passenger transport, such as light-rail (Arvidsson et al., 2016). Several examples for such systems already exist: In Dresden, Germany, trams transported car parts for almost 20 years and in Zürich, Switzerland, a light-rail service assists in disposing of municipal public waste. The LastMileTram in Frankfurt am Main, Germany, currently trials delivering parcels to the city center (Schocke et al., 2020). The research presented here was motivated by early planning steps in a project to create a new, potentially light-rail-based public transport system in the city of Kiel, Germany (von Beckwermert, 2022). To explore the opportunities for shared transport, we discussed the topic with municipal planners and with representatives from a citizen initiative (Tram für Kiel e.V., 2022). As the interviewees point out, rail-based public transport systems benefit from a positive consumer bias and are frequented by a broader range of passengers. Furthermore, since such systems have to be planned for peak loads but demand is highly variable over the day, exploiting capacity overhauls could offer promising financial support. Finally, planners and citizens considered the idea of noticing “your own packages” being “on board as well” in shared vehicles as a highly positive aspect.

Several previous attempts at shared light rail transport have failed, as summarized in Arvidsson and Browne (2013) and Cleophas et al. (2019). On the example of the Amsterdam City Cargo project, Arvidsson and Browne (2013) highlight financial issues and politics as reasons for such failure. As emphasized by Arvidsson et al. (2016), shared transport systems require successful operational planning and policy support for success. In this contribution, we aim to support operational planning by presenting an integrated approach to scheduling that prioritizes passengers. To support policy evaluation, we offer an approach to comparing the effects from alternative system designs in a simulation study, supporting stakeholder involvement.

Implementing shared transport involves various design decisions, e.g., with regard to the system’s *mode of operation*. On the one hand, passengers and freight can share the elements of the infrastructure, e.g., rail or stations (*Shared Infrastructure, SI*). On the

other hand, passenger vehicles can also carry freight in shared or dedicated compartments (*Shared Vehicles, SV*). Of course, two modes may also work in a complementary fashion. At this time, the technical and legislative conditions for transport in shared vehicles are not yet given. However, it is possible to attach cargo compartments to a light-rail passenger train or to implement belly-freight akin to bus transport (Arvidsson et al., 2016; De Langhe et al., 2019). Furthermore, the effort of exploring technical and legislative options needs to be justified by expected gains in service quality. Therefore, this paper considers both operational modes in a simulation system and considers their sensitivity to demand settings and scheduling approaches.

Shared transport systems create several interlinking planning problems. For instance, decision-makers must select stations for unloading and transshipment, e.g., via parcel lockers (Schwerdfeger & Boysen, 2020). Simultaneously, they must schedule vehicles and appropriately allocate cargo (Ozturk & Patrick, 2018). In this regard, existing research rarely considers multiple operational modes or entirely integrated scheduling for both freight and passengers. Motivated by this gap and to exemplify the role of optimization in the planning process, we introduce a model that integrates the tactical scheduling of cargo and passenger trains and the allocation of cargo to vehicles. While other contributions aim to introduce freight to existing systems with minimal impact, we deliberately evaluate a fully integrated approach to examine its implications independently of existing passenger schedules. This creates additional options for synchronizing time and space usage, maintaining passenger service quality while maximizing the degree of freedom for freight transport.

We rely on a stochastic, discrete event-based simulation (DES) to evaluate the interplay of decisions regarding the design and planning of shared freight and passenger transport on a fixed network. The results highlight the resulting potential for different settings and operation modes to support design decisions.

The next section summarizes recent research and pinpoints this paper’s contribution to the literature. Section 2.3 provides a detailed description of the domain model and underlying assumptions. In Section 2.4, we formalize the decision problem of the scheduling of cargo and passenger trains and allocating cargo in terms of a lexicographical optimization model. The decision problem entails, firstly, minimizing the passenger waiting time and, secondly, the delivery delay. In Section 2.5, we detail the stochastic simulation model that we rely on to evaluate the implications of alternative operational modes and approaches to scheduling vehicles and allocating freight. Section 2.6 presents a computational study based on an empirically plausible simulation scenario and related sensitivity analyses. Finally, we reflect on the research documented here and provide a short outlook in Section 2.7.

## 2.2. Literature review

In the following, we shortly review research on empirically appraising shared transport systems. Subsequently, we summarize contributions on operational planning for shared freight and passenger transport on fixed infrastructures. Lastly, we provide references related to the optimization problem of scheduling rail transport vehicles and allocating freight.

### 2.2.1. Shared transport in practice

Interest in integrating cargo transport in public transit is increasing (Cavallaro & Nocera, 2021; Cleophas et al., 2019; Cochrane et al., 2017). As Arvidsson and Browne (2013) point out, light rail combines a good capacity ratio, low environmental impact, low fatality risks and good network linkage.

Unfortunately, the challenge and cost of planning and implementing shared transport is also evident in discontinued projects. Arvidsson and Browne (2013) highlight several barriers to urban rail transport, including financial weaknesses, scale, and stakeholder involvement. Cochrane et al. (2017) note that most success stories were driven by external motivation, and conclude that “with the right business plan and political support the obstacles to [freight on transit] could be overcome”. When considering success factors for rail-based transport, De Langhe et al. (2014) list positive marketing, expensive road transport, and a focus on slow-moving, inexpensive freight. Cochrane et al. (2017) point out that “a key research next step would be to model the impacts of one of the [freight on transit] projects presented here to estimate impacts on congestion, operations, and environmental outcomes”.

On the one hand, municipalities increasing the cost of classical road transport will likely make more sustainable options more financially attractive (Buehler et al., 2017). On the other hand, to evaluate systems’ sensitivity to scale and to support stakeholder involvement through interactive counterfactuals, computer simulations are well suited and repeatedly applied (see, e.g., Kroon et al., 2008; van Heeswijk et al., 2020).

A related research stream explores the potential cost and benefit of rail-based urban transport through empirical estimates. In this area, De Langhe et al. (2014) highlight that a crucial question of extending public transport systems is that of who is gaining from and who is paying for the system. De Langhe (2017) provides a thorough overview of existing contributions, classifying them according to the examined cost types, such as accidents, air pollution, congestion, and noise. De Langhe et al. (2019) evaluate empirical systems with regard to the mode of operation: dedicated freight trams, a freight wagon behind the passenger tram, and parcels and passengers sharing a tram.

Both De Langhe et al. (2019) and Bektaş et al. (2017) point out significant opportunities from shared vehicle use, which we aim to further explore in the paper at hand. Finally, contributions such as Gonzalez-Feliu (2018) point out the need for systematic demand catchment analysis when trying to predict the cost and benefit of transport systems. The author not only highlights this requirement, but also provides a framework for data collection and analysis, and exemplifies the idea on a case in Paris, France.

Simulation modeling may add a new dimension to the empirically driven research stream on evaluating the cost and benefits of alternative transport systems. Accordingly, this paper explores the potential capacity benefits from extending freight transport via urban rail. Nevertheless, any real-world application clearly requires system-specific assessments, e.g., with regard to the selected solution on freight loading, vehicle type, or energy sources. Furthermore, while a simulation can evaluate the system's sensitivity to different levels in both freight and passenger demand, it cannot offer new insights into the actual extent of demand catchment.

### **2.2.2. Operational planning of shared transport systems**

*The shared infrastructure mode* features in a range of existing contributions on operational planning. For example, Motraghi and Marinov (2012) design a freight rail system for the city of Newcastle upon Tyne, United Kingdom, and implement a DES to plan and evaluate the schedule of the cargo vehicles. The authors propose two strategies to solve this dynamic problem and evaluate them in a simulation. Ozturk and Patrick (2018) integrate freight trains within an existing passenger transport infrastructure. The authors present mixed-integer linear programs (MILPs) with varying objectives, e.g., the delivery delay or number of additional freight trains.

*The shared vehicles mode* as applied for a bus-based in city logistic system is analyzed by Masson et al. (2017). A city distribution center releases containers, which are first transported by buses on a fixed schedule. Subsequently, city freighters continue the transport from pre-selected bus stations. This problem of onward transportation is formulated as MILP including a lexicographical minimization and solved by adaptive large neighborhood search (ALNS). Ghilas et al. (2016b) regard a similar problem with buses transporting passengers and goods. Additionally, passengers and containers are picked-up and dropped-off by taxis. The authors also formulate this specialized pickup and delivery problem as an MILP and apply an ALNS algorithm to solve it. Behiri et al. (2018) focus on the Freight Rail Transport Scheduling Problem (FRTSP), where an urban light rail system transports both freight and passengers. They propose two greedy heuristics and test both heuristics within a DES.

Notably, most existing research either examines shared infrastructure or shared ve-

hicle systems. Li et al. (2021) overcome this distinction: The authors assume a given passenger transport timetable and allow for only for small modifications to account for maximizing profit through freight transport.

In this paper, we also compare both operation modes. While acknowledging that the two transportation modes may also work in a complementary fashion, we focus on the choice between them. Implementing a shared transport system calls for several high initial investments, e.g., for modifying the stations for transshipment processes or upgrading the vehicle fleet. We believe that exclusively selecting one of the two modes can reduce initial investment costs and facilitate planning procedures because less modifications are required and the adapted system must only fit a single mode.

As emphasized in Crainic et al. (2021), transport operations needs to both consider the problem of planning ahead and of adjusting plans during execution time. The research presented here focuses on evaluating the impact of planning ahead to support system design. Therefore, as opposed to Li et al. (2021) and Ozturk and Patrick (2018), we do aim to fit freight transport into existing passenger schedules but present a model to design these from scratch for both passengers and freight. Furthermore, while assuming the existence of some rules to guide schedule execution under stochastic demand and service times, we primarily test the outcome of implementing a schedule that is optimized ahead of execution for different operational modes. To complement existing research, we consider in the mutual effects between the passenger and freight transportation services by measuring the service quality through, e.g., the average passenger waiting time, schedule deviations, delivery delay and successful deliveries.

Table 2.1 categorizes existing models according to operational *mode*, considered *problem classes*, and used *paradigm*. While some references also consider further problems, we differentiate the allocation of freight to vehicles (*Alloc*), the freight train scheduling (*FTS*), and the passenger train scheduling (*PTS*). As this table highlights, our main research contribution lies in evaluating allocation and schedules for shared freight and passenger transport in a simulation with regard to alternative modes of operation.

### 2.2.3. Rail transport scheduling

The related problems of railway operation planning are surveyed, e.g., in Cacchiani and Toth (2012) and Lusby et al. (2018). Guihaire and Hao (2008) and Ibarra-Rojas et al. (2015) provide dedicated reviews of research related to urban transit systems. Here, we focus exclusively on the train scheduling problem for *urban transit systems*. We specifically regard these from the perspective of city logistics systems as reviewed in Crainic et al. (2021).

Such transit systems can follow either *aperiodic* or *periodic* timetables. While aperi-










	Mode		Problem Class			Paradigm	
	SI	SV	Alloc.	FTS	PTS	MILP	Sim.
Motraghi and Marinov (2012)		-	-	x	-	-	x
Masson et al. (2017)	-		x	-	-	x	-
Ghilas et al. (2016b)	-		x	-	-	x	-
Ozturk and Patrick (2018)		-	x	x	-	x	-
Behiri et al. (2018)	-		x	-	-	x	x
Li et al. (2021)			x	x	-	x	-
This work			x	x	x	x	x

Table 2.1.: Overview of existing models with shared freight and cargo transport

odic timetables consider an individual schedule per train, periodic timetables repeat a cyclic pattern (see, e.g., Martin-Iradi & Ropke, 2022; Schiewe & Schöbel, 2020). Especially in urban areas, aperiodic timetables are receiving more attention, as they allow for flexible planning with dynamic passenger flows (see, e.g., Barrena et al., 2014a; Yin et al., 2021). Barrena et al. (2014a) give an exact linear formulation for a unidirectional corridor with dynamic passenger demand and design a branch-and-cut algorithm. We adopt the idea of an exact formulation for passenger train scheduling and extend it by adding cargo allocation, limited capacities and transshipment constraints. The model proposed in this paper also focuses on an aperiodic, demand-driven scheduling solution. We argue that an aperiodic time schedule both only better adapts to dynamic passenger demand and more flexibly serves the needs and restrictions of the freight service.

Common objectives in urban timetabling include meeting a specific passenger load, synchronizing transfers, or minimizing waiting times (see, e.g., Barrena et al., 2014a; Hassannayebi et al., 2016; Yin et al., 2021). A repeated concern of practitioners regarding the integration of freight in public transport is the risk of disruptions in the passenger service (Arvidsson & Browne, 2013). Therefore, we consider the average number of waiting passengers as our primary objective. This measure let us directly decrease the passenger congestion at the platform without the need of modeling individual passenger behavior. When passengers arrive and depart on a discrete time horizon, the average number of waiting passengers per period equals the average waiting time per passenger. Hence, the indicator simultaneously reduces long waiting times of a few passengers and a large number of passengers crowding the platform.

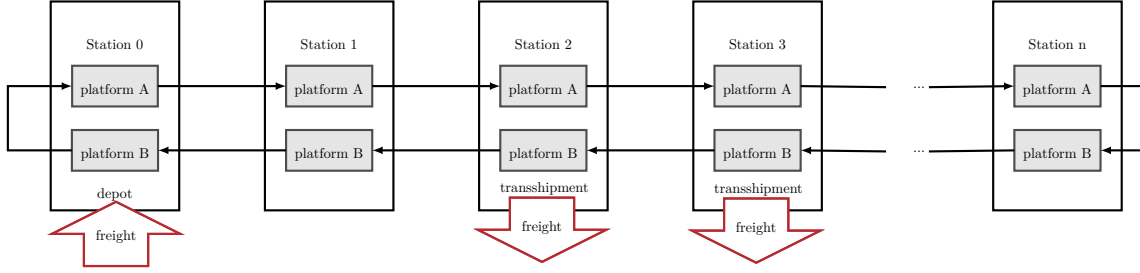


Figure 2.1.: Assumed network topology: A circular, bi-directional single route

### 2.3. Problem description

The domain model features an existing public transit network with a fixed set of stations and connecting legs. As an example, consider a light-rail network, where trams transport passengers and freight on single-use lanes. However, the model easily applies to other public transportation modes, such as buses, when strategic decisions on stations and routes are given. Figure 2.1 illustrates the network topology as a directed graph. The network constitutes a *circular, bi-directional single route*, where vehicles turn at boundary stations.

For simplicity, we consider each circular line in isolation. Each station features two platforms, i.e., stops  $s_i^A, s_i^B \in \mathcal{S}$ , for two opposite directions. The ordered set  $\mathcal{S}$  includes all consecutive stops. The *depot* ( $s = 0$ ) is the starting stop of each tour and releases freight containers at fixed times. *Containers*  $r \in \mathcal{R}$  are standardized boxes of size  $Q_r$ . The containers are loaded on vehicles and carried to a particular *destination* or *transshipment stop* within the city. There, the containers are unloaded, e.g., to parcel lockers or cargo bikes.

The modeled time horizon consists of a discrete set of periods  $\mathcal{P}$ . During each period, passengers can arrive and the depot can release containers. Each container comes with a deterministic release time  $p_r^{\text{start}} \in \mathcal{P}$ , a destination stop  $s_r^{\text{end}} \in \mathcal{S}$  and a soft planned arrival time  $p_r^{\text{end}} \in \mathcal{P}$ . The latter is especially important to guarantee the synchronization of transshipment processes.

Let  $\mathcal{V}$  be the set of *vehicles*. Each vehicle operates according to a given *schedule*. The schedule specifies the arrival, dwell, and departure times per stop. In a feasible schedule, a vehicle passes all stops within the given time window. The parameter  $\mu_{s,t}$  represents the expected travel time between two stops  $s$  and  $t \in \mathcal{S}$ . Only a single vehicle can dwell at each stop at the same time. If the stop is occupied, newly arriving vehicles queue up and wait. Additionally, any two vehicles must keep a given headway  $H > 0$  between two consecutive departures from the same stop.

When a vehicle enters the platform, passenger alight and containers are unloaded.

Afterwards, passengers waiting at the platform board the vehicle and assigned containers are loaded. Given the circular network topology, all vehicles passing a particular stop travel in the same direction. Therefore, the number of embarking passengers is the minimum of the number of passengers waiting at the stop and the vehicle's remaining capacity after the alighting process. The parameter  $\lambda_{p,v}^{\text{alight}}$  represents the probability that a single passenger alights at stop  $s$  at period  $p$ . We assume that passenger and cargo processes are handled in parallel.

Jointly transporting passengers and freight relies on two types of *resources*: vehicles' dwell time and capacity. Firstly, *the dwell time* restricts boarding and loading processes. The parameters  $\beta^{\text{board}}$  and  $\beta^{\text{alight}}$  give the expected boarding and alighting time per passenger while parameters  $\beta^{\text{load}}$  and  $\beta^{\text{unld}}$  represent the expected time for loading and unloading a container. Furthermore, the dwell time per stop is limited by parameters  $\beta^{\text{min}}$  and  $\beta^{\text{max}}$ . The minimal dwell time  $\beta^{\text{min}}$  describes, e.g., the time the driver needs to stop and start the vehicle. Maximal dwell time  $\beta^{\text{max}}$  limits loading and unloading times while passengers wait in the vehicle. For SI, the dwell time limitations of freight vehicles,  $\beta_{\text{fre}}^{\text{min}}$  and  $\beta_{\text{fre}}^{\text{max}}$ , can differ from those for passenger vehicles. We regard dwell time as adjusting flexibly when passengers arrive ahead of the vehicle's scheduled departure, such that the dwell time extends to let those passengers may embark, too. Thus, during peak travel times, the extended dwell time can delay vehicles' departures. In contrast, when maximal dwell time  $\beta^{\text{max}}$  is reached, any remaining containers are not loaded, and the vehicle leaves as soon as possible. When all passengers boarded, the maximal loading time of containers is exceeded, or the scheduled departure time passes, the vehicle leaves to travel to the next stop.

The second resource is the *vehicle capacity*. We assume that all vehicles have the same capacity. The shared infrastructure (SI) mode distinguishes *cargo vehicles* and *passenger vehicles* with capacity parameters  $C^{\text{fre}}$  and  $C^{\text{pas}}$ . The shared vehicles (SV) mode lets passengers and freight units share the same space through a single global capacity  $C$  or allocates them to different areas of the vehicle through dedicated capacities  $Q^{\text{pas}}$  and  $Q^{\text{fre}}$ . For example, passenger and cargo may share the standing area, while passenger seating is unsuitable for cargo; or vice versa, cargo wagons unsuitable for passengers. If passengers and cargo arrive in the same period and the vehicle's capacity does not suffice for both, passengers are prioritized.

To enable shippers to switch to transport alternatives, planners may *reject* containers in advance. We consider planned containers as *denied* if either the dwell time or the vehicle capacity are insufficient at the time of loading. Denied containers remain at the depot. Accordingly, a container can be either waiting to be delivered, rejected, denied, or delivered.

## 2.4. Lexicographical bi-objective schedule optimization model

This section presents an exact deterministic integrated scheduling formulation for passenger and freight trains. The complete lists of index sets, parameters and decision variables can be found in the appendix, Tables A.1, A.2 and A.3. This section shortly introduces the decisions and objectives of the model before presenting the MILP.

### 2.4.1. Decisions: Designing the time schedule and allocating cargo

A first set of decisions schedules vehicles: The binary variable  $o_v$  determine whether the vehicle  $v \in \mathcal{V}$  operates ( $o_v = 1$ ) or not ( $o_v = 0$ ). While the vehicles' routes are given, the departure and arrival time of each operating vehicle is variable. In the model, the binary variable  $x_{v,s,p}$  is equal to one if and only if vehicle  $v \in \mathcal{V}$  departs at stop  $s \in \mathcal{S}$  in period  $p \in \mathcal{P}$ . Variable  $d_{v,s} \geq 0$  determines the departure time of vehicle  $v \in \mathcal{V}$  at stop  $s \in \mathcal{S}$ . The variable  $a_{v,s} \geq 0$  represents the arrival time and  $h_{v,s} \geq 0$  represents the dwell time of vehicle  $v \in \mathcal{V}$  at stop  $s \in \mathcal{S}$ .

The second set of decisions allocates freight to vehicles: The binary variable  $u_r$  determines whether to transport ( $u_r = 1$ ) or reject ( $u_r = 0$ ) a container. Furthermore, binary variable  $y_{r,v,s}$  is equal to one if and only if container  $r \in \mathcal{R}$  is planned to be on vehicle  $v \in \mathcal{V}$  after departing stop  $s \in \mathcal{S}$ . For SI, the binary decision variable  $z_v$  determines whether  $v \in \mathcal{V}$  is a freight ( $z_v = 1$ ) or a passenger vehicle ( $z_v = 0$ ). The auxiliary variables  $c_{v,s}^{\text{pas}} \in \mathbb{N}$  and  $c_{v,s}^{\text{fre}} \in \mathbb{N}$  represent the space dedicated to passengers and freight, while ensuring that capacity restrictions are satisfied and modeling the designated compartments for passengers or freight.

### 2.4.2. Primary objective: Minimize waiting passengers

The model's primary objective is to minimize the number of waiting passengers at stop  $s \in \mathcal{S}$  arriving at period  $p \in \mathcal{P}$ , represented by variable  $w_{s,p} \geq 0$ . To compute  $w_{s,p}$ , the model requires a number of auxiliary variables. Auxiliary variable  $b_{v,s,p} \in \mathbb{N}$  describes the number of passengers boarding vehicle  $v$  departing stop  $s$  at period  $p$ . Auxiliary variable  $n_{v,s} \geq 0$  represents the total number of passengers on vehicle  $v \in \mathcal{V}$  just after departing from stop  $s \in \mathcal{S}$ .

Optimizing the average number of waiting passengers comes with the risk of underestimating variance in data. But the risk of underproviding to passenger demand on a single stop is low, because the model represents a bi-directional network in which every stop must be passed once.

### 2.4.3. Secondary objective: Minimize the average delay and number of rejections

Since the system also transports freight, we also aim to ensure an acceptable freight service quality. A good solution should accept as many shipments as possible while minimizing the individual delay  $t_r \in \mathbb{N}$  per successfully delivered container  $r \in \mathcal{R}$ . To determine  $t_r$ , the auxiliary variable  $f_r \in \mathbb{N}$  represents the delivery time of container  $r$ . Parameter  $P$  is the incurred penalty for rejecting to transport the container.

Relying on computing the average delay neglects outliers. An alternative objective function would, e.g., minimize the maximal delay. We do not propose this option because it does stops rewarding punctual deliveries as soon as any shipment is delayed. Instead, we let parameter  $T^{\max}$  represent the maximal acceptable delay per shipment. As a result, the model only accepts freight requests if it can guarantee the delivery within a hard deadline. Furthermore, we let parameter  $U$  represent the percentage of deliveries that the system must accept to guarantee a certain service quality.

### 2.4.4. Mixed integer program formulation

To optimize the quality of both services, we propose a mixed integer program with a lexicographical objective. The model prioritizes passenger transport, such that the primary objective is to minimize the average waiting time across periods and stops. The secondary objective minimizes the average penalty for delivery delay or rejection per container.

$$\text{lex min } \left\{ \frac{1}{|\mathcal{S}| \cdot |\mathcal{P}|} \sum_{s \in \mathcal{S}} \sum_{p \in \mathcal{P}} w_{s,p}, \frac{1}{|\mathcal{R}|} \sum_{r \in \mathcal{R}} t_r + P \cdot (1 - u_r) \right\} \quad (2.1)$$

**Subject to time constraints:**

$$\sum_{p \in \mathcal{P}} x_{v,s,p} = o_v, \quad \forall v \in \mathcal{V}, s \in \mathcal{S} \quad (2.2)$$

$$\sum_{p \in \mathcal{P}} p \cdot x_{v,s,p} = d_{v,s}, \quad \forall v \in \mathcal{V}, s \in \mathcal{S} \quad (2.3)$$

$$a_{v,s} = d_{v,s-1} + \mu_{s-1,s} \cdot o_v, \quad \forall v \in \mathcal{V}, s \in \mathcal{S} \setminus \{0\} \quad (2.4)$$

$$h_{v,s} = d_{v,s} - a_{v,s}, \quad \forall v \in \mathcal{V}, s \in \mathcal{S} \quad (2.5)$$

$$a_{v,s} \geq d_{v-1,s} + o_{v-1}, \quad \forall v \in \mathcal{V} \setminus \{0\}, s \in \mathcal{S} \quad (2.6)$$

$$d_{v,s} \geq d_{v-1,s} + H \cdot o_{v-1}, \quad \forall v \in \mathcal{V} \setminus \{0\}, s \in \mathcal{S} \quad (2.7)$$

$$\sum_{p \in \mathcal{P}} \beta^{\text{board}} \cdot b_{v,s,p} + \beta^{\text{alight}} \cdot e_{v,s} \leq h_{v,s}, \quad \forall v \in \mathcal{V}, s \in \mathcal{S} \quad (2.8)$$

$$\sum_{r \in \mathcal{R}_s^{\text{und}}} \beta^{\text{und}} \cdot y_{r,v,s-1} + \sum_{r \in \mathcal{R}:s=0} \beta^{\text{load}} \cdot y_{r,v,s} \leq h_{v,s}, \quad \forall v \in \mathcal{V}, s \in \mathcal{S} \quad (2.9)$$

Constraint 2.2 lets binary variable  $o_v$  determine whether the vehicle  $v \in \mathcal{V}$  operates. Constraint 2.3 links the departure variables  $x_{v,s,p}$  and  $d_{v,s}$ . Constraint 2.4 ensures that vehicles cannot arrive at the next stop before they have departed and traveled. Constraint 2.5 links the dwell time to the time between arrival and departure. Constraint 2.6 ensures that vehicles cannot overtake each other and that only one vehicle can occupy one stop at the same time. Furthermore, constraint 2.7 guarantees a minimal headway time between the departure of consecutive vehicles. Constraint 2.8 ensures that the schedule plans for sufficient dwell time, so that all expected passengers can embark and alight the trains. Analogously, constraint 2.9 establishes the same for loading and unloading freight, where the set  $\mathcal{R}_s^{\text{end}} \subset \mathcal{R}$  includes all containers with destination  $s \in \mathcal{S}$ .

**Subject to passenger related constraints:**

$$w_{s,p} = w_{s,p-1} + N_{s,p-1} - \sum_{v \in \mathcal{V}} b_{v,s,p}, \quad \forall s \in \mathcal{S}, p \in \mathcal{P} \setminus \{0\} \quad (2.10)$$

$$b_{v,s,p} \leq x_{v,s,p} \cdot \sum_{q=0}^{p-1} N_{s,q}, \quad \forall v \in \mathcal{V}, s \in \mathcal{S}, p \in \mathcal{P} \quad (2.11)$$

$$n_{v,s} = n_{v,s-1} + \sum_{p \in \mathcal{P}} b_{v,s,p} - e_{v,s}, \quad \forall v \in \mathcal{V}, s \in \mathcal{S} \quad (2.12)$$

$$e_{v,s} \leq \lambda_{s,p}^{\text{alight}} \cdot n_{v,s-1}, \quad \forall v \in \mathcal{V}, s \in \mathcal{S}, p \in \mathcal{P} \quad (2.13)$$

$$e_{v,s} \geq \lambda_{s,p}^{\text{alight}} \cdot n_{v,s-1} - 1, \quad \forall v \in \mathcal{V}, s \in \mathcal{S}, p \in \mathcal{P} \quad (2.14)$$

$$n_{v,s} \leq c_{v,s}^{\text{pas}}, \quad \forall v \in \mathcal{V}, s \in \mathcal{S} \quad (2.15)$$

$$n_{v,-1} = B_0 \cdot o_v, \quad \forall v \in \mathcal{V} \quad (2.16)$$

Following constraint 2.10, the number of passengers waiting  $w_{s,p}$ , depends on the number of waiting passengers from the previous period,  $w_{s,p-1}$ , the number of newly arriving passengers  $N_{s,p}$ , and the number of passengers boarding  $b_{v,s,p}$ . As formalized by constraint 2.11, boarding can only happen when there is a departing vehicle, where the accumulated passenger demand  $\sum_{q=0}^{p-1} N_{s,q}$  is an upper bound for the number of boarding passengers at stop  $s$  and period  $p$ . As modeled by constraint 2.12, the number of passengers  $n_{v,s}$  on vehicle  $v$  when departing stop  $s$  depends on the number of passengers that departed from the previous stop  $s-1$ , those that boarded at stop  $s$ , and the passengers alighting vehicle  $v$  at stop  $s$ . Constraints 2.13 and 2.14 determine the number of alighting passengers,  $e_{v,s}$ . Constraint 2.15 ensures that the reserved capacity  $c_{v,s}^{\text{pas}}$  is

sufficient for the number of passengers on vehicle  $v$ . Constraint 2.16 models the initial number of passenger  $B_0$  who are already on-board vehicle  $v$  via dummy variable  $n_{v,-1}$ .

**Subject to cargo-related constraints:**

$$\sum_{v \in \mathcal{V}} y_{r,v,s} = u_r, \quad \forall s \in \{0, \dots, s_r^{\text{end}}\}, r \in \mathcal{R} \quad (2.17)$$

$$\sum_{r \in \mathcal{R}} u_r \geq |\mathcal{R}| \cdot U, \quad (2.18)$$

$$y_{r,v,0} \cdot (p_r^{\text{start}} + \beta^{\text{load}}) \leq d_{v,0}, \quad \forall v \in \mathcal{V}, r \in \mathcal{R} \quad (2.19)$$

$$y_{r,v,s} - y_{r,v,s+1} = 0, \quad \forall v \in \mathcal{V}, s \in \{0, \dots, s_r^{\text{end}} - 2\}, r \in \mathcal{R} \quad (2.20)$$

$$f_r \geq a_{v,s_r^{\text{end}}} - M \cdot (1 - y_{r,v,0}), \quad \forall v \in \mathcal{V}, r \in \mathcal{R} \quad (2.21)$$

$$t_r \geq f_r - p_r^{\text{end}}, \quad \forall r \in \mathcal{R} \quad (2.22)$$

$$t_r \leq T^{\text{max}}, \quad \forall r \in \mathcal{R}, \quad (2.23)$$

$$\sum_{r \in \mathcal{R}} Q_r \cdot y_{r,v,s} \leq c_{v,s}^{\text{fre}}, \quad \forall v \in \mathcal{V}, s \in \mathcal{S} \quad (2.24)$$

Constraint 2.17 ensures that each container  $r$  is allocated to at most one vehicle and activates the variable  $u_r$  if the container  $r$  is accepted. Constraint 2.18 guarantees that at least  $U\%$  of the containers are accepted. Because of constraint 2.19, the vehicle that container  $r$  was allocated to must not depart until the container is released and loaded. Constraint 2.20 ensures a continuous transport of container  $r$  by vehicle  $v$  from depot  $s = 0$  to destination stop  $s_r^{\text{end}}$ . Constraint 2.21 ensures that the delivery time  $f_r$  of a container  $r$  after the vehicle's arrival  $a_{v,s_r^{\text{end}}}$  at stop  $s_r^{\text{end}}$ , where the parameter  $M$  is sufficiently large to only account for accepted containers. Constraint 2.22 bounds the delay  $t_r$  to the difference between the container's arrival  $f_r$  and its deadline  $p_r^{\text{end}}$ . Constraint 2.23 limits the delay per container to  $T^{\text{max}}$ . Finally, constraint 2.24 ensures that the containers on vehicle  $v$  do not exceed the reserved capacity  $c_{v,s}^{\text{fre}}$ .

**Subject to SV-mode constraints:**

$$Q^{\text{pas}} \cdot o_v \leq c_{v,s}^{\text{pas}}, \quad \forall v \in \mathcal{V}, s \in \mathcal{S} \quad (2.25)$$

$$Q^{\text{fre}} \cdot o_v \leq c_{v,s}^{\text{fre}}, \quad \forall v \in \mathcal{V}, s \in \mathcal{S} \quad (2.26)$$

$$c_{v,s}^{\text{pas}} + c_{v,s}^{\text{fre}} \leq C \cdot o_v, \quad \forall v \in \mathcal{V}, s \in \mathcal{S} \quad (2.27)$$

$$h_{v,s} \leq \beta^{\text{max}} \cdot o_v, \quad \forall v \in \mathcal{V}, s \in \mathcal{S} \quad (2.28)$$

$$h_{v,s} \geq \beta^{\text{min}} \cdot o_v, \quad \forall v \in \mathcal{V}, s \in \mathcal{S} \quad (2.29)$$

For SV, constraints 2.25 and 2.26 protect vehicle capacity dedicated to passengers or freight. Constraint 2.27 guarantees the restriction to a global capacity  $C$  and ensures that only operating vehicles offer capacity. Constraints 2.28 and 2.29 limit the dwell time per stop.

**Subject to SI-mode constraints:**

$$c_{v,s}^{\text{pas}} \leq C^{\text{pas}} \cdot (1 - z_v), \quad \forall v \in \mathcal{V}, s \in \mathcal{S} \quad (2.30)$$

$$c_{v,s}^{\text{fre}} \leq C^{\text{fre}} \cdot z_v, \quad \forall v \in \mathcal{V}, s \in \mathcal{S} \quad (2.31)$$

$$h_{v,s} \leq \beta^{\text{max}} \cdot o_v + M \cdot z_v, \quad \forall v \in \mathcal{V}, s \in \mathcal{S} \quad (2.32)$$

$$h_{v,s} \geq \beta^{\text{min}} \cdot o_v - M \cdot z_v, \quad \forall v \in \mathcal{V}, s \in \mathcal{S} \quad (2.33)$$

$$h_{v,s} \leq \beta_{\text{fre}}^{\text{max}} \cdot o_v + M \cdot (1 - z_v), \quad \forall v \in \mathcal{V}, s \in \mathcal{S} \quad (2.34)$$

$$h_{v,s} \geq \beta_{\text{fre}}^{\text{min}} \cdot o_v - M \cdot (1 - z_v), \quad \forall v \in \mathcal{V}, s \in \mathcal{S} \quad (2.35)$$

For SI, constraint 2.30 limits the reserved space for passengers to the available capacity if the vehicle  $v$  is a passengers vehicle. Further, constraint 2.31 models the dedicated space for freight if vehicle  $v$  is a cargo vehicle. Moreover, depending on the vehicle's usage, the minimal and maximal dwell time can differ: According to constraints 2.32 and 2.33, the dwell time per passenger vehicle and stop is limited by a minimal  $\beta^{\text{min}}$  and maximal time  $\beta^{\text{max}}$ . The constraints 2.34 and 2.35 limit the dwell time for freight vehicles.

We parameterize the instances solved with the optimization model based on expected values, e.g., the expected number of passengers arriving at a stop during a certain time period. In the following section, we introduce a stochastic DES that allows for the evaluation with varying demand. Figure 2.2 illustrates the respective contributions of optimization and simulation: For a given operational mode, the optimization model uses deterministic parameters on expected demand to *plan* train schedules and cargo allocations. The DES *evaluates* those schedules on stochastic demand instances and compares their success to that from a simple heuristic.

## 2.5. Simulation model

We create a stochastic DES to evaluate the effect of different operational approaches on the success of the shared transport system in terms of various indicators. Notably, the DES does not meet all assumptions implemented by the optimization model from Section 2.4; specifically, it features stochastic passenger demand and processes. Freight demand follows a set of planned and thereby deterministic orders. The next sub-

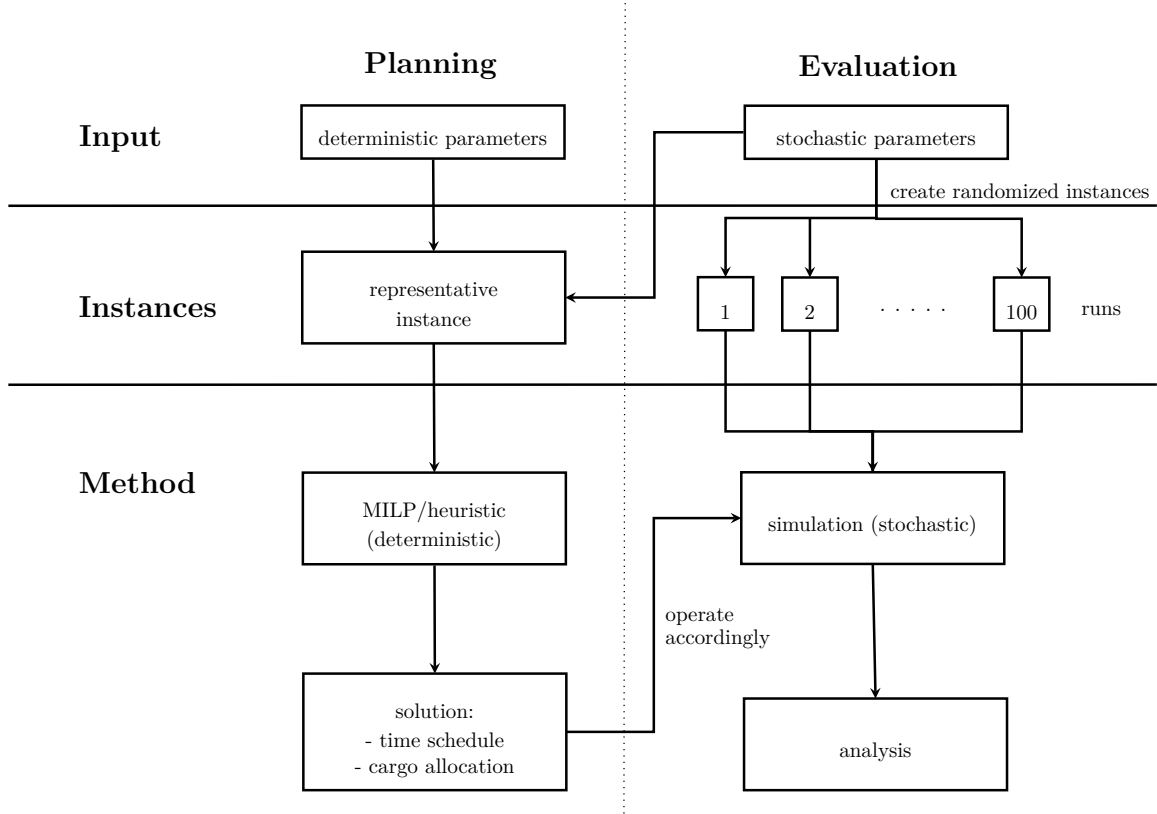


Figure 2.2.: Simulation for planning decision support

section details the stochastic distributions driving the DES processes. Subsequently, Section 2.5.2 documents the simulated scheduling and freight allocation approaches.

### 2.5.1. Stochastic processes

Instead of modeling passengers through agent-based components, the DES represents passenger demand as quantity flows. *Passenger arrivals* follow a Poisson process, where the arrival intensity  $\lambda_{p,s}$  may differ per period  $p$  and stop  $s$ . The number of *alighting passengers* is determined via binomial distributions, the parameter  $\lambda_{p,v}^{\text{alight}}$  represents the probability that a single passenger alights at stop  $s$  at period  $p$ .

The travel time is log-normally distributed, where  $\mu_{i,j}$  is the average travel time between stop  $i$  and  $j$  and  $\sigma$  is the estimated standard deviation. The service time required to handle a single passenger or freight container is exponentially distributed, where  $\beta \in \{\beta^{\text{board}}, \beta^{\text{alight}}, \beta^{\text{load}}, \beta^{\text{unload}}\}$  is the mean expected service time per entity.

Due to the problem complexity, we simulate limited slices of the total time of system operation. To enable a realistic passenger load, we assume an initial number of on-board passengers when a vehicle arrives at the depot. The number of *initial passengers* is also determined via binomial distributions with parameter  $B_0$  indicating the average

number of passengers on-board and  $p_B$  is the probability of one additional passenger on-board.

### **2.5.2. Scheduling vehicles and allocating freight in the simulation**

To schedule vehicles in the DES following the MILP presented in Section 2.4, we use the commercial solver Gurobi. We solve the deterministic scheduling problem for a representative passenger arrival pattern derived from the known arrival intensities. In a real-world implementation, these intensities should derive from empirical estimates and forecasts.

Additionally, as a simple benchmark for the optimized schedules, we implement a simple heuristic to create a static schedule and a first come first serve (FCFS) cargo allocation. We refer to the heuristic as static FCFS in the following. The static FCFS schedule releases vehicles within a constant headway time and a constant dwell time at each stop. The headway times are chosen such that the last tram arrives at its destination at the end of the time horizon and the vehicles are uniformly released across the time horizon.

Given SV, static FCFS allocates containers to vehicles first-come-first-serve, i.e., after the container's release, it is picked up by the first vehicle with available capacity. This process continues until all containers are allocated or until the capacity of all vehicles is used up. For SI, the first vehicle departing after the release of the last container turns into a dedicated freight vehicle. The heuristic allocates containers to each freight vehicle until it is full. The next freight vehicle is the first vehicle leaving after the last container was rejected.

## **2.6. Computational study**

We implement the optimization model (Section 2.4), the static FCFS heuristic and the DES (Section 2.5) in Python 3. The source code is publicly available at <https://doi.org/10.5281/zenodo.6412456>.

### **2.6.1. Scenario settings**

To plausibly evaluate the interplay of operational modes and schedule, we create fourteen small-scale and large-scale scenarios differing in passenger and cargo characteristics from empirical data. For each both scales, we consider one base-case scenario, three additional passenger demand scenarios, and ten additional cargo demand scenarios. In the following, we describe the scenarios in more detail. A list of parameter values can be found in the Appendix.

*The large scenarios' network* features an extract of line S1 traveling between central station and Poppenbüttel (14 stations) in Hamburg, Germany. As the network is bi-directional, it includes 28 stops, where each vehicle passes each station twice at different platforms. *The small scenarios' network* is limited to the stops between central station and Barmbek (7 stations, i.e., 14 stops in total). We estimate the *mean travel times* between two consecutive stations based on the existing schedule for this line. We approximate the standard deviation to be 10 seconds. To model *vehicle capacity*, we consider the tram operating on line S1, the *DBAG Class 474/874* (Website of Hamburg S-Bahn). The tram includes 208 seats and 306 standing places, i.e., a capacity for 514 people in total.

We extract *freight parameters* from the estimates documented by the pilot project *LastMileTram* by Schocke et al. (2020). In this project, a tram transports standardized containers, which are 1.2m long and 0.8m wide and hold 60 parcels on average. For simplification, we assume that each container requires an area of  $1\text{m}^2$ . Based on the standards of Verband Deutscher Verkehrsunternehmen (1990), we estimate the required area for a person standing at  $0.25\text{m}^2$ . Assuming that 20 percent of the standing area can be modified for freight, each passenger vehicle offers capacity for approximately 15 containers. For SI, we assume a dedicated freight vehicle type, which can transport at most 60 containers.

Schocke et al. (2020) point out that unloading and loading a container takes only five to ten seconds but securing it takes several minutes without a customized fastening system. We assume the existence of such a fastening system and expect an average time of 20 seconds per loading and fastening a container, and 15 seconds per loosening and unloading the container. Based on practitioner input, we limit the maximal dwell time per stop to three minutes for passenger vehicles. Moreover, we assume that passenger vehicles dwell at each stop for at least one minute. For SI, we let freight vehicles pass through stops without transshipment processes, i.e., their minimal dwell time is zero. We limit the maximal dwell time per stop and freight vehicle to ten minutes.

The depot and release stop for all containers is the central station; the cargo destination stations represent the offers from Hamburgbox (Website of HamburgBox), i.e., Wandsbeker Chaussee, Friedrichsberg, Barmbek, Olfsdorf and Poppenbüttel. We set the probability distribution of destinations based on the publicly available parcel demand data in Hamburg published by Hermes (2019). We consider a basic daily demand of 1,500 parcels in the base-case scenario, i.e., 25 containers when not evaluating the sensitivity to freight demand. Further, the additional cargo scenarios include 0, 5, 10, ..., 50 containers. The release and deadline per container follow a random uniform distribution with releases in the first sixth of the time horizon. For optimized schedules,

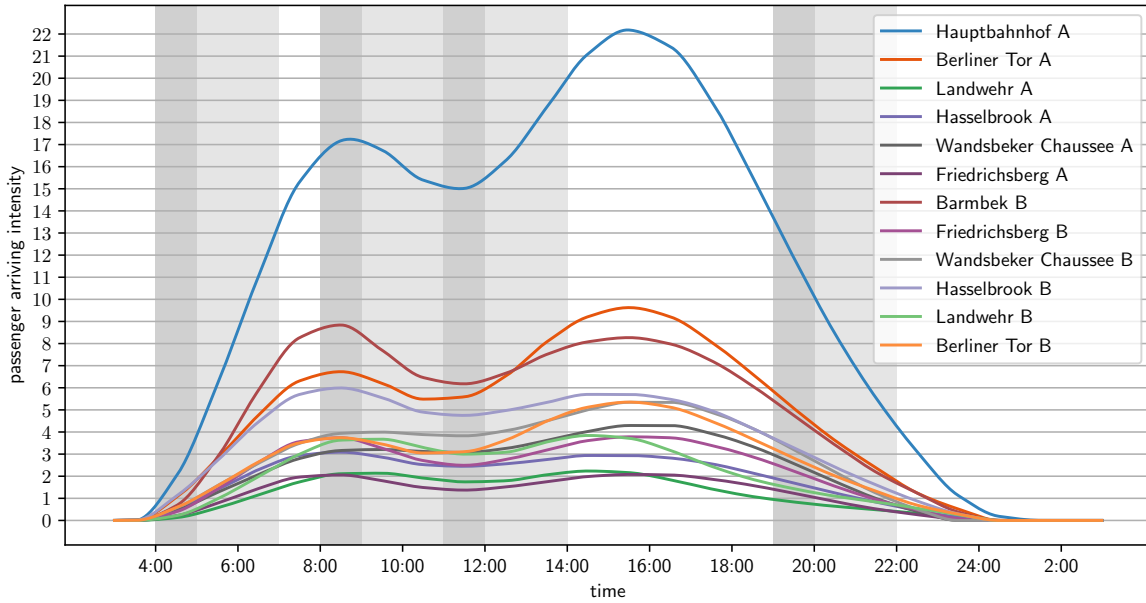


Figure 2.3.: Approximated passenger arrival intensity

we set the the maximal delay per container to ten minutes.

To parameterize *passenger demand*, we rely on open data open for related estimates accessed from Google (2021) and Hamburger Verkehrsbund GmbH (2020). We provide further details in the appendix. Figure 2.3 shows the average arrival intensity per minute across the time of day and across different stops. From this time frame, we select four intervals to generate distinct passenger scenarios. The intervals for the small scenario are highlighted dark gray in Figure 2.3 We approximate the initial passenger load of a starting vehicle on the demand at central station during that interval in relation to the maximal demand at that day. *Early morning* considers the interval from 4am to 5am without initial passengers on-board. The morning *rush hour* considers the interval from 8am to 9am with an initial passenger load of 75%. *Midday time* considers the interval from 11am to 12pm with an initial passenger load of 70%. We chose this setting as the base case scenario. *Evening* considers the interval from 2pm to 5pm with an initial passenger load of 60%. The large scenarios consider the same interval start and initial passenger load but the interval includes three hours instead of one hour (highlighted gray in Figure 2.3). Based on the observations of Li et al. (2020), a single passenger needs on average 0.87 seconds to board or alight a vehicle. Since the vehicle has nine doors, we assume an expected service time of 0.096 seconds per passenger. To evaluate schedules, we draw simulated sets of arrivals from the passenger probability distributions, generating 100 simulation runs per scenario.

### 2.6.2. Optimization results - Challenges of solving large-scale instances

We solve the MILP presented in Section 2.4 with Gurobi 9.0.1. and limit the run-time to 9 hours for both objectives. Without run-time limitations, the software continues solving the problem until it reaches optimality. All computations are run on an INTEL Sandy Bridge processor with 2.6 GHz. Clearly, instance size is a crucial factor in terms of the running time and solution quality. Table 2.2 lists relevant drivers of complexity per scenario by stating the instances size and the dimensions of the resulting MILP after Gurobi’s presolve reductions. For the *large scenario*, the relative optimality gaps

Scenario	periods	stops	vehicles	containers	constraints	variables	integer	binary
small	60	14	5	25	2,693	4,023	3,687	1,972
large	180	28	16	25	50,896	104,896	102,117	58,196

Table 2.2.: Scenario complexity

of the first objective function range from 65% to 99% depending on the number of containers and the passenger scenario. For the small scenarios under SV, the solver finds an optimal solution in the first objective. Under SI, the optimality gaps range from 1% to 27%. Furthermore, for a high number of instances, the second objective is not optimally solved. All in all, the results show that the required run-time to optimality increases exponentially in the size of the time horizon and network. The complete optimization results can be found in the appendix.

To analyze and benchmark the sensitivity of schedules to passenger and freight demand, our further analysis concentrates on the small scenario in the following section. In that analysis, we also discuss the trade-off between the first and second objective in more detail.

### 2.6.3. Sensitivity analysis on the small scenarios

While the analytical optimization model is limited to a fixed number of constraints and objectives, the DES lets us analyze the influence of partial decisions on a multitude of indicators. Specifically, we consider the *number of passengers waiting*, the *deviation from the train schedule*, the *success rate and delay of containers*, and the *resource utilization*. Where appropriate, we visualize results through box plots with outliers indicating the variance of the indicator across simulation runs. The shown line plots and bar charts indicate the mean or maximum across simulation runs. To evaluate

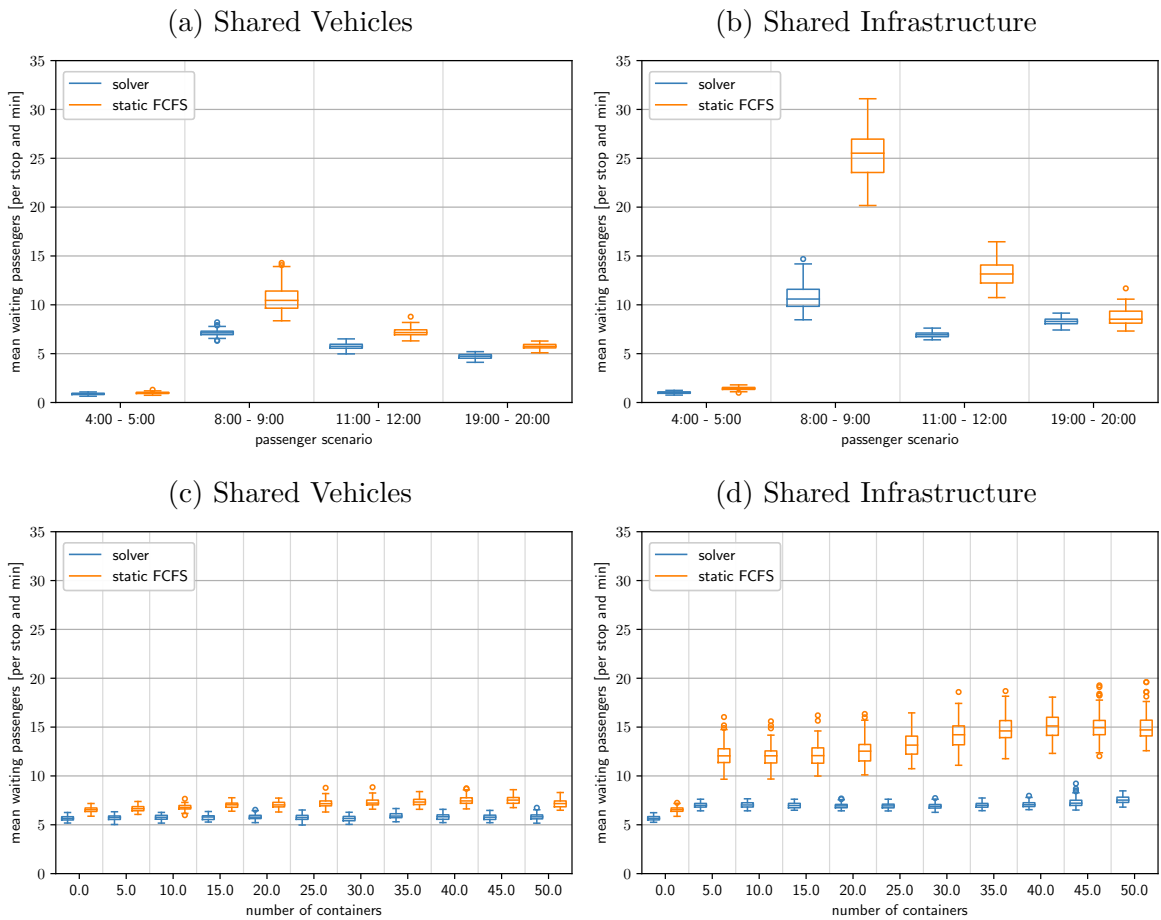


Figure 2.4.: Sensitivity of mean waiting passengers to passenger demand (a, b) and freight demand (c, d)

solution sensitivity, we vary the number of containers and passenger arrival intensity. In the base case, we consider 25 containers and the passenger demand at midday (11:00-12:00).

**Waiting passengers** Figure 2.4 illustrates the mean number of waiting passengers per stop and period as cargo or passenger demand vary. Naturally, the overall level of waiting passengers is higher for SI than for SV, because the passengers arrival continues during the dwell time of cargo vehicles. Nevertheless, the results show that the schedule obtained by the solver is overall robust to changes in passenger and cargo demand. During the rush-hour (8:00-9:00), the variance in the service quality is the highest. This is especially true for SI, where the variance increases not just for the static FCFS schedule but also for the solver schedule.

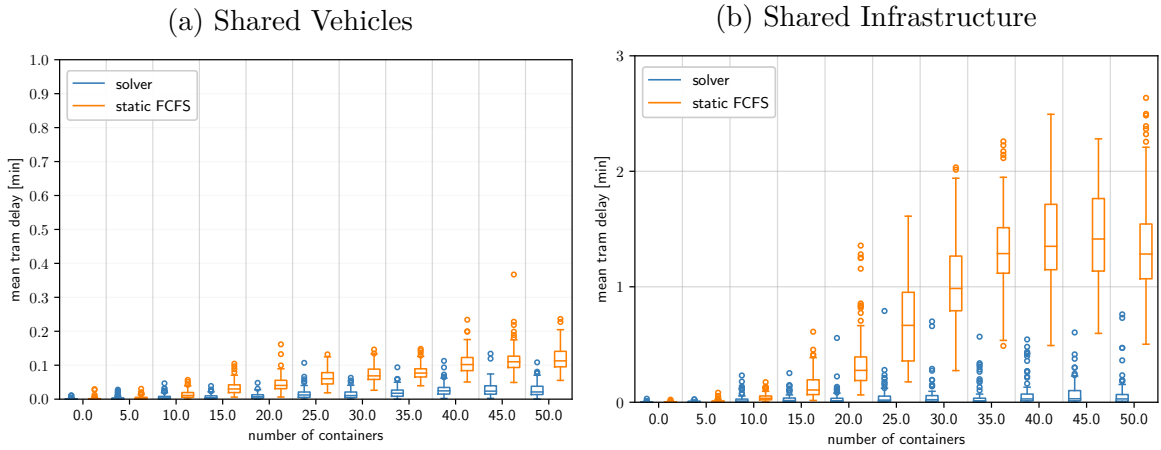


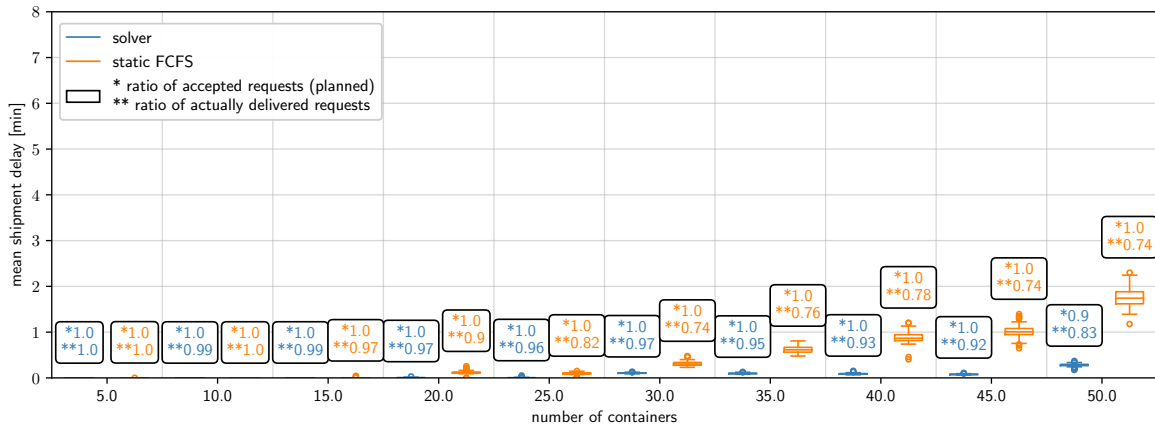
Figure 2.5.: Sensitivity of mean vehicle delay to freight demand

**Deviation from the train schedule** Figure 2.5 shows the average delay per vehicle and minute given varying freight demand. For the static FCFS schedule, the trams' delay increases with the number of containers, whereas the solver schedule causes only a few outliers. For SI, most delays firstly affect cargo trams and have a secondary effect on the following passenger trams.

**Success of cargo delivery** Figure 2.6 shows the box plots of the mean delay per delivered container at the end of each simulation run as the freight demand increases. For containers in transit, we estimate this indicator from the current delay and the expected travel time left to the destination. In addition, Figure 2.6 also states the ratio of accepted requests according to the planned schedule and the ratio of actually delivered requests at the end of the DES. Note that the delay is based on the same set of shipments and deadlines in either case. For SV, Figure 2.6a illustrates that the delay from the solver schedule is consistently lower than that from the static FCFS schedule and fewer containers remain at the depot. When cargo and passengers share vehicles, the solver schedule assigns containers more flexibly. For SI (Figure 2.6b), the average delay is much higher and fluctuates, due to of a low number of dedicated freight vehicles. For high freight demand, the solver does not accept all shipments but converges to the guaranteed service level of  $U = 50\%$ . This improves the average delay under the solver schedule, as the set of accepted containers is chosen according to the optimization objective.

**Resource utilization (service time)** Figure 2.7 shows the time required for boarding and alighting passengers (*passenger service*) as well as for loading and unloading containers (*cargo service*) on SV across the minutes of the passenger scenario at midday

(a) Shared Vehicles



(b) Shared Infrastructure

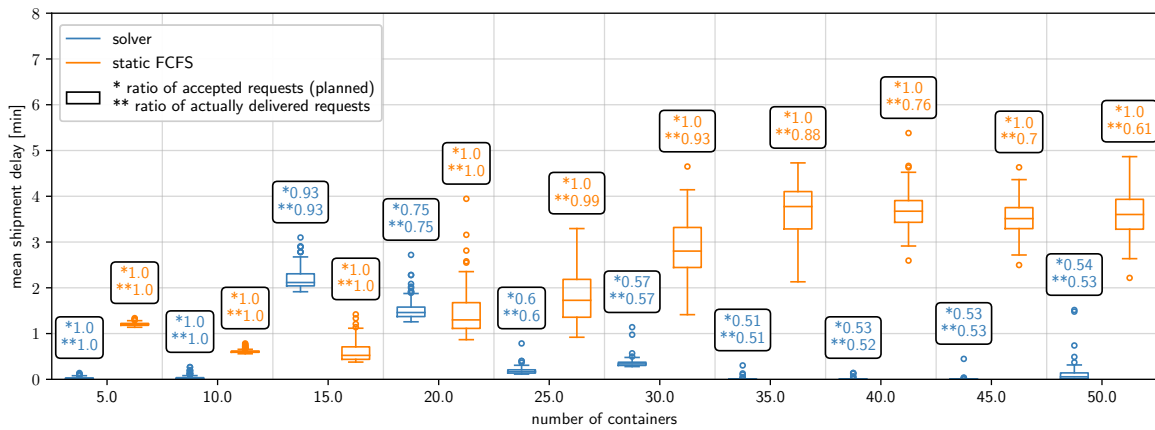


Figure 2.6.: Sensitivity of mean shipment delay to freight demand

(11:00-12:00). The plot presents the mean and maximal service time per vehicle and per simulation run. The maximal service time for freight far exceeds that for passengers. Thus, after boarding, passengers have to wait for cargo loading. For SI, the loading and unloading processes are more evenly distributed across the time horizon than for SV.

**Resource utilization (vehicle capacity)** Figure 2.8 shows the ratio of loaded cargo and boarded passengers relative to the currently available total capacity across time. The plot considers the mean as well as the maximal load ratio per stop and per simulation run. Comparing the results from SV and SI emphasizes the time difference for the loading and unloading processes. While cargo is loaded only in the middle of the time interval for SI, it is continuously loaded and unloaded for SV. Moreover, the passenger load for SI is higher, as the same number of vehicles is used in both modes.

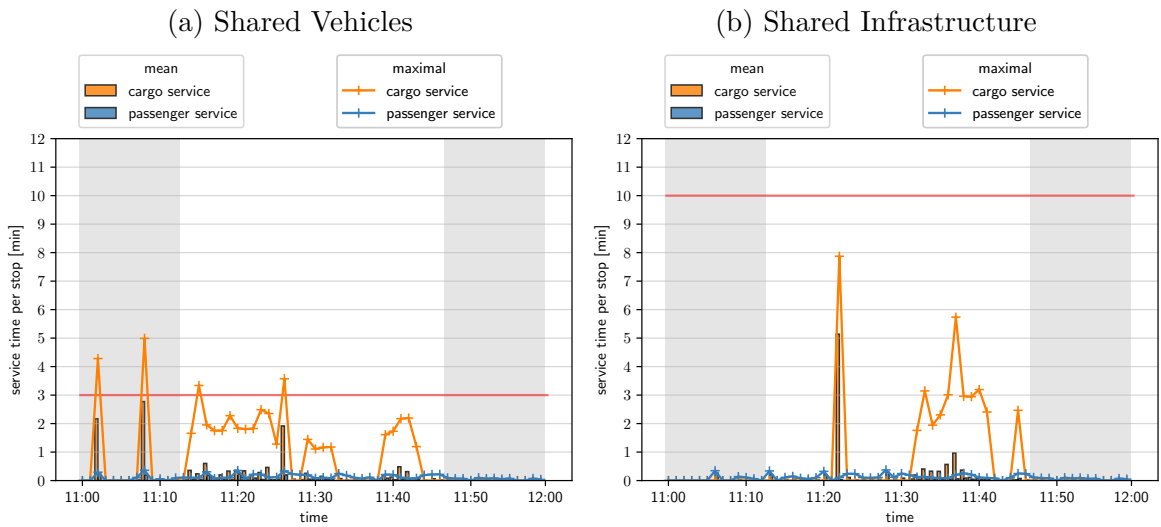


Figure 2.7.: Service time per stop given the solver schedule

#### 2.6.4. Managerial implications

Generally, the results show the importance of optimization to satisfy passenger service quality while enabling cargo transport. Compared to the static FCFS schedule, the solver schedule consistently reduced both the mean and the variance of indicators such as the number of waiting passengers and the tram delay. This holds true across passenger demand scenarios and varying degrees of freight demand.

On SI, delays firstly affect freight trams and have a secondary effect on the following passenger trams. These results emphasize the importance of integratively considering the cargo service process in the planning process to establish a reliable schedule. For SV, passengers may have to allow for longer waiting times while freight is loaded and unloaded, but can expect more frequent vehicle arrivals.

Analyzing the alternative modes separately under various demand scenarios can help planners to explore options for aligning passenger and freight transport. For example, the rush hour scenario (8:00-9:00) is particularly vulnerable to delays introduced by freight vehicles in SI, such that we would not recommend running such vehicles during rush hour at all. Instead, if freight must be transported at that time, shared vehicles are preferable. On the other hand, times of low passenger demand, as in the early morning (4:00-5:00) scenario, are less susceptible to delays based on dedicated vehicles in SI. Such insights could support planners in combining the two modes depending on time or system load.

From an engineering perspective, shared vehicles appear challenging, e.g., due to safety requirements and the simultaneous loading and boarding processes. However, as our results emphasize, such systems can allocate capacity much more flexibly and

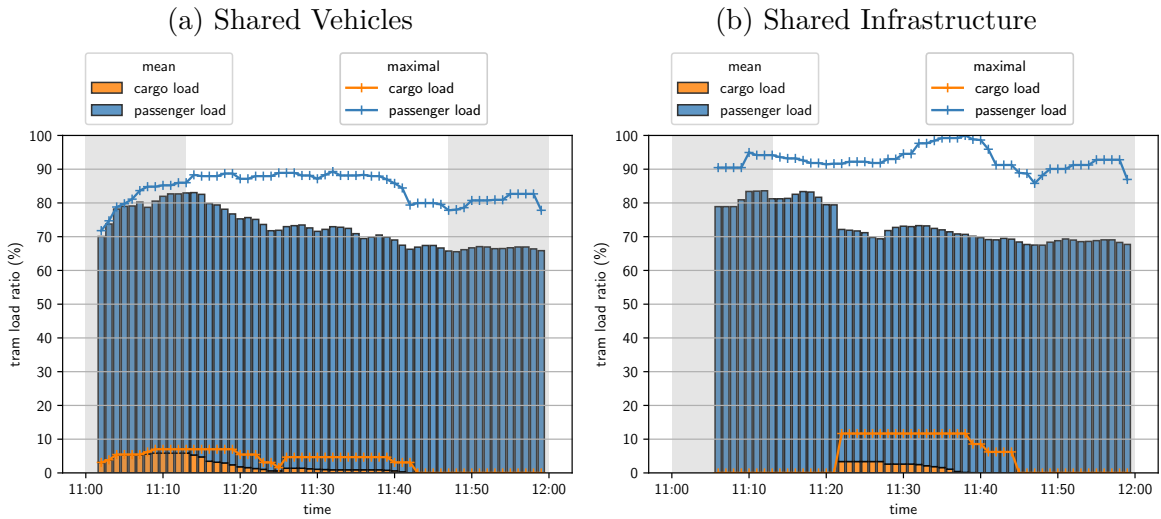


Figure 2.8.: Percentage usage of vehicles' capacity given the solver schedule

therefore induce lower delays and a higher service quality. Accordingly, we regard SV to be more suitable for urgent containers with a tight deadline.

Analyzing the service time needed for passengers versus that needed for freight highlights that freight clearly has the larger impact. Especially in settings where passengers negatively perceive a longer dwell time and consider to abandon the service, a system that relies on shared infrastructure rather than shared vehicles seems preferable. The dwell time represents the bottleneck in this system, whereas vehicle capacity plays only a minor role. A high maximal dwell time for SI further helps to reduce the required number of dedicated cargo vehicles.

## 2.7. Conclusions

In this project, we considered the implications of different operational modes and demand levels on scheduling shared transport of passengers and freight. We distinguished a *shared vehicles mode* and a *shared infrastructure mode* with dedicated passenger and freight vehicles. To find an optimal train schedule and allocate containers to train, we formulated a lexicographical bi-objective linear mixed-integer program. The program minimizes primarily the number of waiting passengers and secondly the containers' delays. Clearly, solving large instances to optimality is computationally expensive. Therefore, we more closely evaluated a set of small scenarios. The results highlight the need of optimization strategies for the success of such systems.

Especially for SV, the optimized schedule maintained a constant solution quality when increasing the number of containers and passengers, while the static FCFS bench-

mark caused to pile-ups and delays. Generally, flexibly assigning and rejecting containers is a great advantage of this operation mode and makes the mode suitable for more urgent deliveries.

The computational results point to the dwell time as a bottleneck for shared transport. The results of the computational study show that some containers cannot be loaded as the required process times exceed the time limitations. Further, for the majority of instances, the freight service time exceeded the passenger service time. In consequence, we argue that freight service time is an important success factor for a shared transport system.

While the high service times for freight compared to passenger represent a disadvantage for SV, they offer advantages for SI. Especially if freight vehicles can operate on dedicated platforms or during idle times, the maximal dwell time underlying our results becomes redundant. However, as shared infrastructure induces more delay, we consider it to be better for freight that is not time-sensitive. When moving towards concepts of reasonable travel time rather than shortest travel time, as suggested in Arvidsson et al. (2016), mean shipment delay may no longer play a large role. Should the system aim to appeal to diverse types of freight, a combination of both modes might be relevant after all.

Future work needs to examine more computationally efficient approaches to solving the scheduling problem presented here, e.g., through meta-heuristics. De Langhe et al. (2014) highlight opportunities from managing intra-city-flows, which argue for not limiting the system to a single depot, but moving it toward pickup-and-delivery-capabilities. Finally, robust optimization is another interesting alternative for jointly scheduling passengers and freight in a shared system.

# 3.

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## Essay 2: Integrating micro-depot freight transport in existing public transport services

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### Code and data

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**Abstract.** As conventional last-mile transport contributes to traffic congestion and pollution, urban areas need new approaches to transporting freight. One promising idea is integrating freight deliveries with existing public transport infrastructures like light rail. However, this concept creates the challenge of offering a high service quality for passengers and freight. In this work, we consider a setting where freight originates from and is transshipped at several public transit stops that serve as micro-depots with a limited storage capacity. Further, the system relies on shared vehicles, where a dedicated share of the capacity can be used to fasten freight containers or as a standing area for passengers. For this setting, we propose an optimization model that integrates the tactical scheduling of transport services and the allocation of freight containers to those services. To solve realistically-sized instances, we propose an adaptive large neighborhood search heuristic. We use this heuristic to evaluate the system's sensitivity to the capacity of micro-depots and vehicles.

**Keywords.** Transportation, Logistics, Shared Transport, Scheduling, Adaptive Large Neighborhood Search

### 3.1. Introduction

Given close quarters and a high population density in urban areas, sustainably moving humans and freight on the "last mile" is challenging (Kiba-Janiak et al., 2021). Both public transport and freight transport require space within cities' infrastructure and meet similar expectations: Passengers expect short travel times and frequent departures, while freight customers expect quick and punctual deliveries. At the same time, citizens expect the municipality to limit air and noise pollution and traffic for a better quality of life.

Integrating freight transport into public transport may offer chances to improve both services: The option to exploit capacity overhangs profitably can justify financial investments in public transport while limiting the adverse ecological effects of freight transport. Capacity overhangs occur in on-demand (Bosse et al., 2023) and in fixed transportation services (Ghilas et al., 2018). Here, we consider the challenge of integrating passengers and freight on a fixed infrastructure, such as light rail, thereby further justifying the investment while exploiting the opportunity of short travel times compared to crowded streets (De Langhe et al., 2019). We allow for a partially shared vehicle capacity, e.g., a dedicated area in each shared vehicle can either carry securely attached freight containers or serve as standing space for passengers. Although this concept currently faces legal restrictions in many European countries, it features in the pilot project LogIKtram in Karlsruhe, Germany (Frey, 2023).

Integrating passengers and freight must not disadvantage passengers to ensure the system's acceptance and keep public transport attractive (Arvidsson & Browne, 2013). The success of such systems depends on strategic decisions, such as the inclusion of public transport lines, vehicle capacity, and the capacity and positioning of depot stations (Cavallaro & Nocera, 2021; Delle Donne et al., 2023), as well as on operational decisions, such as how much freight to accept and which parcels to transport on which vehicle (Li et al., 2021).

To support planning for such an integrated system and to evaluate its sensitivity to strategic decisions, we extend a model first presented in Hörsting and Cleophas (2023a). That contribution proposed a lexicographical model to create demand-oriented schedules and to assign freight containers to shared services given a single depot. The optimization model prioritizes passenger service by minimizing the passengers' waiting time first and minimizing the number of rejections and the delivery delay of cargo requests second. The extended model presented here lets freight originate and end at multiple *micro-depots* with a limited capacity. To solve realistically-sized instances, we propose an adaptive large neighborhood search (ALNS) heuristic as inspired by Yin

et al. (2021).

We evaluate the heuristic’s solution performance and the system’s sensitivity to the vehicle and micro-depot capacities by planning and processing a simulated day of operations. To that end, we generate artificial passenger and freight demand for various combinations of demand scenarios and network designs. Thus, the contribution of this paper is threefold:

- We formulate an extended problem allowing for the flexible pick-up and delivery of freight in a fixed public transport infrastructure,
- we extend destroy and repair operators for an ALNS-based approach to creating demand-oriented schedules and assign freight to transport services,
- and we evaluate the system’s sensitivity to strategic capacity decisions.

In the next section, we briefly review the state of integrated passenger and freight transport research before presenting an overview of related contributions featuring ALNS. Subsequently, in Section 3.3, we describe the problem setting in further detail. In Section 3.4, we introduce the hierarchical optimization model. Section 3.5 describes the proposed ALNS, specifically expounding on destroy and repair operators. We analyze the solution performance of the ALNS compared to simple scheduling rules and the mathematically optimal solution in Section 3.6. Section 3.7 analyzes the resulting system’s sensitivity to alternative combinations of the depot and vehicle capacity given by earlier strategic decisions. Finally, Section 3.8 summarizes our findings and provides an agenda for further research in the domain.

## **3.2. State of the art**

Cooperative transport of freight and passengers becomes possible when the public transport system is not always fully utilized. Cavallaro and Nocera (2021) provide a broad, concept-centric literature review focused on the idea. Hörsting and Cleophas (2023a) survey existing optimization models considering the shared transportation of passengers and freight in an urban area on a fixed infrastructure. However, to provide a path to success for such integrated systems, decision-makers must find operational modes that ensure both passenger and freight service quality. In that regard, the research presented here is further motivated by a call-to-action stated in Cochrane et al. (2017): “model the impacts of [...] the projects [...] to estimate impacts on congestion, operations, and environmental outcomes”.

As shown in Azcuy et al. (2021), significant distance savings can result when public transport systems deliver freight to micro-depots, from where they can reach their final

destination. The idea of these micro-depots motivates the extended model presented here, in which, at a variety of stops, both passengers and freight can leave and enter the vehicles.

As we propose, on the one hand, a prescriptive approach to schedule vehicles and allocate freight and, on the other hand, evaluate the outcomes for various scenarios, our research is related to several further contributions. For example, Motraghi and Marinov (2012) evaluate scheduling decisions for cargo vehicles in a freight rail system based on a discrete event-based simulation. Taking a much broader view of the matter, van Heeswijk et al. (2020) evaluate a range of urban logistics schemes in an agent-based simulation to estimate implications for sustainability and the schemes' attractiveness for stakeholders.

In the remainder of this section, we focus on two aspects that drive the model and the solution approach proposed in this paper: Firstly, we briefly summarize existing research on multi-depot transportation and relate it to the idea of micro-depots on a fixed infrastructure. Secondly, we provide some background for the ALNS algorithm we rely on to solve the scheduling problem.

### **3.2.1. Micro-depot transportation**

Fragmented freight flows and inefficient delivery operations are two challenges in last-mile transportation that increase the need for consolidation (van Heeswijk et al., 2020). At the same time, ecologically friendly transportation modes like cargo bikes and electric trucks often offer a lower capacity and a shorter range than conventional trucks. This conundrum has sparked increasing interest in urban consolidation centers or micro-depots. Katsela et al. (2022) evaluate the advantages and disadvantages of micro-hubs by analyzing and comparing case studies. Planning a micro-depot network involves optimization problems on various levels.

In recent research, Zhao et al. (2018) propose a method to locate distribution hubs in a metro network, while Assmann et al. (2020) consider location planning problems for multiple depots when cargo bikes take over the last part of freight transport. Furthermore, Alumur et al. (2021) review existing hub location problems and propose ideas to improve modeling. Delle Donne et al. (2023) envision a system where freight enters and leaves the public transport system via a set of drop-in and drop-out stations. In that setting, the authors evaluate strategic decisions on which public transport lines to recruit for freight transport and where to locate drop-in and drop-out stations.

In vehicle routing, multiple depots are a prominent concept (Brandão, 2020; Gouveia et al., 2022; Montoya-Torres et al., 2015; Ramos et al., 2020). Multi-depot solutions also combine well with new logistics schemes like crowd shipping or mobile depots (Hof

& Schneider, 2021; Mousavi et al., 2022; Zhen et al., 2022).

In passenger transport, approaches to scheduling focus on depots that describe the starting and ending point of the trip for each vehicle. For example, Kliewer et al. (2006) consider a multi-depot vehicle scheduling problem where buses are assigned to given timetabled trips, whereas Amberg and Amberg (2023) focus on an integrated multi-depot vehicle and crew scheduling problem.

In this work, we consider a micro-depot network for shared passenger and freight transport. In that, we consider location and capacity decisions as given from strategic planning but evaluate their implications for integration success. Given the idea of fixed infrastructure and line plans, scheduling services and allocating freight to services overtakes routing.

### 3.2.2. Adaptive large neighborhood search (ALNS)

The ALNS is a meta-heuristic first proposed by Røpke and Pisinger (2006) to solve a pickup and delivery problem with time windows. It extends the idea of *large neighborhood search (LNS)* by allowing for a variety of destroy and repair operations as opposed to a single pair of one destroy and one repair operator. In each iteration, these destroy and repair operators are selected randomly according to weights that are updated based on different search strategies. For instance, operators leading to an improvement in the objective value are more likely to be selected in future iterations. The advantage of ALNS over LNS is the extended search space, which reduces the risk of getting stuck in local optima. Most ALNS algorithms include operators that aim for diversification and intensification. Diversification means the operator randomly searches a large part of the neighborhood to find new solutions. Intensification implies that the operator searches purposefully to improve the quality of the current solution. For more information, we refer the reader to the definitions by Pisinger and Røpke (2010).

Today, ALNS is applied to various large-scale routing and scheduling problems. For instance, for variants of the pickup and delivery problems (Røpke and Pisinger, 2006; Masson et al., 2013; Ghilas et al., 2016b), two-echelon vehicle routing problems (Hemmelmayr et al., 2012, Enthoven et al., 2020) or workforce routing and scheduling problems (Bilgin et al., 2012; Kovacs et al., 2012; Cinar et al., 2021). Windras Mara et al. (2022) present a detailed survey of the recent development on ALNS.

Barrena et al. (2014b) introduce an ALNS heuristic to solve a rail rapid transit problem with dynamic passenger demand, minimizing the passenger waiting time. They improve the results of a branch-and-bound algorithm in Barrena et al. (2014a) by 26%. Similarly, Yin et al. (2021) propose an ALNS to find a demand-oriented timetable,

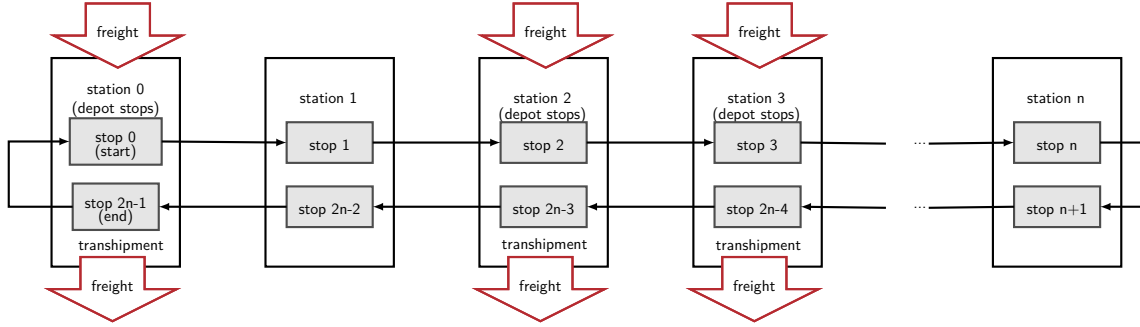


Figure 3.1.: Assumed network topology: A circular, bi-directional single route

minimizing the passenger congestion at stops. Their model includes limited vehicle capacities and multiple lines. Yuan et al. (2022) use ALNS to design an urban network combining a fixed-line transport system and a demand-responsive transport system.

For this work, we are interested in applying ALNS to demand-oriented service scheduling problems. To that end, we adapt the heuristic of Yin et al. (2021) to integrate the freight transport in Section 3.5.

### 3.3. Problem setting

In the following, we explain the problem framework and underlying assumptions. We extend the model of Hörsting and Cleophas (2023a) by considering multiple micro-depots to be located at selected stops and feature a limited storage capacity. Furthermore, we focus on the operational mode featuring shared vehicles, assuming a limited share of the vehicle capacity can be used to secure freight.

The setting features an existing public transit infrastructure with a fixed set of stops and connecting legs, e.g., a single line in a light-rail network. Each *station* consists of two *stops* with opposite directions. Further, we assume that the stops of each station are close to each other, i.e., it is possible to walk from the first to the second stop of the same station in, at most, a few minutes. Such a network configuration is common in many European cities that are the inspiration for this work. The vehicles operate on a circular, bi-directional single route, i.e., they start at a joint *start stop* and turn around when arriving at the boundary station (see Figure 3.1).

The expected passenger demand takes the form of quantity flows driven by the arrival and alighting rates per time period and stop. First, we consider the number of passengers arriving per stop and period. When a vehicle arrives at a stop, a fixed ratio of passengers alights. Since the network is bi-directional and each stop serves a dedicated direction, every passenger waiting at a stop wants to board the arriving vehicle.

Several stops are pre-defined *micro-depots*, where freight can be loaded and unloaded. We consider freight as *containers* carrying parcels with the same requirements, i.e., time and place of release, due time, and destination. Every container should be transported to its destination stop within a soft due time. Additionally, a hard due time per container sets the time of the latest acceptable arrival at the destination. We allow for the rejection of container requests to guarantee feasibility. Note that we assume that the service provider decides on the acceptance of containers before the start of the period so that freight customers can still find alternative means of transport. The micro-depots can only store a limited number of containers between release and pick-up. Containers do not require storage capacity after drop-off at their destination stop, as we assume they are picked up instantly or immediately forwarded to their final destination.

The vehicle capacity is also limited. Specifically, we assume that parts of the standing area for passengers are modified so that parcel containers can be attached there, i.e., we assume that passengers and cargo share a selected vehicle space. Again, the transport of passengers is prioritized. First, passengers alight and board the vehicle. If there is enough space left, the parcel containers are secured in the remainder of the shared area.

This work focuses on satisfying the demand for the passenger and freight service while integrating freight into the public transit system. For this reason, we consider an irregular time schedule with variable dwell times. Each *service* in the time schedule is defined by an individual vehicle's arrival and departure time per stop over the course of the considered horizon. All processes, like boarding and alighting passenger and loading and unloading containers, must be executed during the dwell time. Additionally, there must be a sufficient dwell time between the departure of two subsequent vehicles from the same stop, and no two vehicles must occupy the same platform simultaneously.

In practice, the planners usually determine the lines and the timetable before considering the vehicle routes and crew schedules (Schöbel, 2012). Here, we disregard the challenges of rolling stock. Thus, we set an upper bound for the maximal number of services offered within the planning horizon instead of defining a specific fleet size. Nevertheless, given a time schedule, we can deduce the maximal number of simultaneously operating vehicles and, thus, the minimum required fleet size to operate the line. We aim to determine an irregular, demand-oriented time schedule and assign containers to operating services following the problem formulation detailed in the next section.

### 3.4. Mathematical formulation

The problem considered here entails defining a time schedule  $\mathcal{T}$  as a set of individual services. Since we consider demand-oriented scheduling, we allow for aperiodic services, i.e., vehicles may arrive and depart irregularly. We formally define a schedule in Section 3.4.1. For a given schedule, we compute the passenger flows and the resulting passenger service quality as described in Section 3.4.2.

Additionally, the problem entails assigning cargo containers to vehicles as formalized in Section 3.4.3, while minimizing cargo delay and rejection. In Section 3.4.4, we link both sub-problems through a global lexicographical objective function defined, where we minimize the passenger congestion first and afterward the delay and rejection rate of cargo requests. Tables 3.1–3.3 list the notation for sets, variables, and parameters introduced in the following.

#### 3.4.1. Time schedule formulation

We consider a discrete planning horizon, given as a set of time periods  $\mathcal{P}$ . Further, we define a time schedule  $\mathcal{T}$  as a set of individual services, where each service  $t \in \mathcal{T}$  must pass all stops in the bi-directional network, represented by the set  $\mathcal{S}$ . The number of services in  $\mathcal{T}$  is limited by the parameter  $V \in \mathbb{N}$ . Each service  $t \in \mathcal{T}$  consists of a departure time  $d_{s,t} \in \mathcal{P}$ , an arrival time  $a_{s,t} \geq 0$ , and a dwell time  $h_{s,t} \geq 0$  per stop  $s \in \mathcal{S}$ . The parameter  $\mu_{s_1,s_2} > 0$  gives the time-independent travel time between two stops  $s_1$  and  $s_2 \in \mathcal{S}$ . A given parameter  $\beta^{\min} \geq 0$  defines a *minimal dwell time*. Analogously, a *maximal dwell time*  $\beta^{\max} \geq 0$  per service ensures a limited overall travel time. In a feasible solution, two vehicles cannot dwell at the same stop at the same time. A *minimal headway*  $H \geq 0$  spaces the departure of two consecutive services from the same stop.

Formally, a feasible time schedule  $\mathcal{T}$  solves the following decision model:

$$a_{s,t} = d_{s-1,t} + \mu_{s-1,s}, \quad \forall s \in \mathcal{S} \setminus \{0\}, t \in \mathcal{T}, \quad (3.1)$$

$$h_{s,t} = d_{s,t} - a_{s,t}, \quad \forall s \in \mathcal{S}, t \in \mathcal{T}, \quad (3.2)$$

$$h_{s,t} \geq \beta^{\min}, \quad \forall s \in \mathcal{S}, t \in \mathcal{T}, \quad (3.3)$$

$$h_{s,t} \leq \beta^{\max}, \quad \forall s \in \mathcal{S}, t \in \mathcal{T}, \quad (3.4)$$

$$a_{s,t} \geq d_{s,t-1}, \quad \forall s \in \mathcal{S}, t \in \mathcal{T} \setminus \{0\}, \quad (3.5)$$

$$d_{s,t} \geq d_{s,t-1} + H, \quad \forall s \in \mathcal{S}, t \in \mathcal{T} \setminus \{0\}, \quad (3.6)$$

$$|\mathcal{T}| \leq V, \quad (3.7)$$

$$d_{s,t} \in \mathcal{P}, h_{s,t}, a_{s,t} \geq 0, \quad \forall s \in \mathcal{S}, t \in \mathcal{T}. \quad (3.8)$$

Notation	Set	Description
$\mathcal{S}$		Set of stops
$\mathcal{P}$		Set of periods in the planning horizon
$\mathcal{P}_s^{\text{dep}}$	$\subset \mathcal{P}$	Set of departure times from stop $s \in \mathcal{S}$
$\mathcal{P}_s^{\text{start}}$	$\subset \mathcal{P}$	Set of periods at which stop $s \in \mathcal{S}$ releases a container
$\mathcal{T}$		Set of services
$\mathcal{T}_{s,p}^{\text{dep}}$	$\subset \mathcal{T}$	Set of services that depart from stop $s \in \mathcal{S}$ at period $p \in \mathcal{P}$
$\mathcal{T}_{s,\leq p}^{\text{dep}}$	$\subset \mathcal{T}$	Set of services that depart from stop $s \in \mathcal{S}$ at period $p \in \mathcal{P}$ and earlier
$\mathcal{R}$		Set of containers
$\mathcal{R}_s$	$\subset \mathcal{R}$	Set of containers for which stop $s \in \mathcal{S}$ is included in the delivery path
$\mathcal{R}_s^{\text{start}}$	$\subset \mathcal{R}$	Set of containers with start at stop $s \in \mathcal{S}$
$\mathcal{R}_s^{\text{end}}$	$\subset \mathcal{R}$	Set of containers with stop $s \in \mathcal{S}$ as their destination
$\mathcal{R}_{s,\geq p}^{\text{start}}$	$\subset \mathcal{R}$	Set of containers that start at stop $s \in \mathcal{S}$ at period $p \in \mathcal{P}$ and later

Table 3.1.: List of index sets

Notation	Set	Description
$d_{s,t}$	$\in \mathcal{P}$	Departure time of service $t \in \mathcal{T}$ from stop $s \in \mathcal{S}$
$a_{s,t}$	$\geq 0$	Arrival time of service $t \in \mathcal{T}$ at stop $s \in \mathcal{S}$
$h_{s,t}$	$\geq 0$	Dwell time of service $t \in \mathcal{T}$ at stop $s \in \mathcal{S}$
$w_{s,p+\tau_p^s}$	$\in \mathbb{N}$	Number of passengers at stop $s \in \mathcal{S}$ in the interval $[p, p + \tau_p^s]$ for period $p \in \mathcal{P}_s^{\text{dep}} \cup \{0\}$
$w_{s,p+\tau_p^s}^{\text{cum}}$	$\in \mathbb{N}$	Accumulated number of passengers at stop $s \in \mathcal{S}$ in the interval $[p, p + \tau_p^s]$ for period $p \in \mathcal{P}_s^{\text{dep}} \cup \{0\}$
$n_{s,t}$	$\in \mathbb{N}$	Number of passengers using service $t \in \mathcal{T}$ when departing from stop $s \in \mathcal{S}$
$b_{s,t}$	$\in \mathbb{N}$	Number of boarding passenger for service $t \in \mathcal{T}$ from stop $s \in \mathcal{S}$
$e_{s,t}$	$\in \mathbb{N}$	Number of alighting passenger from service $t \in \mathcal{T}$ at stop $s \in \mathcal{S}$
$y_{r,t}$	$\in \{0, 1\}$	Is one if the container $r \in \mathcal{R}$ assigned to service $t \in \mathcal{T}$ , else zero
$z_r$	$\in \{0, 1\}$	Is one if the container $r \in \mathcal{R}$ accepted, else zero

Table 3.2.: List of variables

Notation	Set	Description
$\mu^{s_1, s_2}$	$\geq 0$	Travel time between stop $s_1$ and stop $s_2 \in \mathcal{S}$
$\beta^{\min}$	$\geq 0$	Minimal dwell time at a stop
$\beta^{\max}$	$\geq 0$	Maximal dwell time at a stop
$H$	$\geq 0$	Minimal headway between two services
$V$	$\in \mathbb{N}$	Maximal number of services
$\tau_p^s$	$\geq 0$	Duration between period $p \in \mathcal{P}$ to the next larger period in $\mathcal{P}_s^{\text{dep}}$
$N_{s,p}$	$\in \mathbb{N}$	Number of passengers arriving at stop $s \in \mathcal{S}$ at period $p \in \mathcal{P}$
$\lambda_{s,t}^{\text{alight}}$	$\in [0, 1]$	Ratio of passengers alighting service $t \in \mathcal{T}$ at stop $s \in \mathcal{S}$
$C^{\text{pas}}$	$\in \mathbb{N}$	Vehicle capacity primarily for passengers
$\beta^{\text{board}}$	$\geq 0$	Boarding time per passenger
$\beta^{\text{alight}}$	$\geq 0$	Alighting time per passenger
$\bar{h}_{s,t}$	$\geq 0$	(Fixed) dwell time of service $t \in \mathcal{T}$ at stop $s \in \mathcal{S}$
$T_{r,t}$	$\geq 0$	Delay of container $r \in \mathcal{R}$ transported according to service $t \in \mathcal{T}$
$P$	$\geq 0$	Penalty for rejection per container
$Q_r$	$> 0$	Space required to load a single container $r \in \mathcal{R}$
$\bar{n}_{s,t}$	$\in \mathbb{N}$	(Fixed) number of passengers using service $t \in \mathcal{T}$ when departing from stop $s \in \mathcal{S}$
$C^{\text{fre}}$	$\in \mathbb{N}$	Vehicle capacity for cargo only
$C^s$	$\in \mathbb{N}$	Micro-depot capacity of stop $s \in \mathcal{S}$
$\beta^{\text{load}}$	$\geq 0$	Loading time per container
$\beta^{\text{unld}}$	$\geq 0$	Unloading time per container
$T^{\text{max}}$	$\geq 0$	Maximal delay per container

Table 3.3.: List of parameters

Through constraints (3.1), each service's arrival time at the next stop results from adding up the departure time of the current stop and the travel time between both stops. Per stop, each service also provides a dwell time for the vehicle defined as in constraints (3.2). The minimal and maximal dwell are modeled in constraints (3.3) and (3.4). Constraints (3.5) set the order of the services, as a service's arrival cannot take place before the previous service's departure from the respective stop. Further, constraints (3.6) ensure the headway between two consecutive departures from the same stop. Finally, constraint (3.7) limits the number of maximal services.

### 3.4.2. First sub-problem: Determine the passenger flow.

We consider minimizing freight transport's interference with passenger transport quality as a crucial success factor for their integration. To quantify the passenger service quality, we measure the average passenger waiting time, overall stops, and times resulting from the passenger flow that a specific schedule produces.

We let a mixed-integer program describe the passenger flow for a given time schedule  $\mathcal{T}$ . The parameter  $N_{s,p} \in \mathbb{N}$  represents the new arriving passengers at stop  $s \in \mathcal{S}$  and period  $p \in \mathcal{P}$ . Note that the number of passengers and containers at each stop only decreases at a service's departure. For this reason, we are particularly interested in the departure times, defined as set  $\mathcal{P}_s^{\text{dep}} \subset \mathcal{P}$  for each stop  $s \in \mathcal{S}$ . Analogously, the set  $\mathcal{T}_{s,p}^{\text{dep}} \subset \mathcal{T}$  includes the services that depart from stop  $s \in \mathcal{S}$  at period  $p$ .

Additionally, the parameter  $\tau_p^s > 0$  describes the duration between period  $p \in \mathcal{P}_s^{\text{dep}}$  to the next larger period in  $\mathcal{P}_s^{\text{dep}}$  for each stop  $s \in \mathcal{S}$ . The parameters  $\beta^{\text{board}} \geq 0$  and  $\beta^{\text{alight}} \geq 0$  give the required boarding and alighting time per passenger. Based on the schedule  $\mathcal{T}$ , the value of  $\bar{h}_{s,t}$  represents the dwell time of service  $t \in \mathcal{T}$  at stop  $s \in \mathcal{S}$ . The parameter  $C^{\text{pas}}$  is the vehicle capacity that can be used by passengers. The parameter  $\lambda_{s,t}^{\text{alight}} \in [0, 1]$  represents the ratio of passengers alighting at stop  $s \in \mathcal{S}$  from service  $t \in \mathcal{T}$ , where the boundary values indicate that none ( $\lambda_{s,t}^{\text{alight}} = 0$ ) or all ( $\lambda_{s,t}^{\text{alight}} = 1$ ) of the passengers alight.

The integer variable  $w_{s,p+\tau_p^s}$  describes the number of passengers waiting during the time interval  $[p, p + \tau_p^s]$  for period  $p \in \mathcal{P}_s^{\text{dep}} \cup \{0\}$  at stop  $s \in \mathcal{S}$ . Analogously, the integer variable  $w_{s,p+\tau_p^s}^{\text{cum}}$  represents the number of passengers accumulated over the time window  $[p, p + \tau_p^s]$  for period  $p$  at stop  $s$ . The accumulation is important to record the waiting times per passenger. The integer variable  $n_{s,t}$  represents the number of passengers traveling via service  $t \in \mathcal{T}$  when departing from stop  $s \in \mathcal{S}$ . Finally, the integer variables  $b_{s,t}$  and  $e_{s,t}$  are the number of boarding and alighting passengers at stop  $s$  and for service  $t$ , respectively.

The overall sub-problem is defined as

$$\min A(\mathcal{T}) := \sum_{s \in \mathcal{S}} \sum_{p \in \mathcal{P}_s^{\text{dep}} \cup \{0\}} \frac{w_{s,p+\tau_p^s}^{\text{cum}}}{|\mathcal{S}| \cdot |\mathcal{P}|}, \quad (3.9)$$

$$\text{s.t. } w_{s,p+\tau_p^s} = w_{s,p} - \sum_{t \in \mathcal{T}_{p+\tau_p^s, s}^{\text{dep}}} b_{s,t} + \sum_{\tau=0}^{\tau_p^s-1} N_{s,p+\tau},$$

$$\forall p \in \mathcal{P}_s^{\text{dep}} \cup \{0\}, s \in \mathcal{S}, \quad (3.10)$$

$$w_{s,p+\tau_p^s}^{\text{cum}} = \tau_p^s \cdot w_{s,p} - \sum_{t \in \mathcal{T}_{p+\tau_p^s, s}^{\text{dep}}} b_{s,t} + \sum_{\tau=0}^{\tau_p^s-1} (\tau_p^s - \tau) \cdot N_{s,p+\tau},$$

$$\forall p \in \mathcal{P}_s^{\text{dep}} \cup \{0\}, s \in \mathcal{S}, \quad (3.11)$$

$$n_{s,t} = n_{s-1,t} + b_{s,t} - e_{s,t}, \quad \forall s \in \mathcal{S} \setminus \{0\}, t \in \mathcal{T}, \quad (3.12)$$

$$n_{0,t} = b_{0,t}, \quad \forall t \in \mathcal{T}, \quad (3.13)$$

$$e_{s,t} \leq \lambda_{s,t}^{\text{alight}} \cdot n_{s-1,t}, \quad \forall s \in \mathcal{S} \setminus \{0\}, t \in \mathcal{T}, \quad (3.14)$$

$$e_{s,t} \geq \lambda_{s,t}^{\text{alight}} \cdot n_{s-1,t} - 1, \quad \forall s \in \mathcal{S} \setminus \{0\}, t \in \mathcal{T}, \quad (3.15)$$

$$n_{s,t} \leq C^{\text{pas}}, \quad \forall s \in \mathcal{S}, t \in \mathcal{T}, \quad (3.16)$$

$$\beta^{\text{board}} \cdot b_{s,t} + \beta^{\text{alight}} \cdot e_{s,t} \leq \bar{h}_{s,t}, \quad \forall s \in \mathcal{S}, t \in \mathcal{T}, \quad (3.17)$$

$$w_{s,p}, w_{s,p}^{\text{cum}} \in \mathbb{N} \quad \forall p \in \mathcal{P}_s^{\text{dep}} \cup \{0\}, s \in \mathcal{S}, \quad (3.18)$$

$$n_{s,t}, b_{s,t}, e_{s,t} \in \mathbb{N} \quad \forall s \in \mathcal{S}, t \in \mathcal{T}. \quad (3.19)$$

The objective function (3.9) minimizes the average passenger waiting time. Constraints (3.10) and (3.11) determine the absolute and accumulated number of waiting passengers. The number of passengers traveling on a service is represented by constraints (3.12). Constraints (3.13) set the number of initially boarding passengers to the number of initially waiting passengers. Constraints (3.14) and (3.15) consider the number of passengers who alight a service at a particular stop. Constraints (3.16) limit the number of onboard passengers to the available vehicle capacity. Constraints (3.17) model the required service times for passenger transportation and limit it to the overall dwell time per stop and service.

### 3.4.3. Second sub-problem: Allocate containers in a given schedule.

Given a schedule that maximizes passenger service quality, we want to reward freight allocations that produce an acceptable freight service quality. Here, we measure freight service quality via delays and rejection penalties.

We introduce several index sets to model the transport of parcel containers, repre-

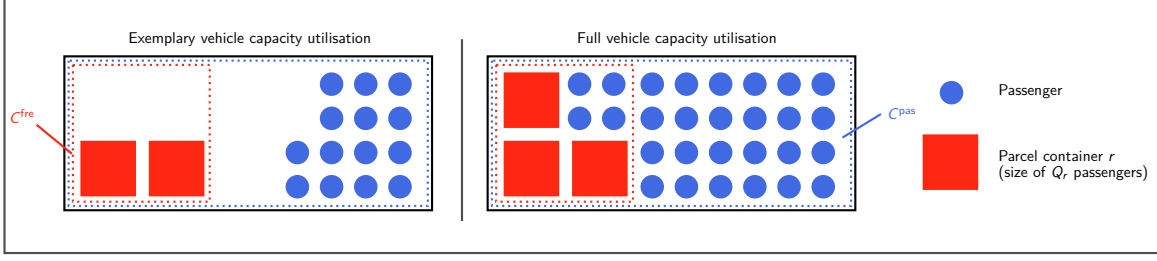


Figure 3.2.: Illustration for the concept of shared vehicle capacity.

sented by the set  $\mathcal{R}$ . The set  $\mathcal{T}_r$  contains all services suitable for transporting container  $r \in \mathcal{R}$ , i.e., ensuring that the service's departure does not occur before the container is released and loaded. The set  $\mathcal{T}_{s, \leq p}^{\text{dep}}$  includes all services that depart stop  $s \in \mathcal{S}$  at period  $p \in \mathcal{P}$  and earlier. The set  $\mathcal{R}_s$  includes all containers for which stop  $s \in \mathcal{S}$  is included in the delivery path. The set  $\mathcal{R}_s^{\text{start}} \subset \mathcal{R}$  ( $\mathcal{R}_s^{\text{end}} \subset \mathcal{R}$ ) includes all containers with start (destination)  $s \in \mathcal{S}$ . The set  $\mathcal{R}_{s, \geq p}^{\text{start}}$  includes the containers released at period  $p \in \mathcal{P}$  and later. The set  $\mathcal{P}_s^{\text{start}}$  includes all periods at which stop  $s \in \mathcal{S}$  releases a container.

The binary decision variable  $y_{r,t}$  models whether container  $r \in \mathcal{R}$  is assigned to service  $t \in \mathcal{T}$  ( $y_{r,t} = 1$ ); or not ( $y_{r,t} = 0$ ). Furthermore, the binary variable  $z_r$  decides whether a container  $r \in \mathcal{R}$  is accepted ( $z_r = 1$ ) or rejected ( $z_r = 0$ ).

The parameters  $\beta^{\text{load}} \geq 0$  and  $\beta^{\text{unld}} \geq 0$  represent the required time for loading and unloading a container. Furthermore, the value of  $\bar{h}_{s,t}$  denotes the dwell time of service  $t \in \mathcal{T}$  at stop  $s \in \mathcal{S}$ . The value  $T_{r,t}$  presents the delay of containers  $r \in \mathcal{R}$  if transported via service  $t \in \mathcal{T}$ . Furthermore, the delay of a container must not exceed the parameter  $T^{\text{max}} \geq 0$ . Each rejected container is penalized with a parameter  $P \geq 0$ .

As stated before, the parameter  $C^{\text{pas}} > 0$  is the total vehicle capacity that can be used by passengers. However, the vehicles standing area can alternatively hold parcel containers; its size is represented by the parameter  $C^{\text{fre}} \geq 0$ . Thus,  $C^{\text{fre}} \leq C^{\text{pas}}$  always holds. The parameter  $Q_r > 0$  gives the space required to transport a single container  $r \in \mathcal{R}$  in relation to the space required by one passenger. Figure 3.2 illustrates the relation of the parameters  $C^{\text{pas}}$ ,  $C^{\text{fre}}$  and  $Q_r$ , for  $r \in \mathcal{R}$ . The number of passengers  $\bar{n}_{s,t}$  traveling on service  $t \in \mathcal{T}$  by departure from stop  $s \in \mathcal{S}$  results from solving the first sub-problem (cf. Section 3.4.2). Additionally, the parameter  $C^s \geq 0$  describes the freight storage capacity of the depot stop  $s \in \mathcal{S}$ .

Thus, allocating containers to vehicles in a given schedule entails solving the following second sub-problem:

$$\min B(\mathcal{T}) := \sum_{r \in \mathcal{R}} \left( \sum_{t \in \mathcal{T}} \frac{T_{r,t} \cdot y_{r,t}}{|\mathcal{R}|} + P \cdot (1 - z_r) \right) \quad (3.20)$$

$$\text{s.t. } \sum_{t \in \mathcal{T}_r} y_{r,t} = z_r, \quad \forall r \in \mathcal{R}, \quad (3.21)$$

$$\sum_{t \in \mathcal{T} \setminus \mathcal{T}_r} y_{r,t} = 0, \quad \forall r \in \mathcal{R}, \quad (3.22)$$

$$\sum_{r \in \mathcal{R}_s} Q_r \cdot y_{r,t} \leq C^{\text{pas}} - \bar{n}_{s,t}, \quad \forall s \in \mathcal{S}, t \in \mathcal{T}, \quad (3.23)$$

$$\sum_{r \in \mathcal{R}_s} Q_r \cdot y_{r,t} \leq C^{\text{fre}}, \quad \forall s \in \mathcal{S}, t \in \mathcal{T}, \quad (3.24)$$

$$\sum_{r \in \mathcal{R}_{s, \geq p}^{\text{start}}} \left( z_r - \sum_{t \in \mathcal{T}_{s, \leq p}^{\text{dep}}} y_{r,t} \right) \leq C^s, \quad \forall p \in \mathcal{P}_s^{\text{start}}, s \in \mathcal{S}, \quad (3.25)$$

$$\sum_{r \in \mathcal{R}_s^{\text{start}}} \beta^{\text{load}} \cdot y_{r,t} + \sum_{r \in \mathcal{R}_s^{\text{end}}} \beta^{\text{unld}} \cdot y_{r,t} \leq \bar{h}_{s,t}, \quad \forall s \in \mathcal{S}, t \in \mathcal{T}, \quad (3.26)$$

$$T_{r,t} \leq T^{\text{max}} \cdot y_{r,t}, \quad \forall r \in \mathcal{R}, t \in \mathcal{T}, \quad (3.27)$$

$$y_{r,t}, z_r \in \{0, 1\}, \quad \forall r \in \mathcal{R}, t \in \mathcal{T}. \quad (3.28)$$

Objective function (3.20) minimizes the average cargo delay and the total rejection penalty. Constraints (3.21) ensure the delivery of each container via exactly one suitable service. Conversely, a service must not be selected if its departure at a stop is set before the containers are released (cf. constraints (3.22)). Constraints (3.23) guarantee the restriction to the left-over capacity after the passengers boarded. Simultaneously, constraints (3.24) limit the used space to the dedicated cargo capacity of the vehicle. Constraints (3.25) model a limited stop capacity to store accepted containers in micro-depots between their release and pick-up by the assigned service. Rejected containers do not require storage. Constraints (3.26) model the required service times for cargo transportation. Constraints (3.27) enforce a maximal delay per container.

#### 3.4.4. Global objective function

We rely on a lexicographical objective as previously implemented in Hörsting and Cleophas (2023a) to optimize passenger and freight service quality. We prioritize passenger transport, such that the primary objective is to reduce the average waiting time  $A(\mathcal{T})$  accumulated over all periods and stops (cf. Section 3.4.2). The secondary objective minimizes the penalty  $B(\mathcal{T}, y, z)$  for average container delivery delay or container rejection (cf. Section 3.4.3). Thus, the global objective function is

$$\text{lex min}_{\mathcal{T}, y, z} \{A(\mathcal{T}), B(\mathcal{T}, y, z)\}, \quad (3.29)$$

where  $\mathcal{T}$  is a feasible time schedule according to Section 3.4.1, and the assignment variable  $y \in \{0, 1\}^{\mathcal{R} \times \mathcal{T}}$  and the acceptance variable  $z \in \{0, 1\}^{\mathcal{R}}$  satisfy the restrictions

stated in Section 3.4.3.

### 3.5. Adaptive large neighborhood search (ALNS)

Hörsting and Cleophas (2023a) show that solving a simpler version of the problem considered here to optimality is computationally expensive. As we aim to support planning and analysis for instances of realistic size in terms of the number of vehicles, stops, and periods, we propose to solve the problem via an ALNS heuristic. In that, we adapt the solution approach of Yin et al. (2021) by integrating cargo transport. To that end, we propose iteratively optimizing the cargo allocation and extending the ALNS by adding an operator that accounts for cargo service quality.

Figure 3.3 illustrates the ALNS procedure for the integrated cargo and passenger scheduling problem. The heuristic starts by constructing an initial time schedule (see Section 3.5.1), which it considers as the *current schedule*. Subsequently, it applies firstly a destroy operator (Section 3.5.2) and secondly a repair operator (Section 3.5.3). It selects operators based on probabilities given by the current weights. Applying the operators results in a new *candidate schedule*. The heuristic evaluates the passenger service quality for this candidate solution by solving the passenger flow problem. After a given number of warm-up iterations and if the candidate solution produces a passenger service quality that is at least equal to that in the current solution, the heuristic computes the optimal cargo assignment, i.e., solving the sub-problem introduced in Section 3.4.3. If the overall objective value improves, the candidate solution becomes the *new best solution*. Finally, the heuristic updates the operator weights and decides whether the candidate solution becomes the *new current solution* based on an acceptance criterion. This procedure repeats until a maximum number of iterations, a maximum number of iterations without improvement, or a maximal running time is exceeded. In the following, we discuss each step in more detail.

#### 3.5.1. Initialization

The ALNS algorithm creates an initial schedule before searching for improvements via destroy and repair operations. Specifically, the initialization constructs a time schedule with regularly-spaced departures and fixed dwell times at each stop. Figure 3.4 illustrates an exemplary initial schedule.

First, the initialization fixes the latest feasible service for an initial constant dwell time  $h$  and stops  $|\mathcal{S}|$ . This service departs from the last stop at the last possible period, i.e.,  $|\mathcal{P}| - 1$ . Thus, the last possible arrival at the starting stop depends on the dwell

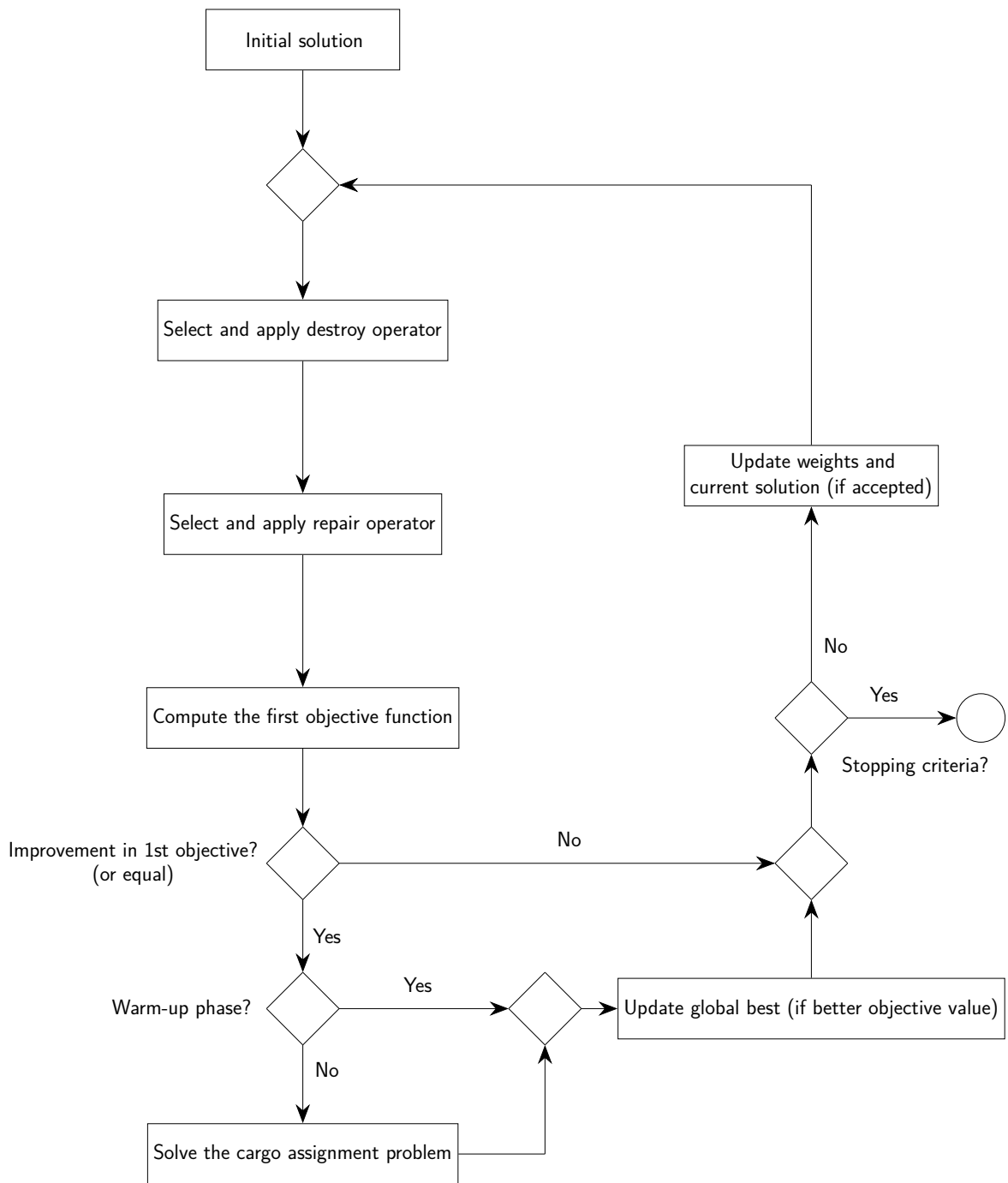


Figure 3.3.: Adaptive large neighborhood search for the integrated cargo and passenger scheduling problem.

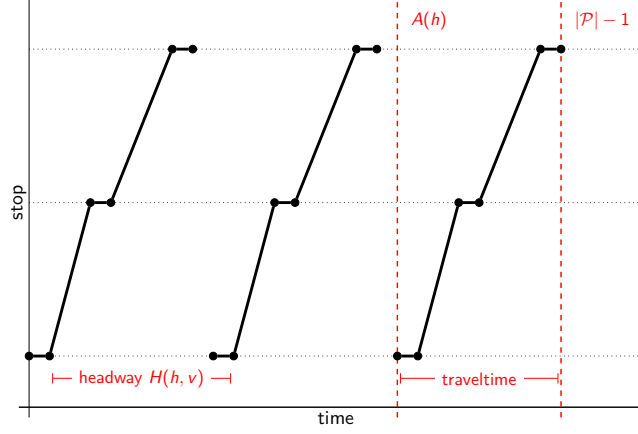


Figure 3.4.: Initial time schedule

time  $h$  and travel time  $\mu_{s-1,s}$  between stops  $s - 1$  and  $s$ ;

$$A(h) := |\mathcal{P}| - 1 - |\mathcal{S}| \cdot h - \sum_{s \in \mathcal{S} \setminus \{0\}} \mu_{s-1,s}. \quad (3.30)$$

If  $A(h)$  is smaller than zero, the initial dwell time  $h$  is too large to ensure a feasible schedule. In that case, the initialization iteratively decrements the dwell time and computes the new resulting  $A(h)$ .

As the initial schedule features a constant headway, the initialization defines this headway between two departures from the same stop for  $V$  services as

$$H(h, V) := \frac{A(h)}{V - 1}. \quad (3.31)$$

If  $\lfloor H(h, V) \rfloor$  is smaller than the given minimal headway time or the dwell time per stop, the initialization procedure iteratively updates  $V \rightarrow V - 1$  until a feasible time schedule with a sufficient headway  $H(h, V)$  results.

Subsequently, the initialization constructs the schedule by fixing the last service and adding the remaining services with headway  $H(h, V)$ . This procedure rounds up the departure times to ensure they are feasible, i.e., included in the set  $\mathcal{P}$ . Accordingly, service  $t \in \{1, \dots, V\}$  ends at

$$D(h, V, t) := \lceil |\mathcal{P}| - 1 - H(h, V) \cdot (V - t) \rceil. \quad (3.32)$$

The remaining departures at previous stops are added according to the given dwell time  $h$  and the travel time between two stops.

### 3.5.2. Destroy operators

The heuristic proposed here features three destroy operators as illustrated in Figure 3.5. The operator *random deletion and shift* supports diversification, while the operators *passenger-driven deletion* and *freight-driven deletion* drive intensification. Figure 3.5 illustrates how the destroy operators' steps change a given schedule.

#### ***Random deletion and shift***

This operator features of two consecutive steps to create space for new services, a random deletion followed by a shift of the remaining service. The first step (see Figure 3.5b) randomly selects a period between the first period and the last departure from the first stop. It removes the next service leaving the first stop after the selected time period from the schedule. The second step (see Figure 3.5c) aims to distribute the gained space across the whole time window. To achieve this, it shifts an either all preceding or subsequent services in a random direction (*left* or *right*). The intensity of the shift is also randomly chosen to fall between zero and the size of the gap gained through the first step. If the direction of the shift is left (*right*), it shifts the service released after (*before*) the previously deleted service and all earlier (*subsequently*) released services.

Due to the limited time window, shifting the first or last service may create an infeasible schedule. Therefore, the operator only shifts the boundary services as far as possible while maintaining feasibility. Then it iteratively shifts the next services following the same approach. The second step is omitted if no shift creates a feasible schedule.

#### ***Passenger-driven deletion***

This operator aims to improve passenger service quality by deleting low-quality services. To that end, it either deletes a service with insufficient dwell times for all passenger processes (see Figure 3.5d) or, if that does not exist, deletes the service expected to carry the lowest accumulated number of passengers. To support the insertion of a new service by the following repair operator (see Section 3.5.3), the destroy operator stores and optionally adapts the pattern of dwell times of the deleted service. As illustrated in Figure 3.6, it adapts the dwell times by increasing it for all stops with insufficient for the boarding and alighting process.

#### ***Freight-driven deletion***

This operator deletes services of poor freight service quality. First, if the current solution includes rejected containers, the operator randomly selects one of those and

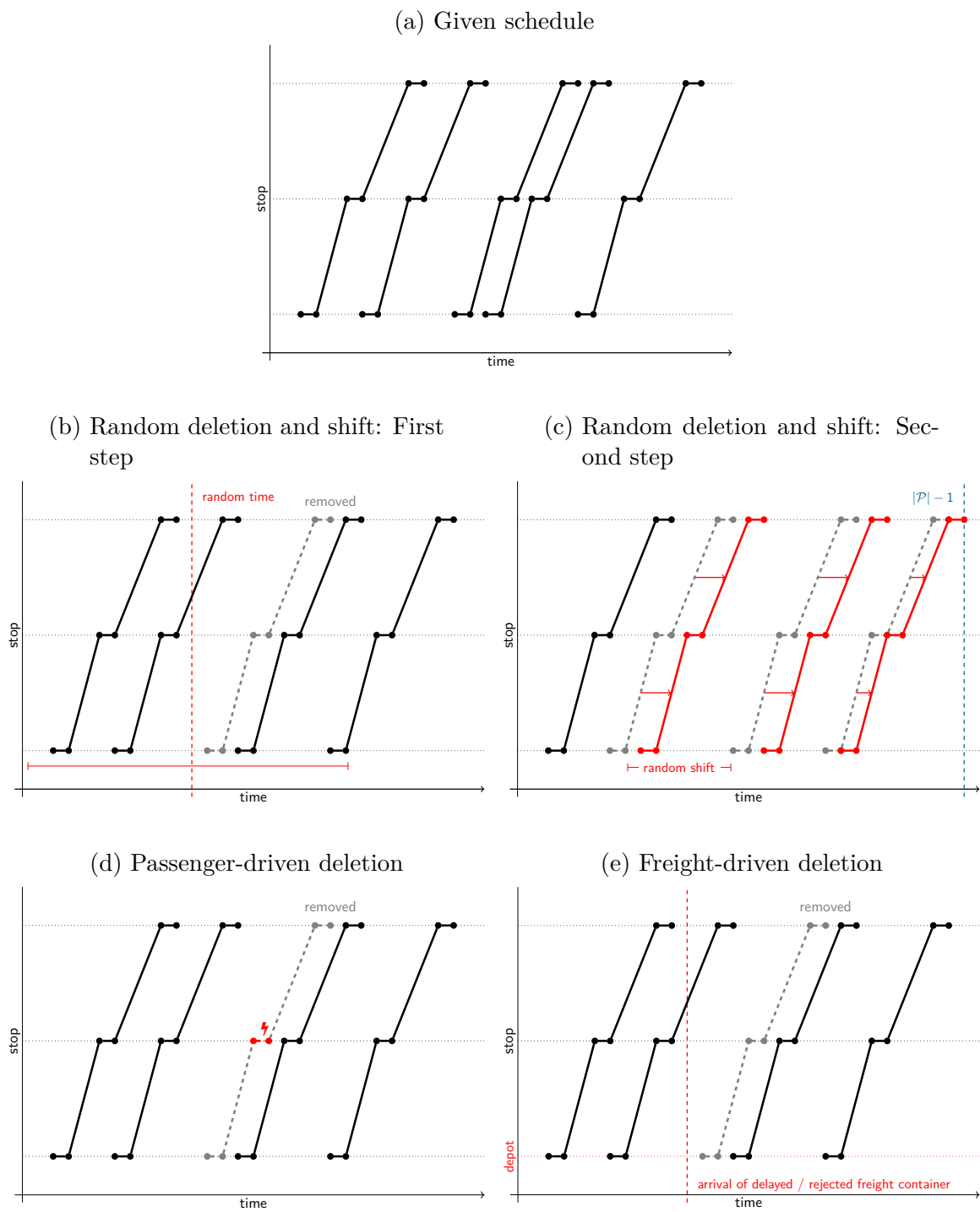


Figure 3.5.: Destroy operators

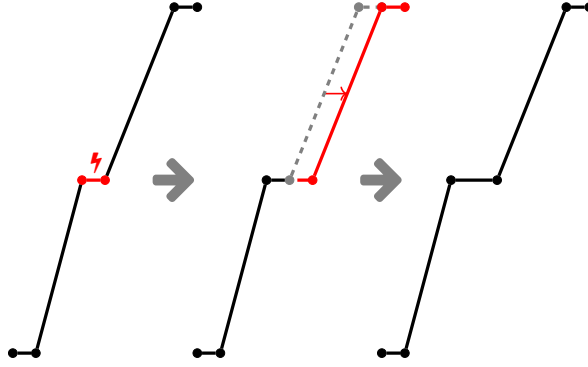


Figure 3.6.: Passenger and freight-driven deletion: Adapt the dwell times for the new service

deletes the service that departs after its arrival. Secondly, if the current solution includes delayed containers, it deletes the service departing after the release of the most severely delayed container. If the current solution plans for all containers to be delivered punctually, the operator returns the current solution without changes. Again, it saves the dwell times for each stop of the deleted service. If the increment of the dwell time at a particular stop allows for loading or unloading an additional freight container, it adapts the pattern accordingly (see Figure 3.6).

Consequentially, for a feasible current schedule, the destroy operators guarantee a feasible output schedule. Repair operators use the resulting gaps between services to introduce new services.

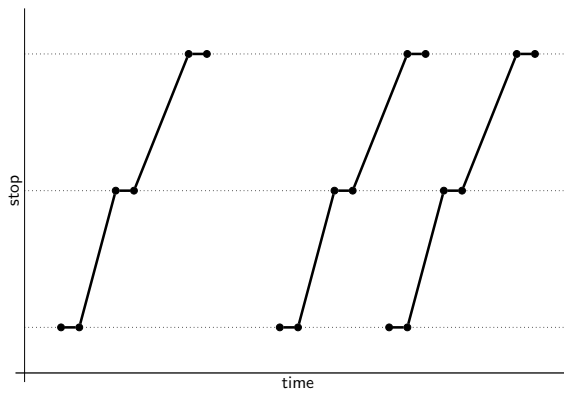
### 3.5.3. Repair operators

Following the destroy operator, the heuristic randomly selects and applies one of two possible repair operators based on the given weights. Figure 3.7 illustrates how each repair operator adjusts the schedule. Each repair operator inserts a new service according to certain criteria. The new services follow either the default or an adapted dwell time pattern, depending on the previously applied destroy operator.

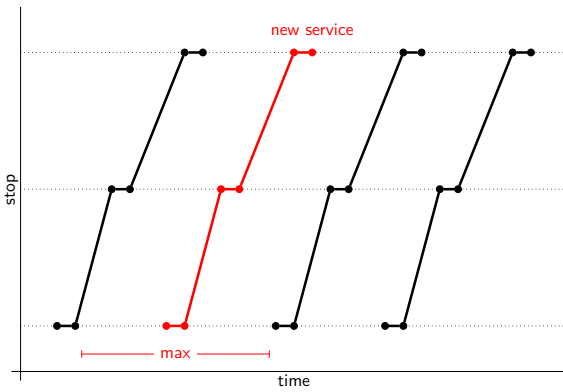
#### ***Greedy time-driven***

The first repair operator (see Figure 3.7b) selects the largest gap between the departure time of one service and the arrival of the next one in the given time schedule. Considering  $A(s, t)$  as the arrival time and  $D(s, t)$  as the departure time of service  $t$  at

(a) Given schedule



(b) Greedy time-driven insertion



(c) Greedy passenger-driven insertion

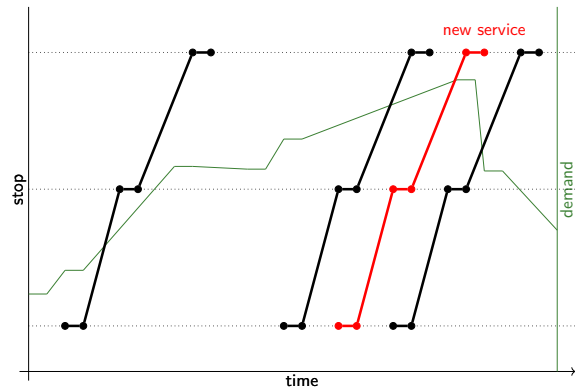


Figure 3.7.: Repair operators

stop  $s$ , it computes this gap as

$$\max_{s \in \mathcal{S}, t \in \mathcal{T}} I(s, t) = \begin{cases} A(s, t), & \text{if } t \text{ is the first service,} \\ |\mathcal{P}| - 1 - D(s, t), & \text{if } t \text{ is the last service,} \\ A(s, t + 1) - D(s, t), & \text{else.} \end{cases} \quad (3.33)$$

The operator inserts a new service at the center of the gap if this still allows for the required minimal headway. Then it selects the now largest gap and repeats the insertion until either reaching the maximal number of services or violating the headway requirement.

### ***Greedy passenger-driven***

The second repair operator (see Figure 3.7c) selects a gap for service insertion based on the expected effect on passenger service quality. To that end, the operator first identifies all time points  $p \in \mathcal{P}$  where a service could be feasibly inserted. For each  $p$ , the operator ignores capacity and time limitations and computes the savings from picking up passengers who are currently waiting via the new service released at period  $p$  at the depot,  $t^{\text{new}}$ :

$$S(p) := \sum_{s \in \mathcal{S}} w_{s, D(s, t^{\text{new}}) - 1} \cdot (D(s, t^{\text{new}}) - D(s, t^{\text{new}} + 1)), \quad (3.34)$$

Then, the operator selects the time to insert the service to maximize the potential savings:

$$S(p^*) := \max_{p \in \mathcal{P}} S(p) \quad (3.35)$$

This operator also repeats insertions until reaching the maximum number of services or violating the headway requirements. Note that the operator computes the number of waiting passengers after each insertion by re-solving the passenger flow problem.

#### **3.5.4. Search strategy and updating weights**

In the proposed ALNS, a simple scheme continuously updates the weights assigned to the two randomly applied repair operators. First, the initialization assigns a uniform weight  $\rho_i$  to each repair operator  $i$ . Then, the probability of selecting the repair

operator  $i$  is defined as

$$\theta_i = \frac{\rho_i}{\sum_{\rho_k \in \Omega^+} \rho_k}, \quad (3.36)$$

where  $\Omega^+$  is the set of all repair operators. Thus, the larger the weight  $\rho_i$ , the higher the probability of selecting operator  $i$ . The weights of destroy operators are computed analogously with a set  $\Omega^-$  including all destroy operators.

Whenever a new candidate solution results from applying the destroy and repair operators, we define the new weights of the operator that contributed to creating that candidate solution as

$$\Psi := \begin{cases} \omega_1, & \text{if the new solution is new global best,} \\ \omega_2, & \text{if the new solution is better than the current solution,} \\ \omega_3, & \text{if the new solution satisfies the acceptance criterion,} \\ \omega_4, & \text{otherwise.} \end{cases} \quad (3.37)$$

Since the algorithm favors operators resulting in an improvement, we assume the order  $\omega_1 \geq \omega_2 \geq \omega_3 \geq \omega_4$ .

Furthermore, an *acceptance criterion* decides whether the current solution should reflect the newly found candidate solution. Thereby, the acceptance criterion sets the searching strategy through the neighborhood. The hill climbing (HC) criterion accepts only solutions that are as good as or better than the current best. I.e., a candidate solution  $x$  is accepted if

$$f(x) \leq f(x^*), \quad (3.38)$$

where  $x^*$  is the best solution observed so far and  $f$  is the objective function.

Following the recommendation by Santini et al. (2018), we also implement a linear record-to-record-travel (RRT). The RRT criterion accepts a new solution if the relative difference to the global best is less than a continuously updated threshold. First, we define an initial threshold  $T^{\text{start}}$  and a smaller end threshold value  $T^{\text{end}}$ . A candidate solution  $x$  is accepted if

$$f(x) - f(x^*) \leq T. \quad (3.39)$$

At the end of each iteration, we linearly update the threshold value by

$$T \leftarrow \max\left\{T - \frac{T^{\text{start}} - T^{\text{end}}}{I_{\text{max}}}, T^{\text{end}}\right\}, \quad (3.40)$$

where  $I^{\max}$  is the maximal number of iterations.

Finally, the algorithm updates the weight as

$$\rho_a = \lambda\rho_a + (1 - \lambda)\Psi, \quad (3.41)$$

where the *decay parameter*  $\lambda \in [0, 1]$  controls the sensitivity to changes. If  $\lambda$  is close to one, the weighting distribution only changes slowly, whereas a value close to zero highly rewards those operators that lead to improvement or acceptance in past iterations.

### 3.6. Performance analysis

Before evaluating the sensitivity of the resulting system on instances of realistic size, we validate the performance of the ALNS versus the outcome from solving the problem to optimality. To this end, we implement the mixed-integer program given in Section 3.4 in Gurobi (v9.0.1) and limit the run time to nine hours for both objectives. We implement the ALNS from Section 3.5 in Python 3 based on the open-source package *ALNS (v4.1.0)*. The hill climbing (HC) and record-to-record-travel (RRT) acceptance criterion rely on a starting threshold of 25% and an ending threshold of 1% of the initial first objective value. The algorithm starts with at most 100 warm-up iterations for both criteria, followed by at most 1,900 regular iterations. Additionally, the heuristic stops after 500 iterations without an objective value improvement or after a maximal running time of one hour. All computations are run on an INTEL Sandy Bridge processor with 2.6 GHz.

As performance indicators, we consider the global run time and the run time per objective function. Additionally, we consider the average relative gap to the best value found and the average relative optimality gap, defined as

$$\frac{\text{solution value} - \text{best value}}{\text{solution value}} \quad \text{and} \quad \frac{\text{lower bound} - \text{solution value}}{\text{solution value}}. \quad (3.42)$$

The source code underlying these results is publicly available at <https://doi.org/10.5281/zenodo.7576383>. Furthermore, all instances and results presented in the following are publicly available under the same link.

For the performance analysis, we evaluate five problem settings with 60, 70, 80, 90, and 100 periods. We choose small instances to solve the problem to optimality within an acceptable run time. We create 10 stochastic instances for each setting by randomly drawing the number of released containers per stop from a uniform probability distribution. Additionally, we consider ten instances of an exemplary large-scale scenario with 2,880 periods. The scenario, termed *uniform freight flow, all-depots*, is

<i>periods</i>	method	1st objective				2nd objective		
		time <sup>a</sup> (sec.)	time <sup>a</sup> (sec.)	gap (best)	gap (opt)	time <sup>a</sup> (sec.)	gap (best)	gap (opt)
60	solver	1853.4	167.0	0.00	0.00	444.1	0.00	0.00
60	ALNS HC	509.3	12.2	0.03	0.03	634.9	0.11	0.11
60	ALNS RRT	42.3	12.2	0.04	0.04	5.0	0.11	0.11
70	solver	11655.2	791.6	0.00	0.00	1688.5	0.00	0.00
70	ALNS HC	318.9	12.0	0.03	0.03	388.3	0.08	0.08
70	ALNS RRT	65.7	15.2	0.03	0.03	22.2	0.09	0.09
80	solver	75629.5	14060.3	0.00	0.00	19125.5	0.00	0.02
80	ALNS HC	822.8	12.7	0.05	0.05	577.9	0.05	0.07
80	ALNS RRT	87.4	14.9	0.04	0.04	40.4	0.05	0.07
90	solver	102163.0	27431.5	0.00	0.07	22730.7	0.00	0.03
90	ALNS HC	380.4	11.7	0.03	0.09	424.9	0.04	0.07
90	ALNS RRT	59.0	12.2	0.03	0.10	15.9	0.04	0.07
100	solver	102318.1	32404.1	0.00	0.17	9779.8	0.00	0.01
100	ALNS HC	534.4	11.4	0.02	0.19	415.2	0.05	0.07
100	ALNS RRT	76.7	17.3	0.02	0.19	22.3	0.05	0.06
2880	ALNS HC	2822.8	617.8	0.00	-	691.4	0.18	-
2880	ALNS RRT	1432.7	478.2	0.03	-	65.8	0.06	-

<sup>a</sup> Run time limit for solver set to of 32,400 seconds (9h) per objective.

Table 3.4.: Average run time and solution quality for a varying number of periods. The column *time (sec.)* includes the average optimization time. Additionally, we consider the average *time*, the average relative *gap* to the best value found (*best*), and the average relative optimality *gap* to the best lower bound found (*opt*) for both objective functions individually.

introduced in more detail in Section 3.7. Due to their size, these instances are not solvable to optimality; therefore, we exclude a comparison to the solver.

Table 3.4 shows the average run time and solution quality for the varying number of periods. Noticeably, the solver run time rises exponentially with increasing periods. The solver cannot solve the problem to optimality within the given time limitations of 9h per objective for more than 100 periods.

The overall results in terms of the objective values and run time of attempting to solve the problem to optimality are similar to those of solving the predecessor model introduced in Hörsting and Cleophas (2023a) under the equivalent computational settings. That contribution compared large-scale instances with 180 periods and small-scale instances with 60 periods. For the small-scale instances, the solver found an optimal solution for the majority of instances; only instances with a high number of parcel containers could not be solved to optimality in the second objective. None of the large-scale instances could be solved to optimality, remaining with optimality gaps between 65% and 99% for the first objective function. Hence, extending the model to allow for multiple micro-depots with limited and stop-dependent storage capacities

seems to have no significant effect on the problem’s computational cost. Both models show that the scale of the planning horizon is the primary driver of run time and solving the problem for realistic horizons calls for efficient solution approaches like the ALNS presented in this paper.

To evaluate the heuristics’ performance, we first consider the results for instances with at most 100 periods. In these instances, both ALNS variants still find a close-to-best solution with a gap of 2% to 5% to the best solution found by the solver in the first objective. The run times are at most 14 minutes for HC and at most two minutes for RRT. The difference in run time mostly stems from HC solving the MILP for the second objective function more frequently. As described in Section 3.5, it only pursues the second objective if the first objective of the candidate solution is at least as good as the current solution. Additionally, HC often includes more iterations because of the improvement stop criterion.

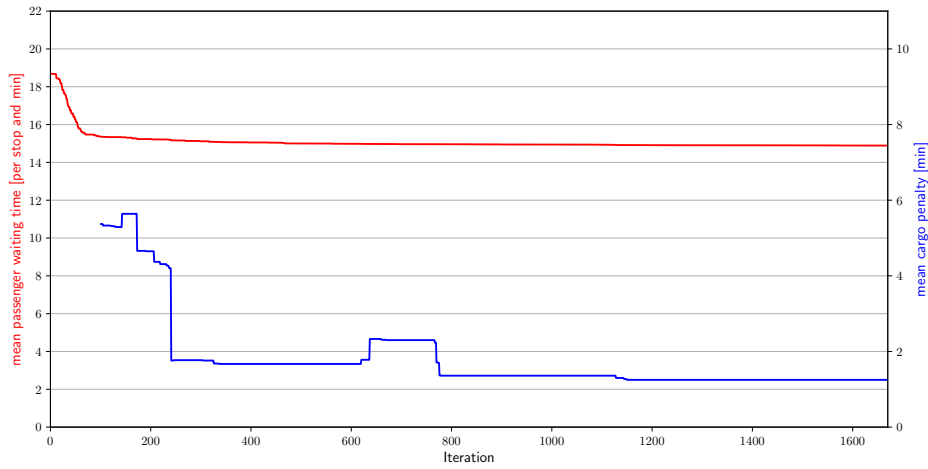
Different results emerge regarding the solution quality for the second objective value. Here, the ALNS cannot achieve the same performance as the solver. However, the average gap to the best solution reduces from 11% to 5% for more periods. This suggests that the heuristic is still valid for finding acceptable solutions for larger-scaled instances.

For the instances featuring 1,880 periods, the average run time is 47 minutes for HC and 24 minutes for RRT. HC finds better solutions in the first objective function (3% gap to RRT). RRT is more successful in the second objective but probably also the least restrictive because of the higher first objective value.

Figure 3.8 illustrates the progress of solution development when applying the ALNS based on HC or RRT to the large-scale instance. As visible in Figure 3.8a, HC achieves the most improvement during the very first iterations. After the first hundred iterations, the first objective plateaus and only slowly improves. At the same time, the second objective incrementally decreases over time, interrupted by a temporary increment because of an improved first objective. Figure 3.8b shows that, for RRT, the first objective value oscillates between the current best and given threshold. As the threshold shrinks, the amplitude also shrinks. Overall, HC achieves the most improvement in the earlier iterations, whereas RRT might require even more iterations to achieve the same level. Running HC only for a low number of iterations, followed by a more intense search through RRT might be an acceptable compromise for a low run time and a good global solution quality.

Table 3.5 indicates the average number of times that each destroy and repair operator from Section 3.5 was applied in the large scenario. It also lists the average number of times the candidate solution was the new *best* solution, *better* than the current solution,

(a) Hill climbing (HC)



(b) Record-to-record-travel (RRT)

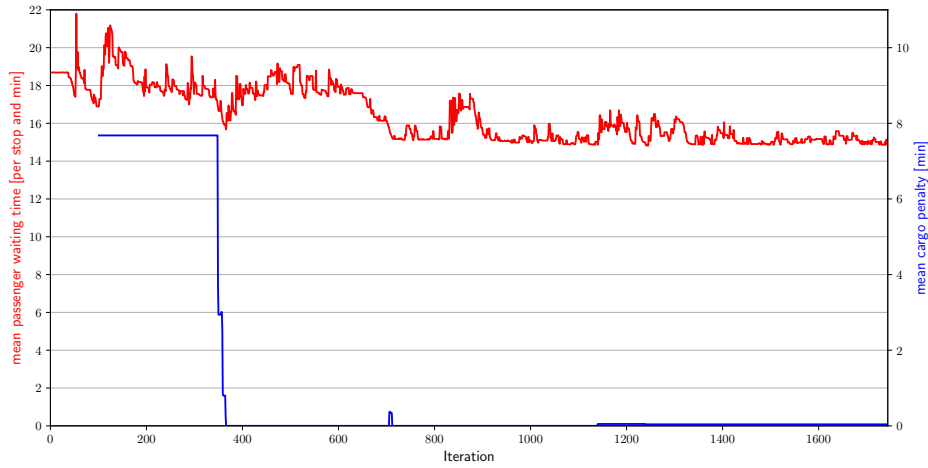


Figure 3.8.: Objective value across iterations for an exemplary instance

crit.	operator	total	best	better	accepted	rejected
RRT	deletion and shift	450.8	14.4	198.7	224.9	12.8
RRT	deletion (freight)	348.8	4.4	92.1	246.3	6
RRT	deletion (passenger)	484.5	33.1	233	195.9	22.5
RRT	insertion (passenger)	777.2	49.1	442	284.5	1.6
RRT	insertion (time)	506.9	2.8	81.8	382.6	39.7
RRT	total	1284.1	51.9	523.8	667.1	41.3
HC	deletion and shift	638	109.8	-	184.7	343.5
HC	deletion (freight)	376.6	23	-	5.7	347.9
HC	deletion (passenger)	566.4	38.5	-	318.6	209.3
HC	insertion (passenger)	1064.7	168.3	-	502	394.4
HC	insertion (time)	516.3	3	-	7	506.3
HC	total	1581	171.3	-	509	900.7

Table 3.5.: Average count of operator usage for an exemplary set of instances

*accepted* according to the chosen criterion, or *rejected*.

For HC, the candidate solution is either the new best, the same as the current solution (*accepted*), or worse than the current solution (*rejected*). *Random deletion and shift* is the most successful destroy operator, followed by the *passenger-driven* deletion. Nevertheless, HC regularly applies *freight-driven* deletion, and this accounts for approximately 13% of the iterations where the best solution is found. The *passenger-driven insertion* significantly outperforms the temporal-driven insertion. RRT stops after fewer iterations than HC. Here, the *passenger-driven* deletion induces more improvements than the *random deletion and shift*. A possible reason might be that the overall algorithm design includes more randomization than HC and therefore, requires more operators for intensification.

Having thus validated and benchmarked the ALNS variants, we use HC to create schedules and allocate freight for larger instances that cannot be solved to optimality in an acceptable time. Based on the results, we analyze the system’s sensitivity to capacity settings given different depot, freight-flow, and demand settings in the next section.

### **3.7. Sensitivity analysis**

When implementing a system for shared passenger and freight transport, the available capacities for freight transport, storage, and transshipment are important factors. While strategic fleet planning determines the vehicles’ capacity, the strategic choice and design of micro-depots determine the capacity for storage and transshipment. To support such considerations, we showcase a sensitivity analysis that considers two depot-location settings and three freight-flow settings. Section 3.7.1 describes the experimental setting including the design of problem settings and instances. Subsequently, Section 3.7.2 presents the results for the computational experiments.

#### **3.7.1. Instance and scenario design**

In general, we consider a bi-directional network of ten equidistant stations, i.e., each service must pass twenty stops in total when going back and forth. The travel time between any two stops is one minute. We limit the analysis to equidistant stations, as we also test for certain network characteristics.

Each experiment covers one day of operations. We discretize this time horizon into 2,280 periods, such that each time period equals 30 seconds. Within the time horizon, given travel times, at most 100 services can circulate through the network.

To describe the temporal curve of the daily passenger demand, we extract the popular times for exemplary stations in the light rail network of Hamburg, Germany from Google (2021). According to a field study by Li et al. (2020), a single passenger needs 0.87 seconds on average to board or alight a vehicle. To account for simultaneous passenger processes in a vehicle with nine doors, we set the boarding and alighting parameters  $\beta^{\text{board}}$  and  $\beta^{\text{alight}}$  to  $0.87/9 = 0.09$  seconds. In addition, we set a minimum dwell time  $\beta^{\text{min}}$  of 30 seconds to guarantee sufficient time for boarding and alighting processes.

Furthermore, we expect a loading time of 20 seconds and an unloading time of 15 seconds per container. We assume that service times increase linearly with the number of passengers and containers. Each vehicle fits 500 passengers. The cargo releases are uniformly distributed between 7 am and 4 pm. The soft deadline is one hour after release and the maximal delay is set to one hour. The shared capacity for cargo ranges between 1 and 5 cargo containers for sensitivity analysis.

### ***Freight Flow***

To consider structural effects from differences in freight demand, we consider three freight-flow settings governing the probability of containers originating from certain arrival stops and ending at certain destination stops.

**Uniform Freight Flow** The first scenario considers *uniformly distributed freight demand*, i.e., each container may originate at or be destined for each stop with the same probability. We do not consider this a realistic setting but use it as a benchmark for the two alternative settings described in the following.

**Central Freight In-Flow** The second setting implements the idea that goods are transhipped from long-distance transport in the suburbs for further transport to destinations in the city center. Thus, most containers originate in the outer areas of the network and have destinations in the center (cf. Figure 3.9a).

**Directed Freight Flow** The third scenario implements the idea that goods must be transported from an appropriate transshipment area in the city to an industrial area outside of the city. Hence, the majority of containers originate on one side of the network and must be transported to the other side (cf. Figure 3.9b).

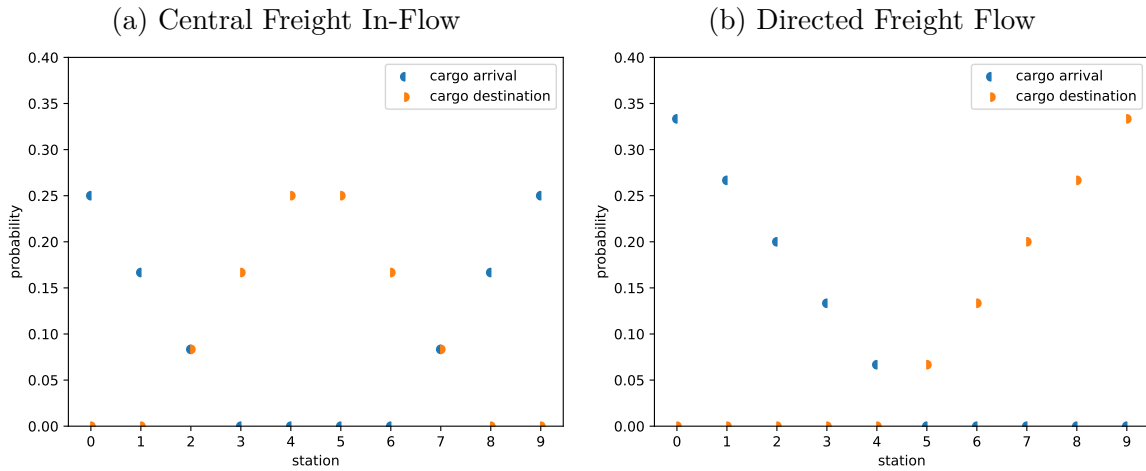


Figure 3.9.: Probability distributions for the freight-flow-settings

### Depot Locations

Depending on the network layout, not all stops might be suitable for transshipping freight through micro-depots. As a strategic decision, the designers of a shared passenger and freight system must choose appropriate locations for depots. These choices result in alternative depot-location settings.

We assume that freight demand can arise at any stop, but that containers are always transported to the micro-depot closest to the original source and destination. These are the stops we term origin and destination stops here. To render different settings comparable, we adapt the deadline and release time of each container by adding up the travel time from the selected depot stops to the underlying source or destination.

For the sensitivity analysis, we consider two depot-location settings.

**All-Depots** In this setting, all stops are available as micro-depots. Thus, all stops in the public transit networks offer sufficient capacity to store at least a small number of freight containers (cf. Figure 3.10a). For the sensitivity analysis, the stop capacity ranges from one to five containers. To guarantee only minimal disturbance for the passenger service, we limit the maximal dwell time at each stop. All freight processes must be executable within a maximal dwell time of one minute, i.e. two periods.

**Edge-Depots** The second setting assumes that the network does not allow for transshipment at intermediate stops. Instead, only stops that are situated at the outer edges of the network are depots (cf. Figure 3.10b). To compensate for the lower depot density, we assume that the edge depots offer more capacity and consider stop capacities of two, four, six, eight, and ten containers in the sensitivity analysis. Since vehicles

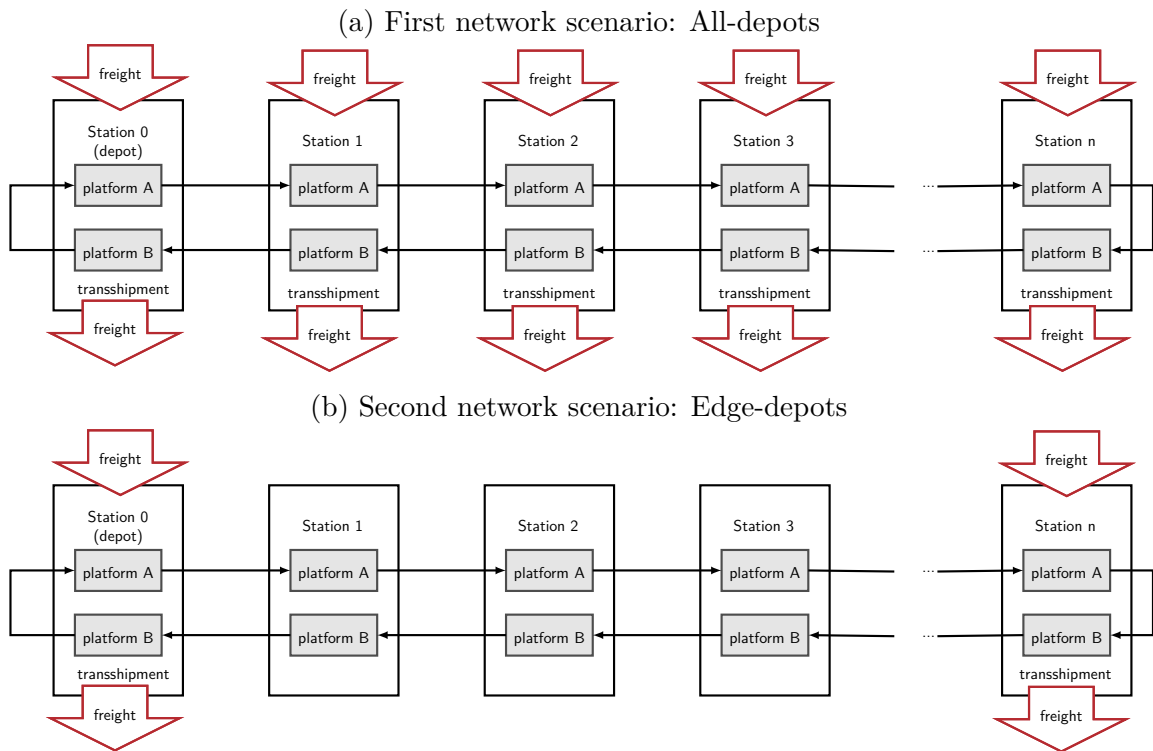


Figure 3.10.: Scenarios depending on the location and design of depots

must also change directions at the related stations, additional dwell time results. We set the maximal dwell time in this design to 10 minutes, i.e., 20 periods.

To summarize, we consider three freight-flow settings, two depot-location settings, and twenty-five demand variants in the sensitivity analysis, creating 150 variations of the problem. As the freight demand is randomly drawn from a probability distribution, a single instance has only limited significance for the overall view of the problem. At the same time, we can only solve a limited number of instances, given a large number of problem variations. To balance efficiency and reliability, we randomly generate 10 instances for each of the 150 variations. Hence, we solve 1,500 problem instances in total. All instances and result files are publicly available at <https://doi.org/10.5281/zenodo.7576383>.

### 3.7.2. Computational results

We use the ALNS with hill climbing (HC) to solve the randomly-generated instances generated from the parameter settings in the previous sub-section. As result indicators, we consider the passenger waiting time, the cargo acceptance rate, and the cargo delay. As expected, the passenger waiting time is stable across scenarios (results not shown). Because of the lexicographical objective, solutions with lower passenger waiting times

are always prioritized. This results in only a 2% gap between the best and worst passenger waiting time found. Thus, the ALNS ensures a stable level of passenger service quality. From the maximal 100 services, all instances include at most five simultaneous services in peak times. Thus, the minimum fleet size to operate the computed time schedules is five vehicles.

Figure 3.11 shows the average number of accepted cargo containers for varying vehicle and stop capacities. Following intuitive expectations, the all-depots setting is advantageous. The larger number of depots makes up for the more restrictive dwell times, letting this design outperform the turning-depot-design by 0.91% (for central freight flow and high capacity values) to 25.52% (for directed freight flow with minimal capacity values). To analyze under what settings the edge-depot setting enables good results, we further consider the structural characteristics.

First, we evaluate the results for the all-depot setting. When freight demand follows a uniform pattern, the average load per vehicle can be reduced to a minimum, and less vehicle and stop capacity is required. Figure 3.11a shows that the stop capacity threshold for accepting all freight is two and that this is independent of the vehicle capacity. If stops include only capacity for one container, the acceptance rate is still greater than 94%. Thus, the all-depot setting allows for an almost ideal acceptance rate given a uniform freight flow.

The central freight in-flow setting causes a lower acceptance rate (cf. Figure 3.11c). As, in this setting, most freight originates at the outer stops, the required storage capacity at those stops increases. If a stop can only store a single container, the acceptance rate ranges between 73% and 80%, i.e., 11% to 18% less than for a uniform freight flow. The acceptance rate grows logarithmically with increasing stop-capacity. Containers with closely spaced release times will probably be picked up by the same service, leading to overlaps in storage time. The probability of overlapping storage times decreases with increasing capacity. The vehicle capacity also gains more relevance in the central freight in-flow setting. The acceptance rate rises by 4% to 18% when vehicles can carry an additional container. Given a uniform freight flow, certain containers are already delivered before new containers are picked up. This is much less likely under central freight in-flow.

For the directed freight-flow setting, freight originates at yet fewer depot stops. Additionally, the origin and destination stops do not overlap, i.e., all containers of the service must be picked up before any container reaches its destination. For this reason, the vehicle capacity becomes more crucial (see Figure 3.11e). If there is only space for one cargo container in each vehicle, the acceptance rate ranges between 50% and 60%.

Next, we discuss the results for the edge-depots setting. As freight always originates

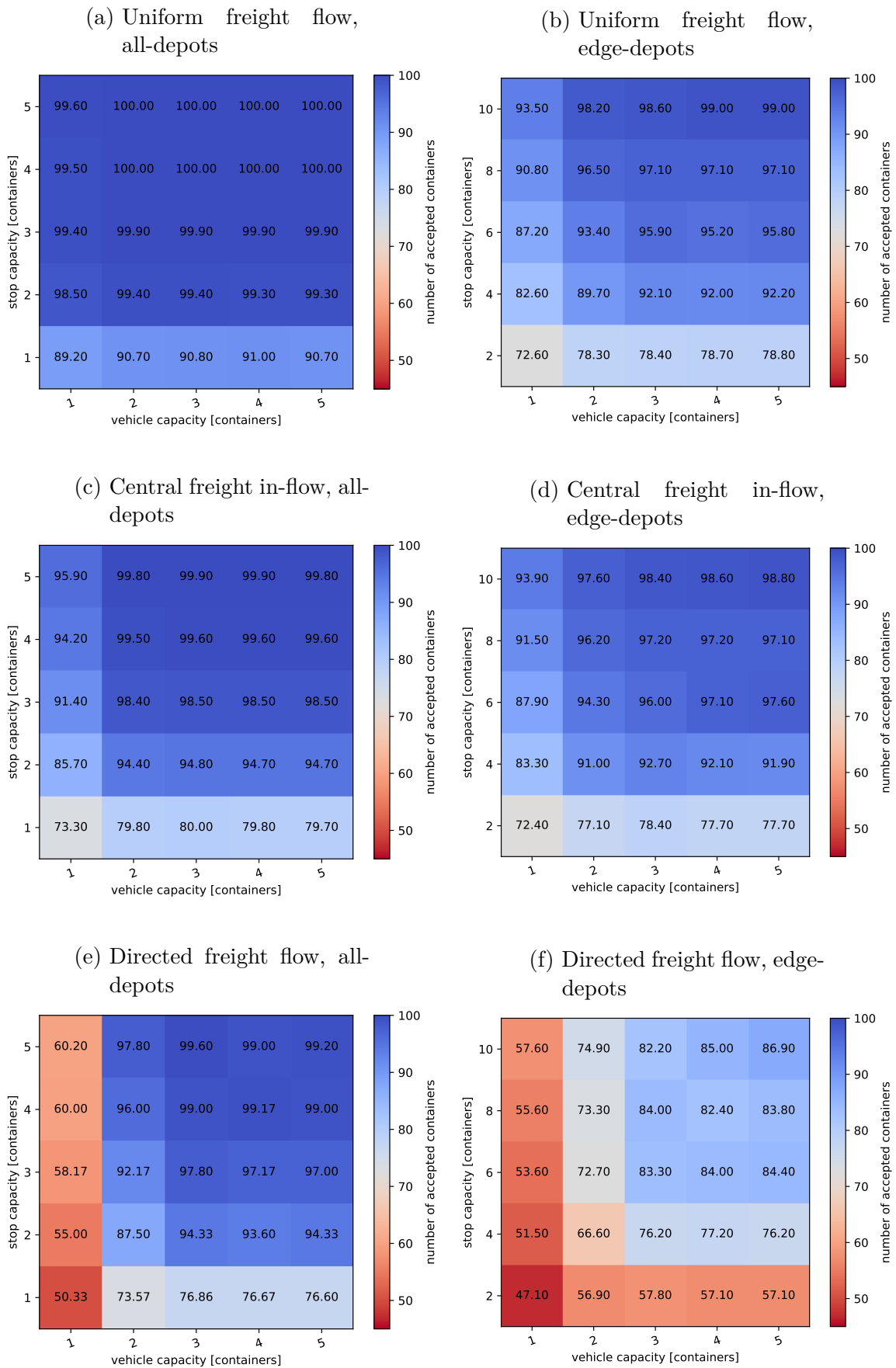


Figure 3.11.: Average number of accepted cargo containers for different scenarios

from the nearest stop featuring a micro-depot, the origin distribution resulting from the uniform flow and the central freight-in-flow settings is the same given edge-depots. The results of the two depot-location settings are most similar for the central freight in-flow. From a practical perspective, a better use case for the edge-depot setting is the directed freight-flow setting. However, sufficient vehicle and stop capacity are crucial factors for the system's success (cf. Figure 3.11b).

Figure 3.12 visualizes the average delay of accepted containers in the various scenarios. Since we only evaluate the delay of accepted containers, a higher capacity does not automatically result in a lower delay. Overall, we observe low delay rates from zero to two minutes. Especially with a high stop capacity and a low vehicle capacity, a high number of containers is accepted, but the average delay increases up to almost 19 minutes (cf. Figures 3.11a, 3.12c and 3.12e).

### 3.7.3. Managerial implications

To highlight the managerial implications, we compare our findings to the computational study in Hörsting and Cleophas (2023a). In particular, this predecessor model differed from the one considered here in that it assumed both unlimited stop capacity and that all freight originates from a single depot.

In general, the findings of Hörsting and Cleophas (2023a) emphasize the importance of optimization techniques to satisfy passenger and freight demand simultaneously. In that setting, a shared capacity between passengers and freight appeared more suitable for urgent containers with a tight deadline than a system with vehicles dedicated to either passenger or freight transportation. Further, Hörsting and Cleophas (2023a) highlight the impact of the freight loading and unloading processes. In that study, the dwell time represents the bottleneck in the considered system and the vehicle capacity plays only a minor role.

Beyond demonstrating that the ALNS is an appropriate alternative to solving the problem to optimality, our results indicate that the storage capacity of micro-depots is an essential factor for the system's success when allowing for pick-ups beyond a central depot. Additionally, the dwell time still has a high impact on the system's service quality. Especially for the edge-depot network design, a sufficient maximal dwell time is crucial to enable acceptable acceptance rates. However, for a high micro-depot capacity but a low vehicle capacity, the solutions can accept most of the containers but lack punctuality. Thus, we conclude that the shared capacity mode is only suited for urgent parcel containers when both stops and vehicles offer sufficient freight capacity.

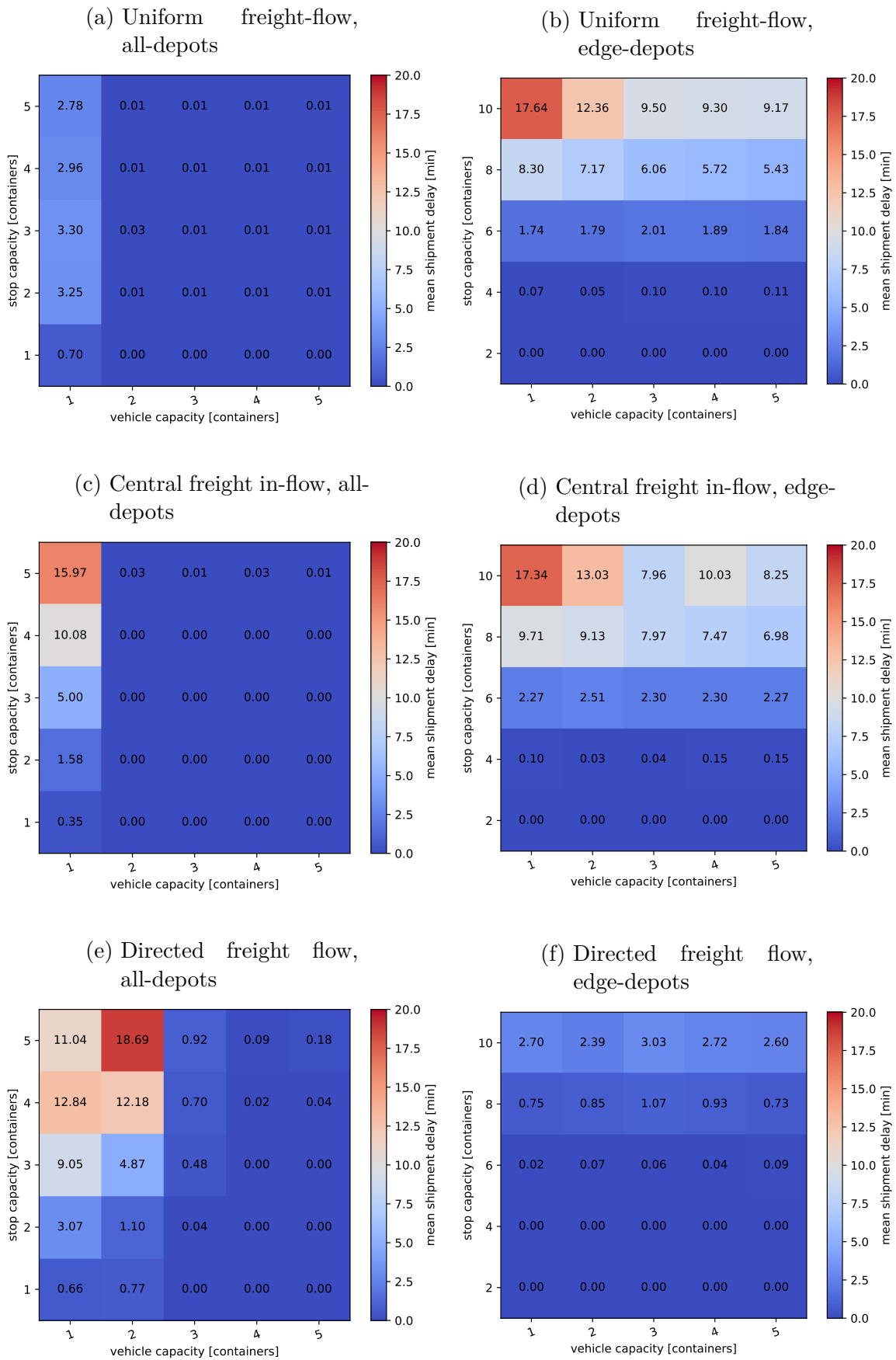


Figure 3.12.: Average delay of accepted freight

### 3.8. Conclusion

In this work, we considered the problem of scheduling services and allocating cargo in a shared passenger and freight transit system featuring multiple micro-depots with limited storage capacity. To prioritize the passenger service, we considered a lexicographic objective function, where the first of the two objectives is to increase the average passenger waiting time across stops. The second objective function reduces the average freight delay. Furthermore, we presented an ALNS to find good solutions for large-scale problem instances. As acceptance criteria, we implemented and compared hill climbing and record-to-record travel.

The performance analysis results indicated that the ALNS is appropriate for solving realistic-sized problems. The hill climbing approach achieved the best improvement in early iterations, while the record-to-record travel required more iterations to adapt.

Sharing resources, e.g., vehicle capacity, is one of the main advantages of such a system and one of its main challenges. We considered the effect of freight flow settings and depot locations in a sensitivity analysis for varying vehicle and stop capacities. Due to the lexicographic objective function, we found that the average waiting time was stable for various settings. The result showed that dense freight demand flows require sufficient depot and vehicle capacity.

Lower storage capacities can suffice if every stop is a micro-depot. However, this requires sufficient space at each stop to handle the transshipment process and to store containers. Additionally, the design might come with higher initial costs because of the reconstruction work to enable transshipping at depot stops. At the same time, the realism of an edge-depot setting under a central freight flow is questionable. Apart from the adaptation of release and deadline times, the distance between the depot station and desired demand locations might be too large to ensure a valid satisfactory transportation service.

Our results when evaluating freight delay illustrate that a high stop capacity is insufficient to reach a high service degree if the cargo delay is also an important factor. A high storage capacity at the stops may ensure a high acceptance rate for freight, but vehicle capacity is an important factor in reducing delays.

The model presented here only considers a single line. Extending the model to a network of intersecting lines, where freight can change lines at transshipment depots, is an interesting concept for future work. Further extensions could also include the problem of rolling stock, i.e., assigning the vehicles in the fleet to services instead of setting an approximated upper boundary for the number of services. In the computational study, we evaluated a network with closely situated stops for each station. In

future work, a transit system with sparsely distributed stops is also worth analyzing. Additionally, this work did not consider further transport from the micro-depots over the "last meter". Future work could also anticipate the capacity request acceptance over time to avoid late denials. At the moment, the ALNS algorithm solves the freight assignment problem with a commercial solver. The evaluation of different algorithms to find a feasible assignment and further accelerate the heuristic might also be a promising approach.

# 4.

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## Essay 3: Conceptualizing an agent-based simulation for integrated urban transport

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**Abstract**

Integrating urban parcel transportation into a public passenger transport system is a promising concept to reduce traffic congestion and use resources more efficiently. However, the last decade saw several pilot projects failing due to the lack of long-term support and profitability. Integrated transport relies on a range of stakeholders, which differ in their incentives and want to profit from the system. Existing reviews show that financial viability is an important aspect for the long-term success of such projects. For example, partially financing the public transit system with the revenue gained from parcel transportation may contribute to the success of a shared transport system from the point of view of public transit providers. This work conceptualizes an agent-based simulation model to evaluate business schemes for an integrated passenger and freight urban transport system.

**Keywords**

Simulation, Transportation, Public Transport.

## 4.1. Introduction

Many European city administrations seek to reduce traffic and emission in the urban area. The implementation of low emission zone (LEZ) policies is a frequently used approach to strive for this goal, e.g., applied in Rome, London and Milan. However, Euro 6-compliant diesel vehicles are still exempt from European LEZ policies (Ku et al., 2020). The reason why an attempt of banning all types of diesel vehicles failed is the strong industrial opposition. With rising e-commerce sales, the last-mile delivery became a very competitive and challenging field. High time pressure, failed home-deliveries, congested road and high personnel costs require the logistics service providers (LSPs) to ensure a cost-efficient delivery (Boysen et al., 2020). As consequence, additional measures to LEZ policies are required, including new forms of mobility as well as a high quality public transport (PT) (Ku et al., 2020). A successful PT network includes immense costs for personnel, infrastructure, maintenance and handling services. The public transport service provider (PTSP) cannot cover those costs with the revenue gained through ticket sales while maintaining an affordable PT system. For this reason, PT is also financed by governmental subsidies (Berger, 2019). In times of booming e-commerce, the transportation of parcels in idle times might be another income stream. To create additional revenue, the PTSP might offer the LSPs to share capacities in the PT system. The work of Hörsting and Cleophas (2023a) and Elbert and Rentschler (2021) summarizes the state of the art on integrated passenger and freight transport.

In summary, alternatives for last-mile transportation and the inclusion of all stakeholders interests seem necessary to create a real impact. Prescriptive analytics can help to find the best planning solutions for a variety of complex transport situations. However, a single optimization model can hardly take every planning aspect into account. Computer simulations allow for evaluating the interplay of different optimization problems and finding more holistic and approachable solutions. This work conceptualizes a simulation model to evaluate business schemes implementing an urban integrated passenger and freight system on light-rail. As it considers the perspectives of the main stakeholders involved in the process, this work suggests an agent-based model (ABM) framework. The following section describes the simulation concept, gives an overview of the considered entities, and details the processes as well as decisions. Section 4.3 provides an outlook to future research.

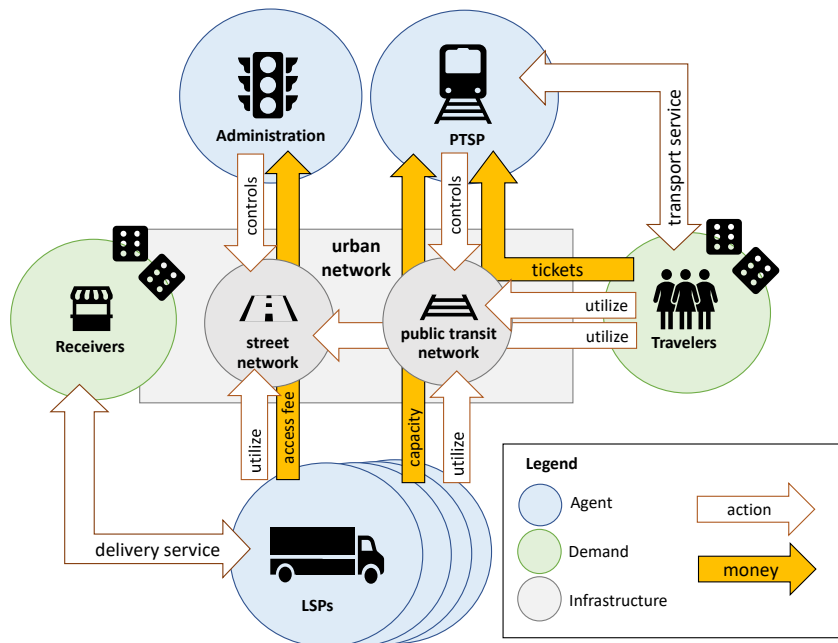


Figure 4.1.: Relations of the simulation entities

## 4.2. Simulation concept

The following section conceptualizes an agent-based simulation. The purpose of the model is to evaluate different business schemes for the integration of parcel transport in a public transit network and learn how stakeholder can benefit from different implementations. The model considers strategic, tactical and operative planning levels over multiple epochs. In each epoch, the stakeholders make decisions based on their individual objectives. Section 4.2.1 shortly introduces the entities and transport infrastructure. Section 4.2.2 gives an overview of the simulation processes and detail the decisions for the three planning levels.

### 4.2.1. Entities and network infrastructure

Figure 4.1 gives an overview of the relation and interaction between the entities. There are three *types of agents*. The city *administration* is in control over policies affecting the urban street network, i.e., the ban from heavy vehicles from the streets or the implementation of a fee to enter the urban area. Similarly, the *public transit service provider (PTSP)* controls the PT network by setting a passenger ticket fare and allocating the given capacity to passengers and parcels. Finally, the model includes multiple *logistics service providers (LSPs)*. Each LSP individually decides on the form of last-mile transportation, i.e., whether it prefers to utilize transporters from their

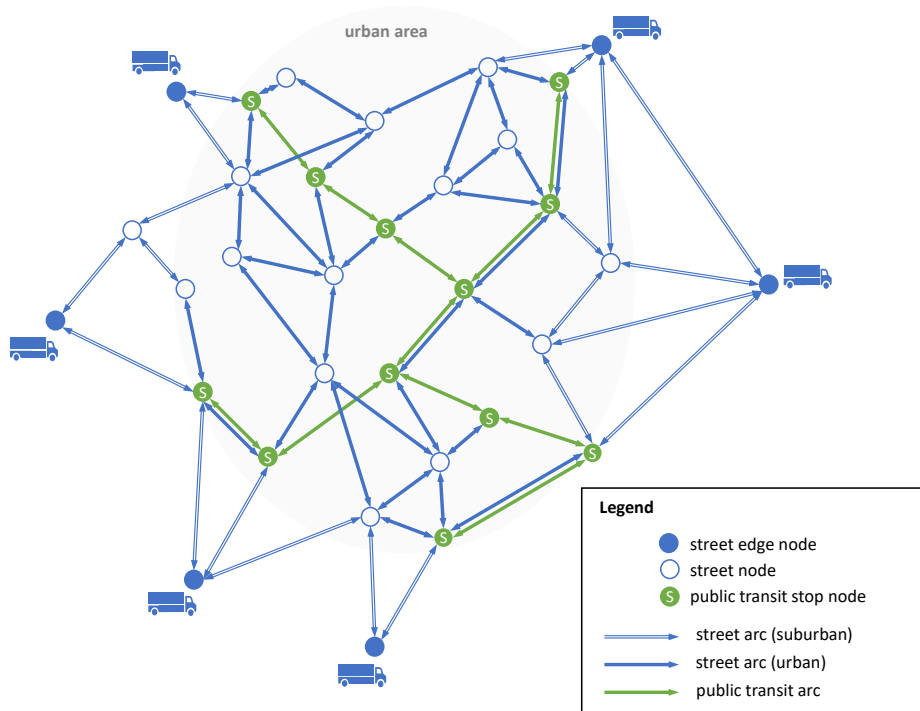


Figure 4.2.: Transport infrastructure consisting of a street and a public transit network

fleet or the integrated transport service offered by the PTSP.

Further, there are two streams of *demand*. The *receivers* are entities ordering parcels according to stochastic probability distributions. As the focus is on the last-mile transport, the model disregards the carrier in the supply chain and assumes that the receivers order directly at the LSPs. The distribution of order arriving at an available LSP also depends on the past performance of the service, i.e., LSPs with increasing delivery times may lose customers. Equivalently, *travelers* are potential clients of the PT service. The passenger flow is modeled with time-dependent origin-destination pairs and dependent on stochastic distributions. Similarly to the parcel service, delays and disruption of the PT service can lead to fewer passengers and, as a consequence, to less revenue for the PTSP.

The model focuses on the transportation services in an urban area, illustrated in Figure 4.2. The area includes the *PT network* as well as the *street network* of an exemplary city. Both networks are represented by directed graphs and connected via the stops in the PT network. The depots of the LSPs are located outside of the urban area and represent the start and end of each vehicle in the fleet of the respective LSP.

## 4.2.2. Simulation process overview and main decisions

The following section gives an overview over the processes considered in the simulation as well as the main decisions made by the agents. Figure 4.3 illustrates the main simulation framework. First, the algorithm initializes an empty network and the entities. Additionally, the simulation counter is set to zero. Each simulation run features a discrete and finite time horizon. In constant intervals, the agents make decisions concerning strategic and tactical planning decisions. In addition, each simulation run processes an operative epoch where new demand is randomly generated and the agents act based on operative planning decisions. The decisions are detailed in the following.

### ***Strategic Level***

The strategic planning horizon covers long-term decisions and typically includes one to multiple years. In this work, the strategic planning horizon consists of five years.

As a strategic decision, the city administration can implement *LEZ policies* for transporters in the form of access restriction measures for transporters or *an access fee* to enter in the urban area.

The PTSP must decide on the mode for *freight transport*, i.e., whether passengers and parcels share the same area in the trains, the parcels are transported in wagons, or dedicated parcel trains are provided to the customer.

### ***Tactical Level***

The tactical planning horizon covers medium-term decisions and typically includes months up to one year. For the given stakeholders, the strategic decisions involve the kind of collaboration between stakeholders and on the height of the service fees.

If the city administrator decided on an access fee for the urban area, the fee level that the LSPs are charged can be updated each tactical epoch.

The PTSP designs a *freight capacity contract* that includes the capacity reserved for parcel transport as well as a fixed contract fee paid by the LSP. In addition to the contract-based freight, the PTSP offers to buy available capacity on a spot market. As tactical decision, the PTSP decides on a *freight spot fare structure* for remaining capacity. The spot market allows for a flexible booking of capacity but does not guarantee a price or volume. The spot fare may also vary depending on the available capacity left. Additionally, the PTSP also updates the *passenger ticket fare* in a tactical interval. The arrival probability of passengers in the following operative epoch also depends on the given ticket price.

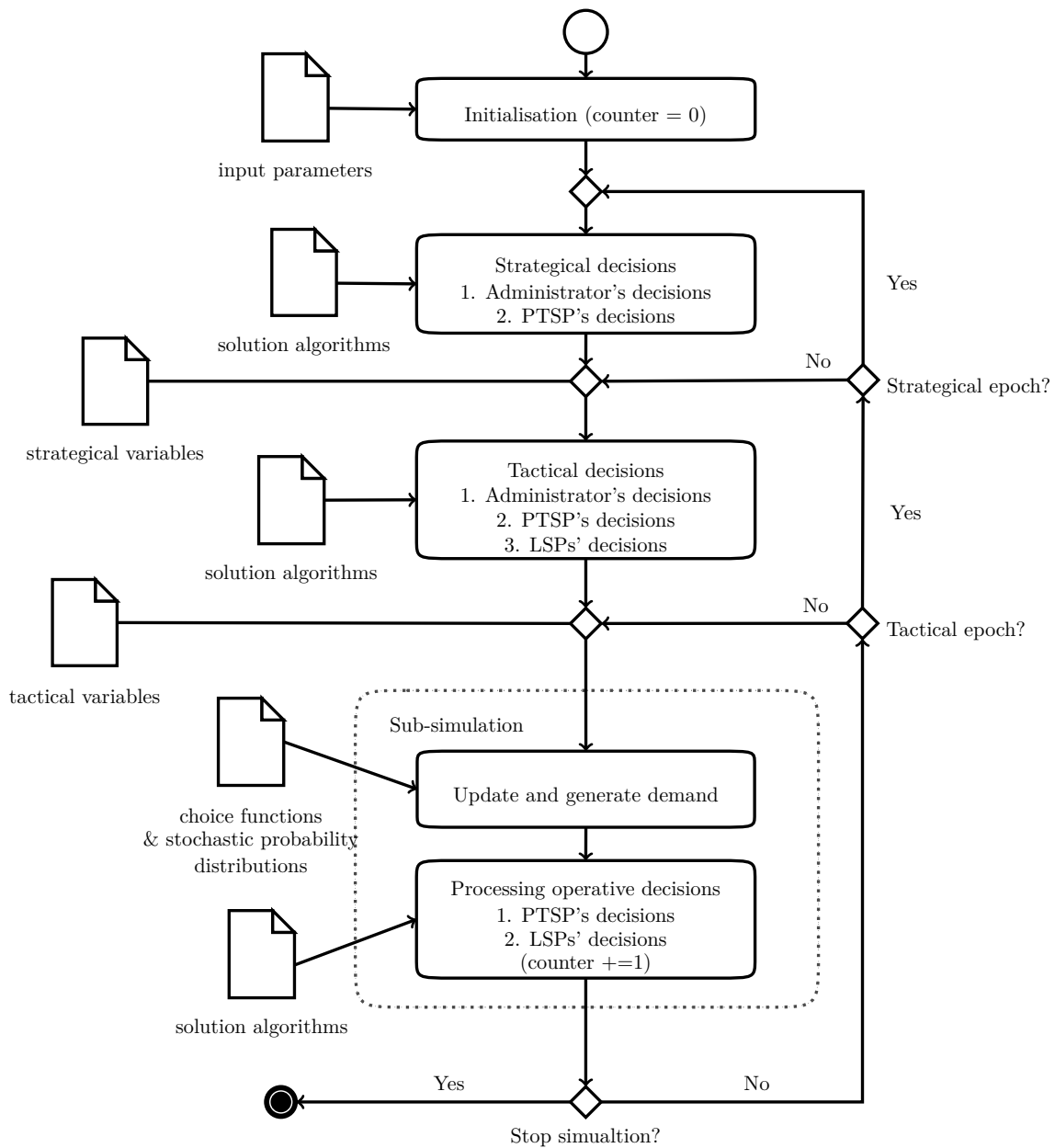


Figure 4.3.: Overview of the simulation procedure

As a tactical decision, the LSP decides to what degree and in which form they consider the PT system as an alternative on the last-mile. On the one hand, the LSP chooses the *degree of cooperation with the PT*, i.e., they can either *reject a cooperation*, include the PT for *deliveries to parcel lockers*, or also use the PT as alternative for *home deliveries*. On the other hand, the LSP decides on the *form of cooperation* with the PTSP. They can choose to cooperate in the form of a *freight capacity contract* to buy a fixed capacity volume for a fixed fare per parcel. For an LSP that rejects the proposed contract, the PTSP offers available capacity on a spot market.

### ***Sub-simulation: Processing an operative epoch***

As part of the simulation, a sub-simulation processes the decision-making and outcomes for the operative epoch. The operative planning horizon covers short-term decisions and the model assumes that an operative time horizon includes one day.

The LSP solves a vehicle routing problem based on the daily demand. The capacity and speed of vehicles depends on the current business scheme. In general, cargo bikes have a lower capacity and speed than transporters. However, the model assumes that the risk of delivery delays by transport via a regular transporter increases when the streets become congested.

Part of the capacity is already promised to LSPs through freight capacity contracts. However, the PTSP must decide how it distributes the capacity units remaining for the passengers and volumes sold on the spot market. In neither case, the real demand is known in advance.

The trains of the PTSP operate according to a predefined timetable. During the dwell time of trains at the PT stop, travelers can board and alight the vehicle and parcels can be loaded and unloaded. If the travelers and parcel containers share the same space, those processes take place sequentially. Travelers have always priority. They alight the vehicle before parcel containers are unloaded, and they board the vehicle before parcel containers are loaded. If the vehicles have additional parcel containers, the passenger and freight processes take place simultaneously. Therefore, passengers board and alight at the same time, while parcels are loaded. Furthermore, passengers and parcel containers that cannot enter due to capacity limitation must wait at the stop.

## **4.3. Conclusion and outlook**

This work conceptualized an agent-based simulation modeling an integrated passenger and freight transport system. It considers the perspective of multiple stakeholders rep-

resented as agents and demand streams in the simulation. Additionally, stakeholders make decisions on an operative, tactical and strategical level. For instance, an exemplary planning decision is the degree of freight integration into the passenger service network. Thus, if passengers and parcels are transported in a shared area of the same trains or if the parcel transport takes place in dedicated freight trains. Another interesting decision is whether a home attended delivery for integrated transport a valid option or if parcel lockers at the stops are necessary.

The simulation's purpose is to evaluate business schemes for integrated passenger and freight urban transport. To analyze the system's success, future work will focus on a selection of performance indicators, e.g., the number of vehicles operating, the estimated last-mile delivery costs, or the expected revenue for the public transit service provider. The research objective is to learn how different stakeholders of an exemplary city can benefit from the business schemes for integrated urban transport. Additionally, future work will propose algorithms and optimization models to solve the occurring decision problems.

# 5.

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## Essay 4: Two sides of shared passenger and freight transport? An agent-based perspective

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### Code and data

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### Abstract

Integrating parcels into urban public passenger transport systems promises to reduce traffic congestion and enhance resource efficiency. However, their long-term success depends on aligning the goals of various stakeholders. To support this alignment, this paper first identifies incentives of stakeholders through a literature review. Subsequently, it presents an agent-based model of shared passenger and freight transport. In a simulation study, we evaluate two business schemes for shared transport: The static scheme uses dedicated trains and contract-markets, while the flexible scheme lets passengers and parcels share trains and relies on spot-markets for capacity assignment.

Our findings show that smaller logistics providers benefit from consolidation in the flexible scheme, whereas the static scheme requires accurate demand forecasting and advanced planning.

### Keywords

Agent-based Model, Logistics, Public Transport, Shared Transport

## 5.1. Introduction

In the Paris Agreement (2015), 195 countries committed to mitigate climate change. Achieving this goal requires action at the local government level. As one measure, many European cities try to reduce traffic and emissions in urban areas by implementing low emission zones (LEZs), as seen in Rome, London, and Milan. However, Ku et al. (2020) argue that such policies alone do not significantly reduce emission rates, particularly since Euro-6-compliant diesel vehicles remain exempt from European LEZs (Georgiev, 2018). Efforts to ban all types of diesel vehicles have failed due to strong industrial opposition. Instead, such vehicles frequently transport freight on the last mile in urban areas, supporting the unbroken trend to increase e-commerce deliveries.

Last-mile delivery is by nature highly competitive and challenging, with high time pressures, expensive failed deliveries, congested roads, and high personnel costs necessitating cost-efficient solutions for logistics service providers (LSPs) (Boysen et al., 2020). Although a study by Hebditch (2023) suggests that electric vans will soon offer low operating costs, their limited travel range and the need to recharge must be integrated into the planning of the tour (Boysen et al., 2020). Accordingly, Ku et al. (2020) conclude that additional measures beyond LEZ are needed, and recommend new forms of mobility and high-quality public transport (PT).

However, implementing high-quality PT comes with its own challenges. PT systems incur significant costs for personnel, infrastructure, maintenance, and handling services. Public transport service providers (PTSPs) cannot cover these costs solely through ticket sales while maintaining affordability. Therefore, they also rely on government subsidies. For instance, the subsidy rate for German public transport was 26% in 2018 (Berger, 2019). In the era of booming e-commerce, transporting parcels on a structured infrastructure or even in shared vehicles as proposed in Hörsting and Cleophas (2023a) could provide an additional income stream. However, this requires business schemes that account for the needs and incentives of LSPs, PTSPs, passengers, and municipalities. In summary, alternative solutions for last-mile transport, balancing all stakeholders' interests are essential for creating a sustainable change towards emission goals (Arvidsson & Browne, 2013).

This work first distills the perspectives of different stakeholders and how they shape and experience business schemes for integrated passenger and freight transport from a literature review, focusing on the following research questions:

- What incentives drive relevant stakeholders to collaborate on a shared passenger and freight transport system?
- What stakeholder decisions affect the success of the shared passenger and freight

transport system?

Further, we propose an agent-based model (ABM) to evaluate stakeholder decision-making in various experiments based on two business schemes, offering insights regarding further research questions:

- What are potential environmental benefits of the proposed business schemes?
- How do stakeholder benefit or suffer from the proposed business schemes?
- When do LEZ policies facilitate the shift to a shared passenger and freight transport system?

Our results indicate that LSPs of any size can benefit from the flexible business scheme. Low spot fares particularly incentivize LSPs and the PTSP to collaborate. However, this business scheme reduces planning reliability for the PTSP. Contract-based schemes provide planning reliability for PTSPs but require low entry prices to remain a viable alternative. Finding an appropriate contract freight volume challenges the LSPs and requires accurate demand forecasts and planning. LEZ policies and the chosen business scheme must complement each other. When the systems are set up well, small LSPs benefit from the consolidation of parcels. However, LSPs require effective decision making to stay profitable. Additionally, the increased transport costs may increase delivery fees for consumers.

In the following section, we review the literature on evaluating shared passenger and freight transport systems. Section 5.3 discusses the incentives of various stakeholders as derived from literature, while Section 5.4 outlines the business schemes evaluated in the remainder of the paper. Section 5.5 introduces the framework of the ABM and defines the relevant parameters. Subsequently, Section 5.6 presents the results of the computational experiments. Finally, Section 5.7 summarizes the findings and presents the conclusions of this study.

## **5.2. Evaluating shared transport systems**

The concept of integrating freight delivery into passenger transport is not new, but the demand for low-emission transport has rekindled interest in the idea. Elbert and Rentschler (2021) and Cavallaro and Nocera (2021) provide comprehensive reviews on shared passenger and freight transport systems.

Given the scarcity of practical examples, researchers often rely on expert opinions or potential user surveys to identify opportunities and barriers for such systems (Arvidsson & Browne, 2013; Cavallaro et al., 2023; Cochrane et al., 2017; Kikuta et al., 2012).

Computer simulations are another popular and valuable tool to plan and evaluate logistics systems. In that regard, Nuzzolo et al. (2018) review the literature on agent-based logistics models. For example, Schröder and Liedtke (2017) use the MATSim software to simulate passenger and freight behavior under a LEZ. As a relevant predecessor to the work presented in the paper at hand, van Heeswijk et al. (2020) apply an ABM to evaluate urban logistics schemes, focusing on the financial viability of urban consolidation centers across different planning levels.

To further contextualize our contribution, we focus on simulation research that models urban transport integrating passenger and freight transport. To that end, Motraghi and Marinov (2012) use a discrete event simulation (DES) to evaluate a fixed scheduled operation service versus an improvised operation prioritizing freight service. The simulation models an urban rail freight system in Newcastle upon Tyne, UK. Potti et al. (2019) simulate an urban rail freight system in Birmingham, UK, using the SIMUL8 software. Hu et al. (2020) propose a System Dynamics model to study the integration of freight in urban passenger rail transit for Beijing, China.

Furthermore, computer simulations are frequently used to evaluate the performance of optimization approaches. For example, Hassannayebi et al. (2014) optimize the headway of two consecutive departures to minimize the expected waiting time for passengers, proposing a two-stage genetic algorithm-based simulation optimization approach. Behiri et al. (2018) formulate a Freight-Rail-Transport-Scheduling problem as a mixed-integer program, evaluating the proposed heuristics with a discrete event-based simulation. Similarly, Hörsting and Cleophas (2023a) propose a mixed-integer program to schedule freight and passenger trains while minimizing the average passenger waiting time and shipment delay, using a DES for evaluation. Based on the principal-agent theory, He and Guan (2023) design a government subsidy incentive contract for an integrated passenger and freight bus system.

Another notable use case for simulation models is testing the performance of anticipatory planning for on-demand services. For example, Fehn et al. (2023) propose an ABM to evaluate the integration of parcel deliveries in a mobility-on-demand service. Bosse et al. (2023) examine priority rules for combining passenger and goods transport within a computer simulation. Ji et al. (2024) introduce a multi-agent simulation model to analyze pricing strategies for a taxi service transporting passengers and parcels.

To the best of our knowledge, no contribution to-date simultaneously models decisions on operational, tactical, and strategic levels for integrated passenger and freight transport systems. Existing research generally addresses decision problems at a single planning level. This work aims to start filling this research gap. To that end, we present an ABM that allows agents to make decisions for various timelines, on operational, tac-

tical, and strategic levels. In that, our approach is most closely related to that of van Heeswijk et al. (2020). However, while those authors evaluate the implementation of consolidation centers, we focus on shared passenger and freight systems.

### 5.3. Stakeholders in shared transport systems

For PT, Daraio et al. (2016) differentiate three main stakeholder groups: *The service provider, the travelers, and the community*. To model decisions in the interest of the community, we let the *municipality* stand for a governmental entity representing the interests of the political decision-makers, citizens, and local businesses – more on that in Section 5.3.1

The municipality’s ecological policies, for example, the ban of gasoline vehicles (Dia, 2019; Meckling & Nahm, 2019), toll charges (Flämig & Wolff, 2016; Gomez & Vassallo, 2020; Grimsrud et al., 2020; Lehe, 2019), or fuel taxes (Santos, 2017) impact both logistics service providers and private car owners. As a result, *LSPs* face pressure to electrify their fleets (Liu et al., 2022; Slowik et al., 2019) or adapt their route choices (Oka et al., 2019). Governmental policies also affect citizens’ lifestyles, including their choices to travel by PT or car (Brown, 2017; Nieuwenhuijsen & Khreis, 2016). In consequence, current and expected regulations also impact the success of shared passenger and freight transport systems. We discuss the related stakeholders of PT in more detail in Section 5.3.2.

In terms of e-commerce, the supply chain consists of the shipper selling the product, the carrier transporting the product, and the customers buying the product (Blanchard, 2021; Bosona, 2020). According to Hugos (2018), common stakeholders of the supply chain are the producers, the distributors, the retailers, the logistics service providers, and the customers. The model proposed here focuses on the *LSPs* and the customers receiving goods, as they are primarily affected by implementing a shared passenger and freight system on the last mile. Thus, we emphasize the motives of the *LSPs* and the *recipients* in Section 5.3.3.

#### 5.3.1. Municipality

As part of public governance, the *municipality* may aim to lower emissions by enhancing zero-emission transport modes for passengers and freight. At the same time, cities pursue economic growth by attracting profitable businesses, viable employers, and employees. An attractive municipality design includes good transport infrastructure and safe, quiet public spaces (Kourtit et al., 2021; Leyden et al., 2011; Mouratidis & Yiannakou, 2022). To reduce emissions and noise, the municipality can introduce

policies such as LEZs with access restrictions and fees, as reviewed by Ku et al. (2020), Panteliadis et al. (2014), and Y. Wang et al. (2017). As decision making processes are opaque and in the domain of political science, our model focuses on representing outcomes as the background experiments for evaluating business schemes.

### **5.3.2. Public transport: Service provider and travelers**

In recent years, urbanization has led to an increase in short-distance travel demand (Kholodov et al., 2021). Travelers' transport choices depend on various factors, including the type of traveler, municipality geography, and the type of transit available (Litman, 2004). This growing demand emphasizes the need for efficient PT planning.

However, challenges remain, particularly when integrating freight and passenger transport. One significant issue is the potential disruption to passenger services caused by freight operations. (Arvidsson & Browne, 2013; Cochrane et al., 2017). For example, loading and unloading cargo may cause delays for travelers. To mitigate such disruptions, Hörsting and Cleophas (2023b) introduce a scheduling model that ensures sufficient dwell time at stops, balancing the needs of both freight and passenger services.

A well-studied area in PT research is estimating service and fare elasticities for different demand segments (Cervero, 1990; Kholodov et al., 2021; Paulley et al., 2006). Big data collected through smart cards or automated fare collection systems provide detailed insights into passenger demand, which are invaluable for PT planners (Kholodov et al., 2021; Pelletier et al., 2011; Z.-j. Wang et al., 2015; Welch & Widita, 2019). Such data helps in understanding patterns and making informed decisions regarding transit services.

Many studies suggest passenger demand is highly price-sensitive, with an average price elasticity of  $-0.3$  (Bresson et al., 2003; Holmgren, 2007; Webster & Bly, 1981). This means that a 10% increase in prices could result in a 3% decrease in passenger demand. Understanding this relationship is crucial for PT planners, especially when considering fare adjustments.

Free-fare PT services have been proposed as a solution to increase ridership and reduce administrative costs. However, these initiatives carry risks, such as vandalism and reduced passenger satisfaction (Cats et al., 2017; Kębłowski, 2020; Perone & Volinski, 2003). Therefore, the impacts of fare-free policies must be carefully considered.

In addition to fares, several other factors related to service quality play a critical role in attracting travelers to PT. The speed of the service, frequency, network coverage, comfort, and parking prices are all key attributes that influence passenger decisions (Litman, 2004; Redman et al., 2013).

Many PTSPs face financial challenges, making it essential to provide reliable services

at acceptable prices while covering operational costs. Despite this, researchers and practitioners widely agree that ticket-sale revenue alone will never cover total PT costs, necessitating ongoing subsidies. Hence, while most cities finance their PT systems mainly through ticket sales, governmental subsidies are also crucial (Berger, 2019).

To ease the burden on taxpayers, governments are exploring alternative decentralized funding sources. For instance, France charges companies with the “Taxe de Versement Transport” (Institut des Poliques Publiques (IPP), 2021), and Wien’s employees must pay the “Dienstgeberabgabe” (Bundesministerium für Finanzen, 1969) – local employer’s levies to fund PT. Integrating shared passenger and freight systems could serve as a potential additional revenue stream for funding PT.

### **5.3.3. Freight logistics: Service provider and recipients**

Due to urbanization and the e-commerce boom, delivery volumes are steadily growing (Boysen et al., 2020). At the same time, increasing customer expectations put pressure on service providers, with many online retailers promising next- or same-day deliveries. LSPs organize and execute the transport of cargo, aiming to keep costs low while maximizing revenue.

Revenue-maximizing contracts between carriers and shippers, as well as pricing and price allocation, are beyond the scope of the paper at hand but have spawned independent research streams (Brabänder, 2020a; Chen et al., 2017; Chu et al., 2020; Lambert & Burduroglu, 2000). Instead, we focus on transport costs which aggregate personnel, capacity, and operating costs.

Brabänder (2020a) estimates last-mile transport costs at 27% for less-than-truckload deliveries and up to 77% for parcel deliveries of total supply chain costs. Due to low stop and tour productivity, that is, a high number of stops for small and sparsely distributed shipments, parcel deliveries are especially costly. Transport costs include working hours and resources like fuel, with personnel costs being the most significant (Boysen et al., 2020; Brabänder, 2020b; Milioti et al., 2020).

By considering distinct business schemes, we aim to contribute to related research by evaluating the effect of LEZ policies and cooperation with the PTSP on LSP performance. We estimate potential effects on outsourcing costs, such as paid fares for utilizing PT capacities and fees to access LEZ.

## 5.4. Business schemes

Based on the work of van Heeswijk et al. (2020), we define a *business scheme* as a “set of company-driven initiatives and administrative policies aimed to improve efficiency and/or reduce environmental and societal costs”. In the following, we introduce a conventional scheme and apply it to benchmark two alternatives for integrated freight and passenger transport systems.

All schemes share the following assumptions: We focus on the transport of parcels in the urban area via light rail trains, such as trams. The PT system operates independently from the street network. The parcels are collected and transported in standardized containers, as suggested by, for example, Behiri et al. (2018), Hörsting and Cleophas (2023a), and Li et al. (2021). Transport via light-rail trains offers several advantages. In contrast to road vehicles such as buses or taxis, the standing room on trains provides enough capacity for goods transport and the option for additional wagons. Additionally, the stations are often centrally located in the municipality, are easily accessible, and offer sufficient space to store parcel containers (Bogdanski & Cailliau, 2022).

**Conventional scheme: Status quo with separate systems** As a benchmark for the proposed integrated business schemes, we consider the conventional state of last-mile delivery transport and PT. In the *status quo*, LSPs use standard transport vehicles to deliver freight by road, while the PT system is reserved for passenger use.

**Static business scheme: Fixed contracts and dedicated cargo trains** The *static business scheme* involves transporting freight in dedicated cargo trains operating within the same rail network as regular passenger trains, as suggested, for example, by Ozturk and Patrick (2018) and Motraghi and Marinov (2012). Because purchasing and operating additional trains is very costly, the PTSP will only consider this option if there is a constant and reliable stream of demand (Cochrane et al., 2017). To ensure such conditions, the PTSP and LSPs must agree on a contract that defines the capacity and price of the transport service. The contract conditions include specific time slots for deliveries, maximum capacity volumes per time slot, and a fixed fare per shipment. LSPs decide how much capacity to purchase from the PTSP and must pay the agreed price regardless of whether they utilize the full capacity.

**Flexible business scheme: Spot-market allocation and shared trains** The *flexible scheme* involves sharing space in PT vehicles between passengers and freight as suggested by Behiri et al. (2018) and Ghilas et al. (2016a). Unlike the first scheme, this

approach requires fewer investment costs and less intervention in the current timetable (Cochrane et al., 2017). Consequently, this scheme offers more flexibility in allocating capacity to both passengers and goods. In this model, the PTSP relies on a spot-market to sell available capacity to the LSPs.

## 5.5. Simulation framework

We evaluate the business schemes introduced in the previous section by implementing a simulation model conceptualized in a preliminary version in Hörsting (2025). To that end, we represent the stakeholders’ characteristics discussed in Section 5.3 in an ABM. We implement the model in Python 3, using the package *agentpy* (Foramitti, 2021). The resulting code and experimental data can be found at <https://doi.org/10.5281/zenodo.15367734>. Due to the innovative nature of integrated passenger and freight transport, historical empirical data are scarce. To circumvent the need for such data and still produce relevant results, we adopt a structural analysis approach rather than calibrating the model to a specific city. Similar to van Heeswijk et al. (2020), we aggregate data to represent a typical Western European city with a medieval center, similar to, e.g., Cologne or Ghent. The resulting exemplary network, which we detail in Section 5.5.1, allows us to explore systemic interactions without being constrained by location-specific details. This approach lets us identify overarching trends, dependencies, and scalability factors that can be generalized across urban contexts. By focusing on broad patterns rather than city-specific nuances, we provide insights that remain relevant for policymakers and transport planners seeking to implement shared transport solutions in diverse urban environments.

The model includes five types of agents: The *municipality*, the *public transport service provider (PTSP)*, the *logistics service providers (LSPs)*, the *recipients*, and the *travelers*. Figure 5.1 illustrates the relationships between these agents, particularly highlighting the flow of money and interaction.

The municipality’s policies affect the use of the urban street network, such as banning heavy vehicles or implementing access fees (see Section 5.5.2). Similarly, the PTSP manages the rail network by setting ticket fares and allocating capacity to passengers and parcels (see Section 5.5.3). Each LSP decides whether to use the street or rail network for last-mile delivery of parcels (see Section 5.5.4). Demand is modeled as two streams: To reduce complexity, parcels ordered by recipients (Section 5.5.5) and travelers (Section 5.5.6) are both represented as quantity flows based on stochastic distributions. In this, we follow examples from related research, such as Fatnassi et al. (2015) and Yin et al. (2021).

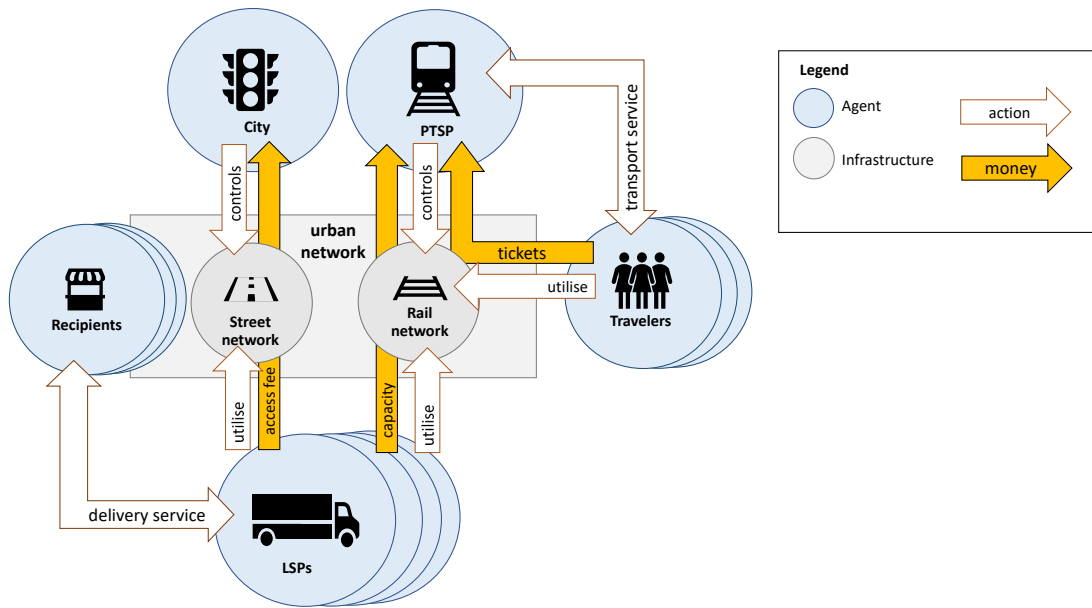


Figure 5.1.: Relations between entities in the simulation

Figure 5.2 illustrates the simulation process as a flow chart. The simulation models stochastic runs, where each run represents a finite time horizon divided into discrete steps. The first step initializes the urban network and agents based on a set of input parameters while the simulation clock is set to zero. Each simulation step represents one day of chronological time. The model considers strategic, tactical, and operational planning levels. Each run represents a day where new passenger and parcel demand is generated and agents implement operational decisions. Additionally, agents can update their strategic and tactical decisions at constant intervals. Strategic decisions are updated every 365 days and tactical decisions are updated every 30 days. The following sections detail the policies and parameters underlying these decisions. In addition, Tables B.1 to B.6 in the appendix contain the parameters used in this study.

### 5.5.1. Network infrastructure

Directed graphs represent the modeled municipality's rail and street networks, where each simulation run features a different randomized city network. Dickinson (1951) provides a geographical interpretation of the Western European city, and identifies three distinct types of spatial patterns: the grid system, common in U.S. cities like Washington, D.C., and New York; the radial-concentric system, typical of medieval European cities like Paris and Berlin; and the irregular system, which is less suited for modern transport planning. Focusing on Western European city patterns, we adopt a radial-concentric network design featuring a densely populated urban center surrounded

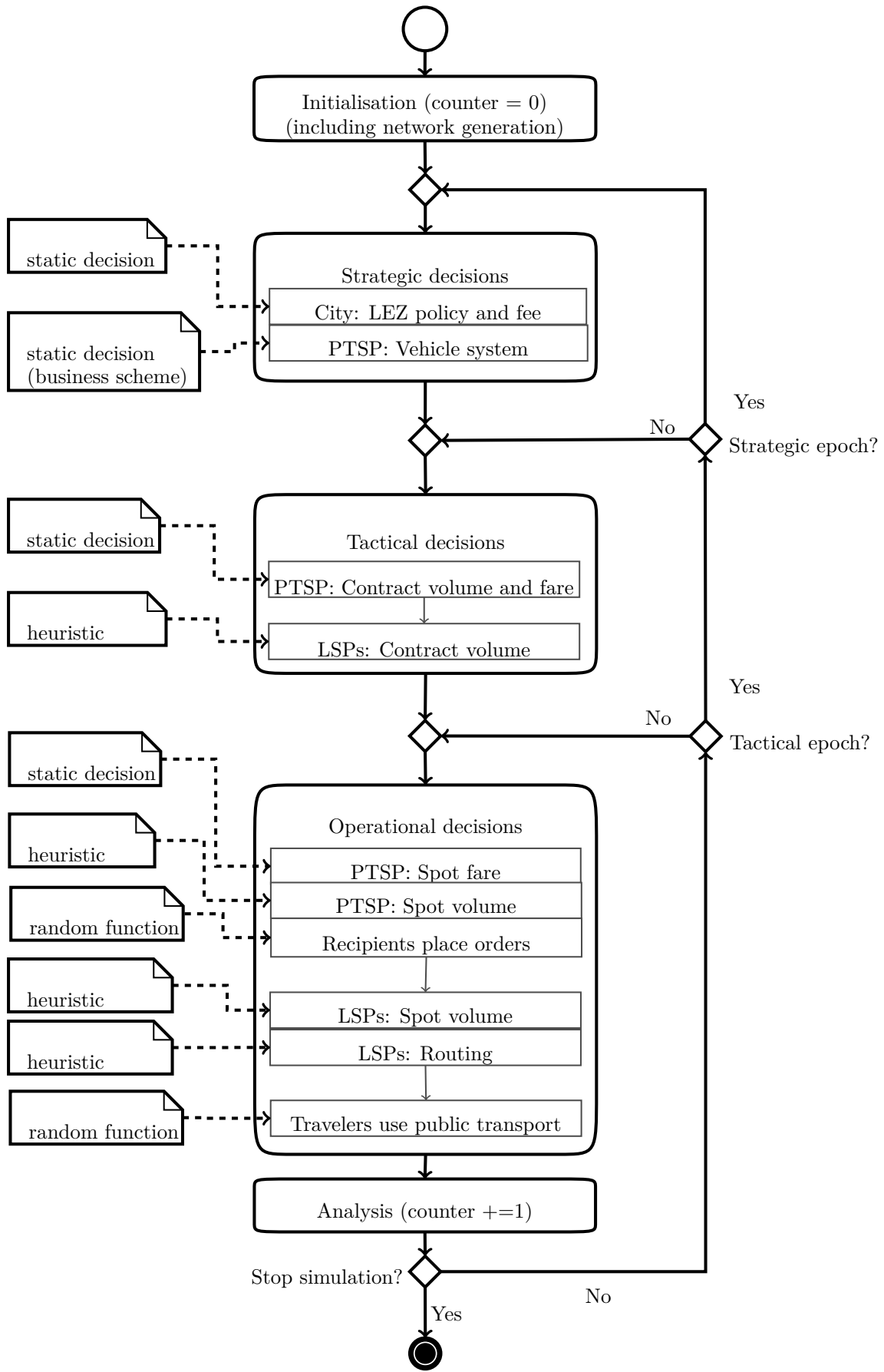


Figure 5.2.: Process overview of a single simulation run of the ABM

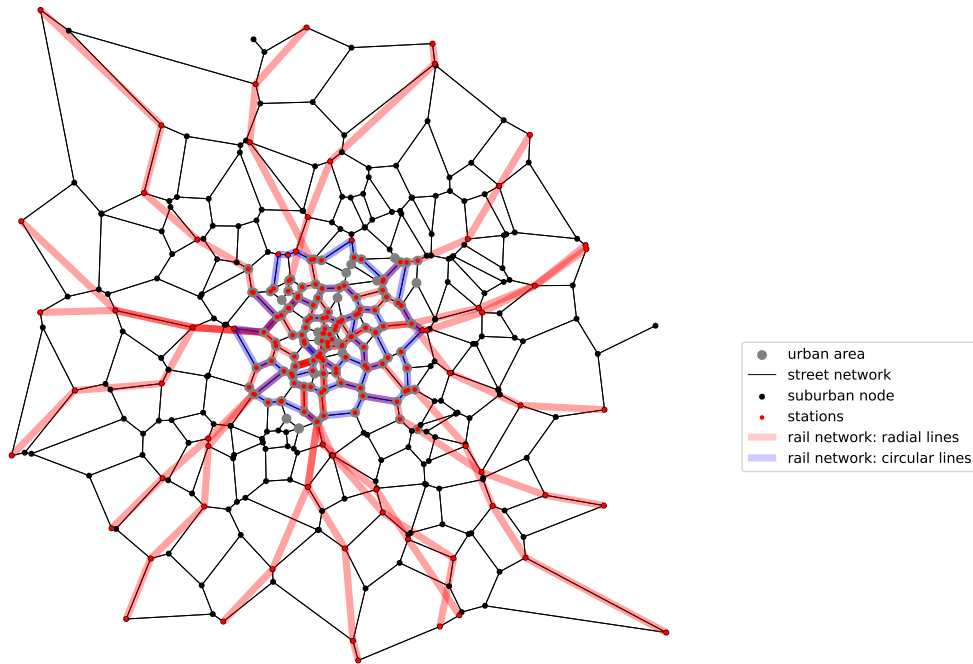


Figure 5.3.: Exemplary graph illustrating the transport network

by a sparsely populated suburban area. Figure 5.3 depicts an exemplary city network of a single simulation run. In 2010, the average residential density for several European cities peaked at distances between 1 km and 4 km from the city center, then gradually decreased and plateaued at a distance of 12 km (Kompil et al., 2015). Based on this background, we let the simulation feature randomized model cities with a 12 km radius, where the urban center extends up to 3 km, and the remaining area constitutes the suburbs. To construct the network, we randomly distribute 200 points within this circular area. These points follow a normal distribution, peaking around 3 km from the city center with a standard deviation of approximately 5 km. This distribution creates a dense urban core that gradually transitions into a sparser suburban area. The selected points serve as the sites for a Voronoi diagram (Aurenhammer, 1991). After removing isolated nodes and merging those less than 100 meters apart, the resulting edges and nodes of the Voronoi diagram form the city network.

Further, the design of the *rail network* is inspired by a radial hybrid model proposed by Badia et al. (2014). Based on the authors' findings on optimal network designs, we randomly generate eleven to fifteen *radial lines* connecting nodes from the suburbs to the urban center, and three to six *circular lines* which link nodes within the same radius in the urban center, operating on a fixed timetable. We assume that parcel

lockers are located in a short distance of the stations, making each station a potential destination of shipments. The LSPs' depots are randomly placed at one of the border nodes of the network, connected to the rail network.

### 5.5.2. Municipality properties and policies

In terms of *strategic planning*, the municipality decides on a static LEZ policy, i.e., the chosen policy determines the setting for the entire simulation process. We implement five settings to evaluate their effects in Section 5.6.2:

- A basic setting without LEZ policies,
- three settings with daily fees for accessing the urban center of €10, €20, and €30,
- and a setting that bans LSP transport vehicles from the urban center altogether, i.e., the LSPs are forced to outsource their shipping destined to nodes in the urban center to the shared passenger and freight transport service.

We do not consider the municipality to engage in *operational or tactical decisions*.

### 5.5.3. PTSP properties and policies

As a *strategic decision*, the PTSP decides on a business scheme to implement. This affects the transport system to realize: Either the PTSP only transports passengers (conventional scheme), or passengers and parcels share the same area in the trains (flexible scheme, as suggested by Behiri et al. (2018) and Ghilas et al. (2016a)), or parcels ride in dedicated cargo trains (static scheme, as suggested by Ozturk and Patrick (2018) and Motraghi and Marinov (2012)). The decision depends on the adopted business scheme and is applied throughout the simulation run.

*On the tactical level*, the PTSP decides to enter freight capacity contracts. This decision is similar to designing a long-term carrier-shipper contract (K. Y. Wang et al., 2021; Yang et al., 2019). The carrier (here: PTSP) offers a contract bundle and the shipper (here: LSP) decides on the optimal shipping quantity. For fairness and model parsimony, we assume that the PTSP offers the same contract conditions to all LSPs. The PTSP provides all LSPs with the same maximum contract volume units and fixed fare. The PTSP offers sufficient capacity so that the LSPs could outsource their entire demand. In a basic setting, the contract fare is set at €0.20. Additionally, we analyze six experiments with contract fares ranging from €0.10 to €0.50 (Section 5.6.1).

*On the operational level*, the PTSP distributes the remaining capacity between expected passengers and freight sold on the spot-market (similar to the problems considered by Shi et al., 2022; Xu et al., 2022). Since actual demand is unknown in advance,

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**Algorithm 1** Capacity allocation of PTSP in flexible business scheme (executed every operational epoch)

---

**Require:** Current epoch  $i^*$ , services  $\mathcal{S}$ , departures  $\mathcal{D}^s$  for service  $s \in \mathcal{S}$ , capacity  $C$ , passengers  $p_d$  after departure  $d \in \mathcal{D}^s$ , number of LSPs  $k$ , leftover capacity  $C_{\text{leftover}}^i$  for  $i$  in previous epochs (if given)

**Ensure:** units ▷ Number of units offered to each LSP

- 1:  $C_{\text{leftover}}^{i^*} = 0$
  - 2: **for**  $s \in \mathcal{S}$  **do**
  - 3:      $C_{\text{leftover}}^{i^*} = C_{\text{leftover}}^{i^*} + \min_{d \in \mathcal{D}^s} \{C - p_d\}$
  - 4: **end for**
  - 5: units =  $\lfloor \frac{\sum_{i=0}^{i^*} C_{\text{leftover}}^i}{k \cdot i^*} \rfloor$
- 

the flexible business model employs a simple heuristic based on peak passenger utilization from previous periods to estimate available capacity for freight transport. This approach is outlined in Algorithm 1. We define a *service* as a route where the train completes a full tour, visiting each stop exactly once and beginning and ending at a terminal station. Apart from the set of services  $\mathcal{S}$ , the heuristic requires the train’s capacity  $C$  and number of passengers  $p_d$  at each departure point  $d \in \mathcal{D}^s$  of a service  $s \in \mathcal{S}$ . It calculates and accumulates the minimum leftover capacity  $C_{\text{leftover}}$  across all services, determined by subtracting the number of passengers from the vehicle’s capacity at each departure during the previous operational epoch. Finally, the heuristic computes the average of the leftover capacities, divides it evenly among LSPs, and rounds down to the nearest integer to determine the freight units offered per LSP. Similar to the static scheme, we analyze six experiments of spot-market fares ranging from €0.10 to €0.50 in Section 5.6.1. In the basic setting, the spot fare is set at €0.30.

#### 5.5.4. LSP properties and policies

We do not consider the LSP to engage in *strategical decisions* within the scope of the simulation. *As a tactical decision*, each LSP determines whether to cooperate with the PTSP by securing a freight capacity contract.

If the cooperation is contract-based, the LSP buys a fixed capacity volume from the PTSP at a fixed fare per parcel (cf. K. Y. Wang et al., 2021; Yang et al., 2019). As presented in Algorithm 2, this decision relies on the LSPs’ observation: To set the contract volume, the LSP applies a heuristic at the start of each tactical epoch, considering the past days  $i$ : Initially, the heuristic determines a set of routes without outsourcing alternatives. It then compares the average costs  $\bar{c}_r^i$  per unit and route  $r$  of the current tour in step  $i$  with the contract fare  $f^{\text{contract}}$ . The stops along the route are added to a candidate list of destinations outsourced to the PTSP’s service, if those average costs

---

**Algorithm 2** Buying contract volume by the LSPs in the static business scheme (executed every tactical epoch)

---

**Require:** Set of past operational *epochs*, current contract fare  $f_{\text{contract}}$ , currently available contract units  $u_{\text{offered}}$

**Ensure:**  $\text{units}$ ,  $\text{candidates}$   $\triangleright$  acquired contract-market volume, candidate stops for outsourcing (sorted by priority)

```

1: for  $i$  in epochs do
2:   routes  $\leftarrow$  HybridGeneticAlgorithm( $i$ )  $\triangleright$  Wouda et al. (2024)
3:    $\bar{c}^i = \{c_{\text{route}}^i / l_{\text{route}}^i \mid \text{for route in routes}\}$   $\triangleright$  costs  $c_{\text{route}}^i$  and load  $l_{\text{route}}^i$ 
4:   Sort routes by  $\bar{c}^i$  in descending order
5:   candidate_stops $^i = \{\}$ 
6:   units $^i = 0$ 
7:   for route in routes do
8:     if  $\bar{c}_{\text{route}}^i > f_{\text{contract}}$  then
9:       for stop in route do
10:        if units $^i + l_{\text{route}}^i \leq u_{\text{offered}}$  then
11:          candidates $^i = \text{candidates}^i \cup \{\text{stop}\}$ 
12:          units $^i = \text{units}^i + l_{\text{route}}^i$ 
13:        end if
14:      end for
15:    end if
16:  end for
17: end for
18:  $\mu = \text{mean} \{ \text{units}^i \mid i \text{ in epochs} \}$ 
19:  $\sigma = \text{std} \{ \text{units}^i \mid i \text{ in epochs} \}$ 
20:  $\bar{c} = \text{mean} \{ \bar{c}_{\text{route}}^i \mid i \text{ in epochs}, \bar{c}_{\text{route}}^i > f_{\text{contract}} \}$ 
21: units =  $\min \left\{ \max \left\{ 0, \mu + \theta^{-1} \left( 1 - \frac{f_{\text{contract}}}{\bar{c}} \right) \sigma \right\}, u_{\text{offered}} \right\}$ 
22: candidates =  $\bigcup_{i \text{ in epochs}} \text{candidates}^i$ 
23: Sort candidates by the occurrence in candidates $^i$ ,  $i$  in epochs, in descending order

```

---

exceed the contract fare, and there is still contract volume available. The algorithm adds routes with the highest average costs first, as those offer the highest potential for improvement. These intermediate results guide the decision on the contract volume, which is inspired by Littlewood’s rule from revenue management (Littlewood, 2005). The contract volume is defined as

$$\mu + \theta^{-1} \left( 1 - \frac{f_{\text{contract}}}{\bar{c}} \right) \sigma, \quad (5.1)$$

where  $\mu$  is the mean and  $\sigma$  the standard deviation of the shipment volume in previous epochs,  $\bar{c}$  are the average costs of all routes exceeding the contract fare  $f_{\text{contract}}$ , and  $\theta^{-1}$  is the inverse of the standard cumulative distribution function. Thus, the acquired contract-volume increases with the difference of the expected routing costs  $\bar{c}$  to the contract fare  $f_{\text{contract}}$ . The list of candidate stops to be outsourced is ranked by costs, and tracked for the dispatching process in the operational epoch.

*In each operational period*, the LSPs decide how many shipments to outsource on the spot-market and plan individual shipment transport and routing within the urban area (seen in, e.g., Ghilas et al. (2018), Mourad et al. (2019), and Zhao et al. (2019)). In the flexible business scheme, they compare the delivery costs of using their fleet versus outsourcing parcels to the PT service. Similar to the contract volume, a heuristic computes the average costs  $\bar{c}_r^i$  per unit and route  $r$  of the current tour in step  $i$  without outsourcing option and compares the results with the spot fare  $f_s$  (compare Algorithm 3). If

$$\bar{c}_r > f_{\text{spot}}, \quad (5.2)$$

shipments aimed for stops across the route  $r$  are outsourced to the PTSP’s service. After purchasing contract or spot units, the LSP determines the shipments to be transported by rail. The LSP then outsources the units assigned to the candidate stops, provided that a sufficient number of units are available. If the municipality’s LEZ policies restrict access to the urban center, the LSPs procure the expected demand on the contract or spot-market to avoid failed deliveries.

Additionally, the LSPs plan individual shipment transport and routing within the urban area. We model and solve the vehicle routing problem using the PyVRP which is a Python package that implements hybrid genetic search (Wouda et al., 2024). The delivery costs for the LSP fleet are influenced by last-mile costs and the urban access fee imposed by the municipality. Last-mile costs increase with both distance and time per vehicle. We assume operating costs are €21.00 per hour and €0.86 per kilometer

---

**Algorithm 3** Buying spot volume by the LSPs in the flexible business scheme (executed every operational epoch)

---

**Require:** Current spot fare  $f_{\text{spot}}$ , currently available spot units  $u_{\text{offered}}$

**Ensure:** units, candidates  $\triangleright$  acquired spot-market volume, candidate stops

- 1: routes  $\leftarrow$  HybridGeneticAlgorithm( $i$ )  $\triangleright$  Wouda et al. (2024)
- 2:  $\bar{c} = \{c_{\text{route}}/l_{\text{route}} \mid \text{for route in routes}\}$   $\triangleright$  costs  $c_{\text{route}}$  and load  $l_{\text{spot}}$
- 3: Sort routes by  $\bar{c}$  in descending order
- 4: candidate\_stops =  $\{\}$
- 5: units = 0
- 6: **for** route in routes **do**
- 7:     **if**  $\bar{c}_{\text{route}} > f_{\text{spot}}$  **then**
- 8:         **for** stop in route **do**
- 9:             **if** units +  $l_{\text{route}} \leq u_{\text{offered}}$  **then**
- 10:                 candidates = candidates  $\cup$  {stop}
- 11:                 units = units +  $l_{\text{route}}$
- 12:             **end if**
- 13:         **end for**
- 14:     **end if**
- 15: **end for**

---

per vehicle. Finally, the transporters travel at an average speed of 25 km/h and have a capacity of 300 parcels.

### 5.5.5. Recipients properties

We do not model recipients as dynamic agents but instead rely on static demand experiments to evaluate the decisions of the municipality, PTSPs, and LSPs. Thus, recipients do not make decisions on the strategic, tactical, or operational level.

The parameters of parcel demand are based on the following arguments: In 2021, the average person ordered 0.11 parcels per day (Bowes, 2022). Assuming a medium-sized municipality with 100,000 inhabitants, the total parcel volume would be 11,000 parcels per day. In Germany, the largest parcel service provider (DHL) holds around 40% of the total volume-based share, while other providers such as Hermes and DPD hold 5% to 15% each (Bundesnetzagentur, 2023). To evaluate the outcome for LSPs of different sizes, three LSPs with varying demand volumes operate in the simulation: the smallest LSP handles 550 shipments (5% of the total volume), the medium LSP handles 1,650 shipments (15% of the total volume), and the largest LSP handles 4,400 shipments (40% of the total volume) per day. Kompil et al. (2015) state that 45% of the European population live in cities, 35% live in suburban areas and 20% live in rural areas. If we assume an equal delivery volume per inhabitant, the majority (56%) of the shipments are destined for the urban center, while the remaining (44%) are delivered

to the suburban area.

### 5.5.6. Traveler properties

Similar to how we handle parcel recipients, we also do not model travelers to make decisions on the strategic or tactical level. However, on the operational level, travelers choose their approach to traveling.

We set passenger demand parameters according to the following arguments: We assume passenger demand for PT to follow a Poisson distribution with an expected value of 10,000 passenger trips per day. Given the average price of an urban one-way transit ticket in Western Europe (Table B.7), the ticket cost is €2.80 in all experiments. We model the movements of passengers to a certain destination as min-cost-flow problems that are solved with the SimpleMinCostFlow interface included in the package ORtools (Perron & Furnon, 2024). The network consists of three main types of nodes, defined by *location* and *time*: *Supply nodes* representing the arrival of new passengers, train departure nodes corresponding to train departures from a stop, and a sink node for each destination. Nodes at the same location are connected chronologically, modeling waiting time at a stop. Nodes at different locations are connected according to the timetable, representing passenger travel. The arc costs reflect waiting or travel time, and the arc capacities correspond to the available vehicle capacity. The model is solved separately for each potential destination, using different sink nodes. After solving, the arc capacities are updated by deducting passenger loads for other destinations.

### 5.5.7. Modeling limitations

While the presented framework provides relevant insights into the integration of passenger and freight transport, it is subject to several limitations which we detail in the following.

First, the model does not explicitly simulate operational processes within a single day and assumes an idealized transport infrastructure. Consequently, it does not account for real-world geographical constraints such as road congestion, station accessibility, or disruptions due to break-downs or passenger flow variations. Previous studies, such as those by Hörsting and Cleophas (2023a), Hu et al. (2023), and Behiri et al. (2018) have addressed specific planning challenges with real-world city data, offering complementary perspectives to our structural approach.

Second, our financial analysis accounts for additional costs for LSPs and potential revenue streams for PTSPs but excludes other financial indicators. Based on the literature review in Section 5.3, we assume these factors play a decisive role in de-

termining whether stakeholders adopt or reject an integrated passenger and freight transport system. However, the model does not consider the full economic picture, including infrastructure maintenance costs and personnel expenses. Additionally, we do not account for the significant initial investment required to implement an integrated passenger and freight transport system, such as modifications to vehicles or storage facilities at transport hubs.

## 5.6. Computational experiments

The computational study documented in this section intends to showcase the use of an ABM for the holistic evaluation of integrated transport systems. In that, the scarcity of real-world data for the empirical validation motivates a more generalized, structural analysis. In consequence, we focus on statistical validation through sensitivity analysis using *design of experiments (DOE)*, as proposed by Kleijnen (1995) and further explained by (Law, 2017). As shown in Table 5.1, we execute a  $2^2$  factorial analysis for the flexible and static scheme, factoring the freight fare per business scheme and the access fee of the LEZ.

Spot/contract fare	Access fee	Response
-	-	$R_1$ (conventional scheme)
intervention	-	$R_2$ (flexible/static scheme)
-	intervention	$R_3$ (LEZ scheme)
intervention	intervention	$R_4$ (interaction scheme)

Table 5.1.:  $2^2$  factorial design table

In Section 5.6.1, we analyze the main effects  $e_1$  of the pricing decision in the flexible and static scheme relative to the conventional scheme response, defined as

$$e_1 = \frac{\frac{1}{2}(R_2 + R_4) - \frac{1}{2}(R_1 + R_3)}{R_1}. \quad (5.3)$$

In Section 5.6.2, we consider the main effects  $e_2$  of the decision on the access fee, and the interaction effects  $e_{12}$  of the pricing decision relative to the conventional scheme response, defined as

$$e_2 = \frac{\frac{1}{2}(R_3 + R_4) - \frac{1}{2}(R_1 + R_2)}{R_1}, \quad e_{12} = \frac{\frac{1}{2}(R_1 + R_4) - \frac{1}{2}(R_2 + R_3)}{R_1}. \quad (5.4)$$

Table 5.2 lists the intervention factors of the chosen business schemes, where the bold values state the intervention values used in the interaction scheme.

Scheme	Intervention
Flexible	Spot fare (€0.1, €0.2, <b>€0.3</b> , €0.4, €0.5)
Static	Contract fare (€0.1, <b>€0.2</b> , €0.3, €0.4, €0.5)
LEZ	Access fee ( <b>€10</b> , €20, €30, ban)

Table 5.2.: Intervention values of the corresponding business schemes. The bold values state the main intervention.

We consider a simulation horizon of 60 days. Tactical decisions are updated every 30 days and operational decisions are updated every day. Each experiment entails seven simulation days as a warm-up period that is not evaluated. We repeat every experiment 10 times in the same setup. Thus, we run 270 experiments in total. The results discussed are averages and we indicate variation by showing the standard deviation of the main and interaction effects.

Tables B.8 and B.9 in the appendix list the 95 percent confidence intervals for the main and interaction effects. The expected effects are statistically significant if the confidence interval does not include zero, indicated in bold print. This applies to most results. However, we cannot validate statistical significance for the effects of a selection of combinations with the static business schemes. The most critical are the experiments with a contract fare of €0.5, the main effects on the costs of the large LSP, and the interaction effects on the *unused capacity* of the transporters in combination with the LEZ policies. *Unused capacity* refers to the daily load allocation per tour relative to vehicle capacity, excluding fluctuations during deliveries.

As detailed in the following, the experimental results demonstrate that smaller LSPs mostly profit from the consolidation effects and the static business scheme requires low entry prices to remain a viable alternative. Moreover, the LEZ policies are only effective if outsourcing demand to an integrative passenger and freight system is an economical alternative.

### 5.6.1. Contract prices and spot-market fares

Based on the conventional scheme of the PT network, we first identify suitable freight transport fares. For each business scheme, we conduct sensitivity analyses across spot-market fares and contract fares. The results show the main effects of the selected freight fares relative to the conventional scheme.

**Financial effects** Figure 5.4a demonstrates that a flexible scheme consistently improves financial outcomes across all LSP sizes. Since demand is known in advance, LSPs only outsource deliveries when they expect them to be financially advantageous.

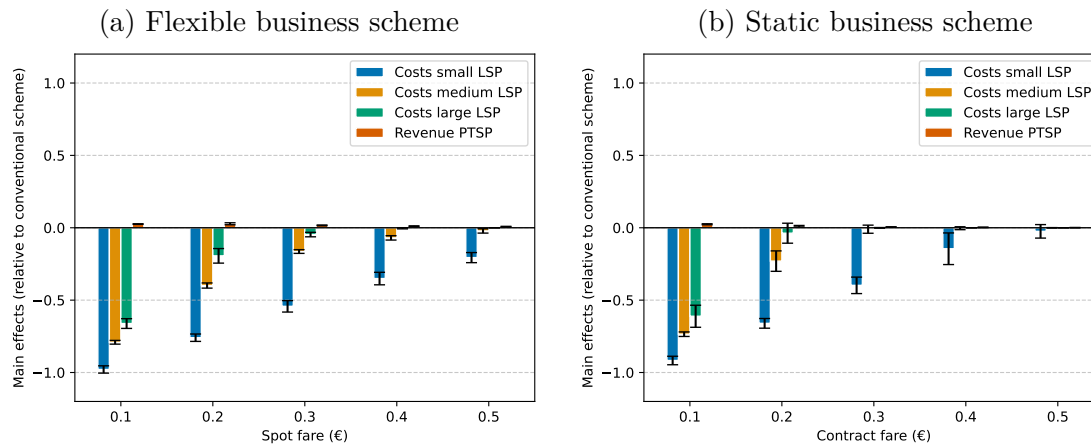


Figure 5.4.: Financial main effects of ranging fares in the flexible and static business scheme

The greatest relative benefit is observed among small LSPs, which can save up to 98% of costs through consolidation. In contrast, large LSPs achieve only significant savings (about 66%) only when spot fares are as low as €0.10. In general, costs increase logarithmically with rising fares. This implies that even a slight overpricing can lead the PTSP to exceed the LSPs' willingness to pay, posing a significant risk when setting fare levels.

Figure 5.4b shows that Littlewood's Rule, based on expected demand, effectively anticipates advantageous contract volumes. However, as the actual demand is unknown at the time of contracting, LSPs risk both over- and underbuying. Overbuying results in paying for unused capacity, while underbuying leads to inefficient routes and detours. Unlike in the flexible scheme, medium and large LSPs only benefit when fares are below €0.2. However, as stated earlier, effects with contract fares above €0.3 are not statistically significant. Given the potential consolidation effect, the small LSP still profit from a higher fare. Revenue changes for the PTSP are similar in both business cases, with gains averaging around 3%, which is relatively modest. However, it is important to note that the model only accounts for LSPs' direct transit costs between locations, leading to very low effective freight fares. Additionally, the model does not feature additional operational costs for the PTSP, for example, personnel costs. For a decision-support application, PTSPs would need to balance these against the gains.

We conclude that LSPs of any size can benefit from outsourcing demand to integrated transport, especially in the flexible business scheme. Choosing appropriate freight fares is a challenging task for the PTSP, as small price changes can reduce demand. The lower the chosen spot fare, the higher the degree of collaboration of LSPs and PTSP, and the potential revenue for the PTSP. However, the high degree of flexibility reduces

the planning reliability of the PTSP.

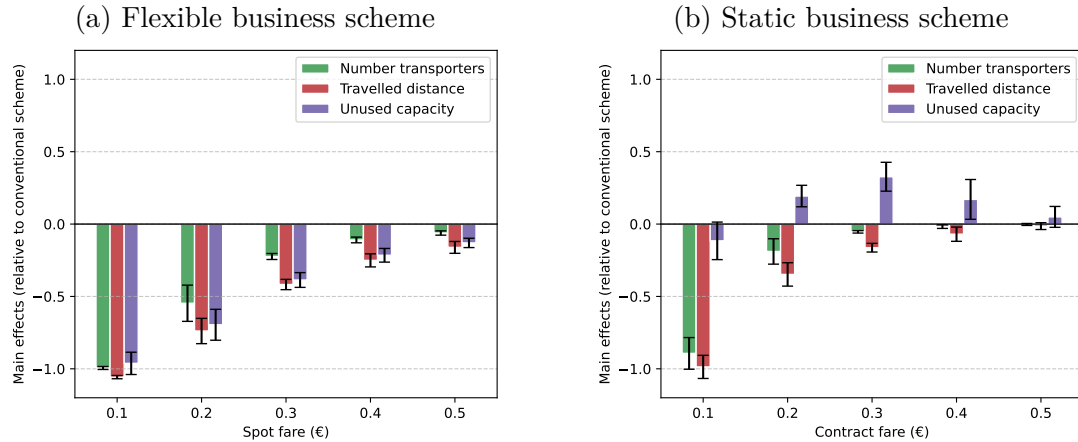


Figure 5.5.: Traffic main effects of the freight fares

**Traffic effects** Figure 5.5 illustrates the main effects of outsourcing fares on traffic attributes. Given the flexible scheme and a low outsourcing fare (€0.10), freight shifts almost entirely from road to rail (Figure 5.5a). This results in substantial reductions in road traffic and improved system-wide efficiency. The static scheme, while capable of reducing the average number of transporters by up to 90%, is less effective in utilizing available vehicle capacity. The flexible approach enables better vehicle utilization, as LSPs can adjust fleet distribution and outsourcing strategies. In contrast, under the static scheme, contract fares of €0.3 increase the average unused capacity by 33%, leading to inefficiently loaded transporters despite a reduction in vehicle count and travel distances.

We conclude that small LSPs benefit most from consolidation, while larger LSPs, handling greater delivery volumes, are less dependent on alternative transport services.

For subsequent analyses, we aim for a setup where outsourcing is a realistic alternative but not so attractive that the LSPs outsource the entire demand by default. Specifically, we seek fares that induce all LSPs to outsource the smallest delivery volume greater than zero. The contract fare should also be lower than the spot fare to incentivize the lack of flexibility. Therefore, we choose a contract fare of €0.20 and a spot fare of €0.30 for the following experiments.

### 5.6.2. Effects of LEZ policies

In a second analysis, we evaluate the main effects of LEZ policies and their interaction effects with an integrated passenger and freight transport alternative. The study in-

cludes three access fee settings (€10, €20, and €30) and a complete vehicle *ban* in the urban area.

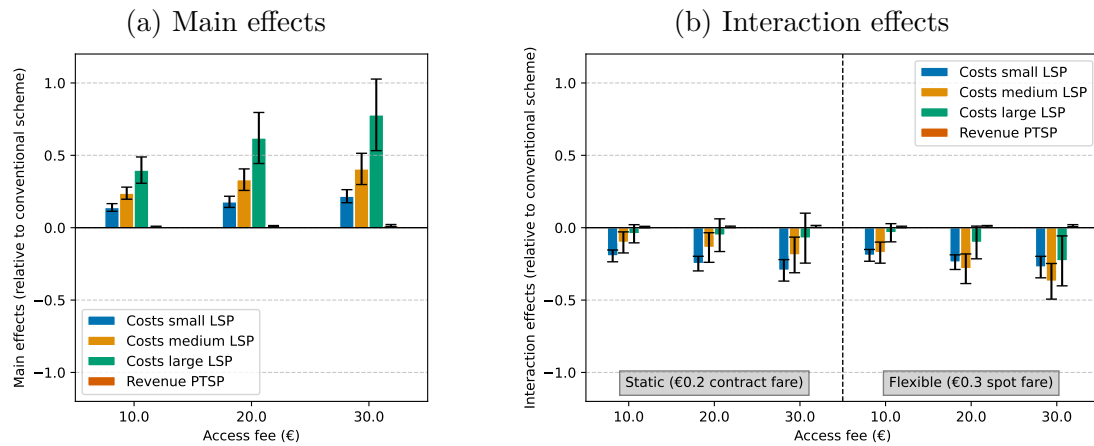


Figure 5.6.: Financial effects of LEZ policies

**Financial effects** Figure 5.6 displays the financial effects in cost for the LSPs and revenue for the PTSP as dependent on LEZ policies. It does not display the financial effects of a complete ban on transporters, as the additional costs for the LSPs depend solely on the costs of rejected deliveries without transport alternatives. As Figure 5.6a illustrates, LEZ policies implemented without suitable transport alternatives lead to a rise in travel costs for LSPs, most notably for large-sized providers. LSPs are forced to either pay urban access fees or reroute around the restricted zone, both of which incur additional costs. On average, costs increase by 13% to 78% across all LSP types, relative to the conventional scheme. The relative increase in cost correlates with LSP size, as larger providers typically operate more vehicles that are affected by the restrictions. Figure 5.6b shows the financial interaction effects of the LEZ policies and the two business schemes with integrated passenger and freight transport. Under the static business scheme, small LSPs benefit the most, with cost reductions of up to 27%. In contrast, under the flexible scheme, medium-sized LSPs experience the greatest advantage, with savings of up to 37%. This could be due to medium LSPs being less able to rely solely on outsourcing, as small LSPs can, while still being significantly impacted by LEZ constraints. Across all experiments, these effects are accompanied by a high variance, especially for a large LSP

**Traffic effects** Figure 5.7 shows the main and interaction effects of different LEZ policies on the three traffic attributes. As Figure 5.7a shows, increasing levels of access fees lead to a notable reduction in transporter activity. For example, a €30 access fee

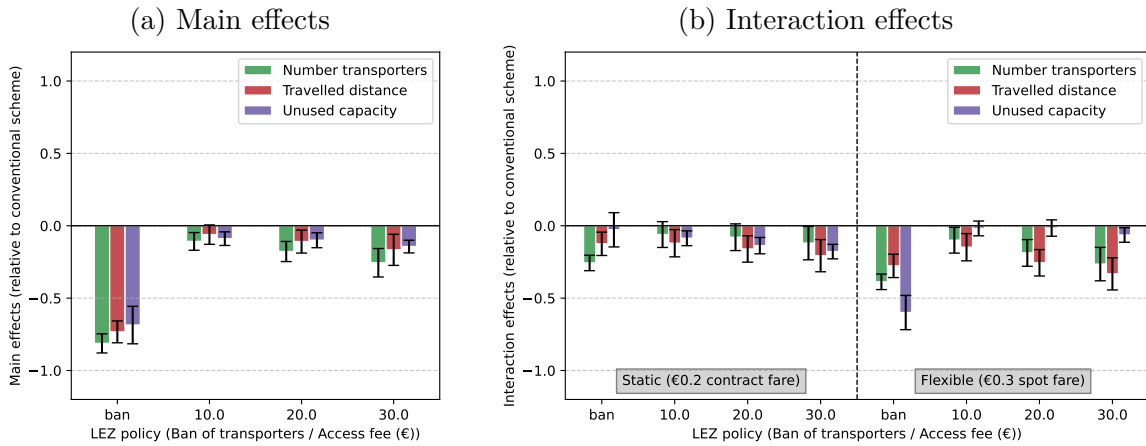


Figure 5.7.: Traffic effects of LEZ policies

results in a 26% decrease in the number of transporters, a 17% reduction in traveled distance, and a 14% decline in unused vehicle capacity. When a complete ban on urban access is implemented, LSPs are compelled to shift from road to rail to reach urban customers. This shift has a substantial impact on traffic attributes, reducing the number of transporters by 81%, traveled distance by 73%, and unused capacity by 69%. Figure 5.7b highlights the interaction effects between LEZ policies and the two integrated passenger-freight business models. Compared to the main effects of LEZ alone, these interactions primarily influence the distance traveled by transport vehicles. With integrated business schemes in place, LSPs can avoid detours by outsourcing deliveries to rail transport, resulting in distance reductions of up to 17%. The interaction effects of the urban access ban are less significant than its main effects. Most traffic-related improvements occur due to the ban itself, with limited additional benefits from combining it with integrated business schemes.

In conclusion, LEZ policies and business models for integrated passenger and freight transport must be aligned to achieve optimal outcomes. Small LSPs tend to benefit the most from such systems due to parcel consolidation opportunities. However, profitability hinges on effective strategic decision-making. Moreover, the added transport costs associated with these policies may ultimately be passed on to consumers in the form of higher delivery fees.

## 5.7. Conclusion

**Summary** This work presented an agent-based simulation framework modeling an urban integrated passenger and freight transport system. Based on state-of-the-art literature, we identified the main stakeholders affected by this transport system and

their specific incentives: The municipality, the freight logistics service provider, the recipients of goods, the PT service provider, and the passengers. The simulation considers strategic, tactical, and operational planning decisions. The decision-making is either defined by the parameter setting or based on heuristics. The simulation implements three alternative business schemes: A conventional scheme where transport is not integrated, a spot-market-based scheme with shared trains (flexible scheme), and a contract-market-based scheme with dedicated trains (static scheme). An exemplary simulation study focused on the financial and traffic effects of the business schemes in an urban area.

The results of the simulation study indicate that for low delivery volumes, logistics service providers will more likely benefit from an integrated system due to consolidation effects. In contrast, LSPs' outsourcing probability decreases if the delivery volume is sufficiently high. Governmental policies such as low emission zones that limit vehicle access to certain areas of the municipality may enable the success of an urban integrated passenger and freight transport system. If the logistics service provider can buy freight capacity in the public transport system on a spot-market, they can flexibly top up the delivery capacity of their vehicle fleet. The static scheme offers higher planning reliability for the public transport service because the logistics service providers buy a fixed capacity volume for a fixed price.

**Barriers to practical implementation** Our results also provide some insight into potential barriers to the implementation of an integrated passenger and freight system. Especially the static scheme may come with higher investment costs to expand the vehicle fleet of the public transport provider. Meanwhile, the public transport service provider should keep the outsourcing fare low to attract larger logistics service providers and compensate for the potential financial risk. Thus, positive revenue effects can only be expected for operations on a long-term horizon, and financial viability is a great barrier for the implementation of an integrated passenger and freight transport system.

**Limitations and further research** The simulation framework and the parameters employed in this study are based on aggregated data and do not account for city-specific use cases. This includes, for example, real traffic infrastructure constraints, regulatory differences, or varying public transport policies. Thus, later empirical validation and pilot projects are necessary to confirm the practical implications of the findings for individual cities. However, this simulation study provides a structured framework as a first analysis of the potential and barriers of an integrated passenger and freight system.

Additionally, future research could delve into refined pricing models and cost-sharing strategies to mitigate financial risks for PTSPs. Additionally, it could evaluate advanced predictive algorithms to enhance demand forecasting for contract-based schemes. On the consumer side, exploring the potential impacts of integrated passenger and freight systems on travel choices presents an interesting direction for future study.

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## Appendix

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**A.**

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**Appendix to Essay 1**

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## A.1. Lists of parameters, index sets and decision variables

Notation	Description
$\mathcal{P}$	Set of periods
$\mathcal{S}$	Set of stops
$\mathcal{V}$	Set of vehicles
$\mathcal{R}$	Set of containers
$\mathcal{R}_s^{\text{end}} \subset \mathcal{R}$	Set of containers with destination stop $s$

Table A.1.: List of sets

Notation	Set	Definition
$x_{v,s,p}$	$\in \{0, 1\}$	Binary variable taking value one if and only if vehicle $v$ departs from stop $s$ at period $p$
$o_v$	$\in \{0, 1\}$	Binary variable taking value one if and only if vehicle $v$ is operating
$d_{v,s}$	$\geq 0$	Departure time of vehicle $v$ from stop $s$
$a_{v,s}$	$\geq 0$	Arrival time of vehicle $v$ at stop $s$
$h_{v,s}$	$\geq 0$	Dwell time of vehicle $v$ at stop $s$
$w_{s,p}$	$\geq 0$	Number of waiting passengers at stop $s$ at period $p$
$n_{v,s}$	$\geq 0$	Number of passengers on vehicle $v$ departing stop $s$
$b_{v,s,p}$	$\in \mathbb{N}$	Number of passengers boarding vehicle $v$ at stop $s$ at period $p$
$e_{v,s}$	$\in \mathbb{N}$	Number of passengers alighting vehicle $v$ at stop $s$
$y_{r,v,s}$	$\in \{0, 1\}$	Binary variable taking the value 1 if and only if container $r$ is on vehicle $v$ departing stop $s$
$t_r$	$\in \mathbb{N}$	Delay of container $r$
$f_r$	$\in \mathbb{N}$	Delivery time of delivery container $r$
$c_{v,s}^{\text{pas}}$	$\in \mathbb{N}$	Reserved capacity of vehicle $v$ for passenger transport
$c_{v,s}^{\text{fre}}$	$\in \mathbb{N}$	Reserved capacity of vehicle $v$ for freight transport
$z_v$	$\in \{0, 1\}$	Binary variable taking the value one if and only if vehicle $v$ exclusively transports freight
$u_r$	$\in \{0, 1\}$	Binary variable taking the value one if and only if container $r$ is accepted

Table A.2.: List of decision variables

Notation	Description
$\mu_{i,j}$	Expected travel time from stop $i$ to stop $j$
$\sigma$	Standard deviation of travel time
$\beta^{\max} (\beta_{\text{fre}}^{\max})$	Maximal allowed dwell time at a station (for freight vehicle)
$\beta^{\min} (\beta_{\text{fre}}^{\min})$	Minimal allowed dwell time at a station (for freight vehicle)
$\beta^{\text{board}}$	Expected service time per boarding passenger
$\beta^{\text{alight}}$	Expected service time per alighting passenger
$\beta^{\text{load}}$	Expected service time per loading a container
$\beta^{\text{unld}}$	Expected service time per unloading a container
$H$	Minimal headway between two vehicles
$N_{s,p}$	Number of new passengers arriving at stop $s$ at period $p$
$\lambda_{s,p}^{\text{alight}}$	Expected ratio of passengers alighting at stop $s$ at period $p$
$s_r^{\text{end}} \in \mathcal{S}$	Destination stop of container $r$
$p_r^{\text{start}} \in \mathcal{P}$	Release time plus loading time of container $r$
$p_r^{\text{end}} \in \mathcal{P}$	Soft deadline for the delivery container $r$
$C$	Total capacity of a single vehicle
$C^{\text{pas}}$	Total capacity of a single passenger vehicle
$C^{\text{fre}}$	Total capacity of a single cargo vehicle
$Q^{\text{pas}}$	Capacity dedicated to passenger transport only
$Q^{\text{fre}}$	Capacity dedicated to freight transport only
$Q_r$	Required units of capacity for container $r$
$P$	Penalty value for rejecting a container
$U$	Percentage of deliveries that the system must accept
$T^{\max}$	Maximal delay per container
$B_0$	Initial number of passengers on vehicle
$p_B$	Probability of an additional passenger initially on vehicle
$M$	Sufficiently large number

Table A.3.: List of parameters

Notation	Value
$\sigma$	= 10 sec ( $\approx 0.1667$ min)
$\beta^{\max}$	= 3 min
$\beta^{\min}$	= 1 min
$\beta_{\text{fre}}^{\max}$	= 10 min
$\beta_{\text{fre}}^{\min}$	= 0 min
$\beta^{\text{board}}$	= 0.096 sec ( $\approx 0.00161$ min)
$\beta^{\text{alight}}$	= 0.096 sec ( $\approx 0.00161$ min)
$\beta^{\text{load}}$	= 20 sec ( $\approx 0.3333$ min)
$\beta^{\text{unld}}$	= 15 sec (0.25 min)
$H$	= 1 min
$C$	= 514
$C^{\text{pas}}$	= 514
$C^{\text{fre}}$	= 240
$Q^{\text{pas}}$	= 454
$Q^{\text{fre}}$	= 0
$Q_r$	= 4, $\forall r \in \mathcal{R}$
$P$	= 10,000
$U$	= 0.5
$T^{\max}$	= 10 min
$p_B$	= 0.5

Table A.4.: List of (one-dimensional) parameter values for the small and large scenario

## A.2. Results of optimization with Gurobi

<i>containers mode</i>		<i>time (sec.)</i>	1st objective <sup>a</sup>			2nd objective <sup>a</sup>		
			<i>sec.</i>	<i>value</i>	<i>gap</i>	<i>sec.</i>	<i>value</i>	<i>gap</i>
0	SV	2090.90	2090.59	5.59	0.00	0.25	0.00	0.00
5	SV	301.81	291.93	5.59	0.00	9.87	0.00	0.00
10	SV	1603.70	1554.36	5.59	0.00	49.30	0.00	0.00
15	SV	1631.52	1513.35	5.59	0.00	118.12	0.00	0.00
20	SV	2521.79	2501.72	5.59	0.00	20.05	0.00	0.00
25	SV	1612.54	1555.60	5.59	0.00	56.90	0.00	0.00
30	SV	35067.15	2658.33	5.59	0.00	32400.67	0.10	1.00
35	SV	34153.69	1749.45	5.59	0.00	32400.36	0.09	1.00
40	SV	4444.49	2824.96	5.59	0.00	1619.30	0.08	1.00
45	SV	354.61	335.38	5.59	0.00	19.21	0.07	0.33
50	SV	2116.72	2047.81	5.59	0.00	68.87	50000.24	0.00
0	SI	4351.91	4351.45	5.59	0.05	0.39	0.00	0.00
5	SI	54887.43	32400.86	6.92	0.13	22486.43	0.00	0.00
10	SI	44705.83	32401.16	6.92	0.16	12303.49	0.00	0.00
15	SI	41302.58	8901.77	6.92	0.07	32400.24	10001.87	1.00
20	SI	64805.15	32401.38	6.92	0.06	32402.12	50001.00	1.00
25	SI	46354.93	13947.33	6.92	0.06	32400.55	100000.08	1.00
30	SI	64812.04	32406.43	6.92	0.27	32401.05	149999.97	1.00
35	SI	51799.22	19393.34	6.96	0.01	32400.99	170000.00	1.00
40	SI	47530.23	15124.63	7.01	0.05	32401.31	190000.00	1.00
45	SI	64803.38	32401.60	7.10	0.15	32400.35	210000.00	1.00
50	SI	52646.22	20244.69	7.30	0.03	32400.82	230000.00	1.00

<sup>a</sup> Run time limit of 32,400 seconds (9h).

Table A.5.: Run time and solution quality for varying number of containers – Small scenario. The column *time (sec.)* includes the total running time. Additionally, we consider the time (*sec.*), the objective *value*, and the relative optimality *gap* for both objective functions individually.

<i>containers mode</i>		<i>time (sec.)</i>	1st objective <sup>a</sup>			2nd objective <sup>a</sup>		
			<i>sec.</i>	<i>value</i>	<i>gap</i>	<i>sec.</i>	<i>value</i>	<i>gap</i>
0	SV	32482.05	32471.16	74.09	0.96	1.14	0	0
5	SV	34859.66	32575.81	30.37	0.9	2283.51	0	0
10	SV	36146.65	32475.76	43.7	0.93	3670.41	0	0
15	SV	33952.56	32473.7	91.97	0.96	1478.13	0	0
20	SV	38773.86	32617.67	49.64	0.94	6155.88	0	0
25	SV	39929.18	32475.19	76.67	0.96	7452.3	0	0
30	SV	36065.17	32608.63	45.54	0.93	3455.84	0	0
35	SV	33723.77	32482.22	115.14	0.97	1241.04	0	0
40	SV	36105.72	32477.37	51.96	0.94	3627.5	0	0
45	SV	34079.86	32478.36	70.84	0.96	1600.74	0	0
50	SV	37843.51	32453.19	26.04	0.81	5389.74	0	0
0	SI	32438.88	32437.3	163.35	0.98	1.21	0	0
5	SI	34056.21	32519.82	137.47	0.96	1536.03	0	0
10	SI	45500.58	32440.63	97.99	0.95	13058.13	0	0
15	SI	39418.8	32493.34	133.58	0.96	6924.15	0	0
20	SI	38017.94	32546.36	141.57	0.97	5471.4	0	0
25	SI	32770.02	32459.67	196.75	0.97	303.55	0	0
30	SI	33010.81	32537.6	153.69	0.97	472.89	0	0
35	SI	59244.83	32448.41	98.17	0.95	26794.9	0	0
40	SI	48468.48	32526.7	153.87	0.97	15941.19	0	0
45	SI	42732.74	32451.05	162.78	0.97	10280.12	0	0
50	SI	33293.41	32442.56	195.23	0.97	850.52	0	0

<sup>a</sup> Run time limit of 32,400 seconds (9h).

Table A.6.: Run time and solution quality for varying number of containers – Large scenario. The column *time (sec.)* includes the total running time. Additionally, we consider the time (*sec.*), the objective *value*, and the relative optimality *gap* for both objective functions individually.

scenario	mode	time (sec.)	1st objective <sup>a</sup>			2nd objective <sup>a</sup>		
			sec.	value	gap	sec.	value	gap
04:00 - 05:00	SV	33322.11	919.06	0.73	0.02	32400.52	0.2	1
08:00 - 09:00	SV	2999.1	2962.7	6.66	0	36.38	0	0
11:00 - 12:00	SV	1612.54	1555.6	5.59	0	56.9	0	0
19:00 - 20:00	SV	1584.84	1576.19	4.38	0	8.61	0	0
04:00 - 05:00	SI	60540.77	28139.16	0.91	0.07	32400.67	100000	1
08:00 - 09:00	SI	44867.55	12462.09	10.01	0.01	32401.54	100000	1
11:00 - 12:00	SI	46354.93	13947.33	6.92	0.06	32400.55	100000.08	1
19:00 - 20:00	SI	64808.73	32405.62	5.45	0.2	32400.8	99999.99	1

<sup>a</sup> Run time limit of 32,400 seconds (9h).

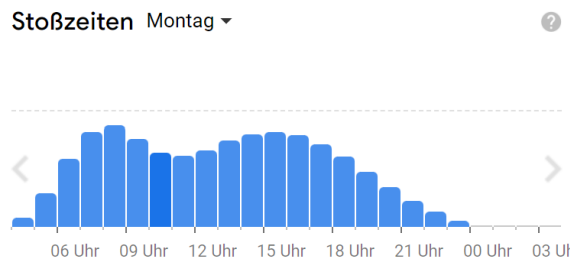
Table A.7.: Run time and solution quality for different passenger scenarios – Small scenario. The column *time (sec.)* includes the total running time. Additionally, we consider the time (*sec.*), the objective *value*, and the relative optimality *gap* for both objective functions individually.

scenario	mode	time (sec.)	1st objective <sup>a</sup>			2nd objective <sup>a</sup>		
			sec.	value	gap	sec.	value	gap
04:00 - 05:00	SV	34410.32	32608.00	5.42	0.81	1802.06	0.00	0.00
08:00 - 09:00	SV	39929.18	32475.19	76.67	0.96	7452.30	0.00	0.00
11:00 - 12:00	SV	64881.21	32473.36	7.70	0.91	32405.49	0.40	1.00
19:00 - 20:00	SV	43337.30	32613.15	47.28	0.65	10723.75	0.00	0.00
04:00 - 05:00	SI	40016.78	32532.33	11.08	0.99	7483.79	0.00	0.00
08:00 - 09:00	SI	32770.02	32459.67	196.75	0.97	303.55	0.00	0.00
11:00 - 12:00	SI	38375.71	32482.73	74.33	0.99	5892.43	0.00	0.00
19:00 - 20:00	SI	33139.73	32544.58	219.23	0.89	595.07	0.00	0.00

<sup>a</sup> Run time limit of 32,400 seconds (9h).

Table A.8.: Run time and solution quality for different passenger scenarios – Large scenario. The column *time (sec.)* includes the total running time. Additionally, we consider the time (*sec.*), the objective *value*, and the relative optimality *gap* for both objective functions individually.

(a) Screenshot of original data  
(Source: Google Maps)



(b) Web scraped popularity as percentage

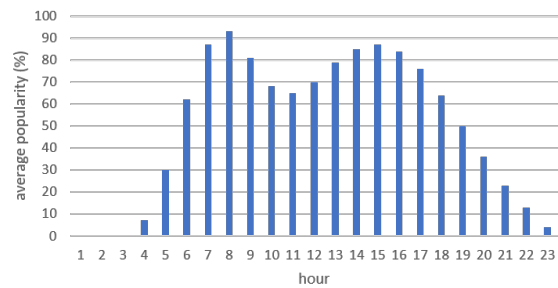


Figure A.1.: Average popularity for station Barmbek on Mondays

### A.3. Estimation of passenger demand

As exact data on passenger demand is not publicly available, we rely on data open to the public for related estimates. We detail the process of deriving parameter values from this data in this appendix.

**Passenger alighting rate** The Hamburger Verkehrsbund GmbH (2020) (HVV) publishes the average number of passenger boarding and alighting trains per day and stop. We use the 2019 data for the line S1 to estimate the alighting probability per stop. We estimate this probability per stop as the ratio of the daily average of alighting passengers at this stop and the average number of passengers on-board the vehicle (considering all passenger who did board and alight up to this stop).

**Passenger arrival intensity** We also rely on the 2019 data of Hamburger Verkehrsbund GmbH (2020) for the line S1 to estimate the average number of passengers arriving per stop. We assume that the daily average number of passengers arriving at a stop is equal to the daily average number of passengers boarding the line S1 at the certain stop.

We derive the relative distribution of hourly passenger arrival rates per station from popular times provided by Google maps. This data shows how the average popularity per hour varies across the time of day. We access the data using an open web scraping tool published on GitHub (see [https://github.com/philshem/gmaps\\_popular\\_time\\_s\\_scraper](https://github.com/philshem/gmaps_popular_time_s_scraper)). The data set includes the Google maps links as well as the web scraped popularity rates used for later passenger demand estimation (cf. <https://doi.org/10.5281/zenodo.6412456>). Figure A.1 illustrates exemplary the popularity for the station Barmbek.

Finally, we use Google (2021) and Hamburger Verkehrsbund GmbH (2020) data to

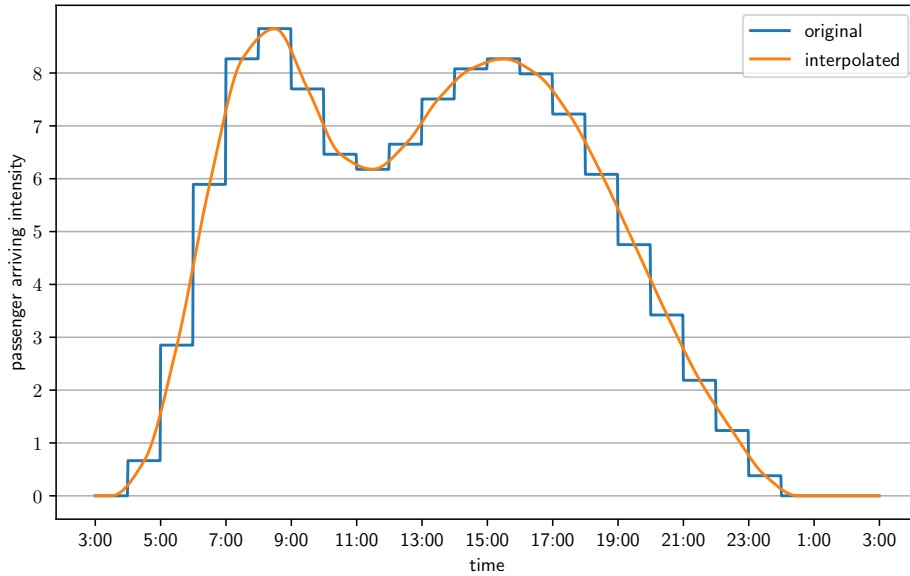
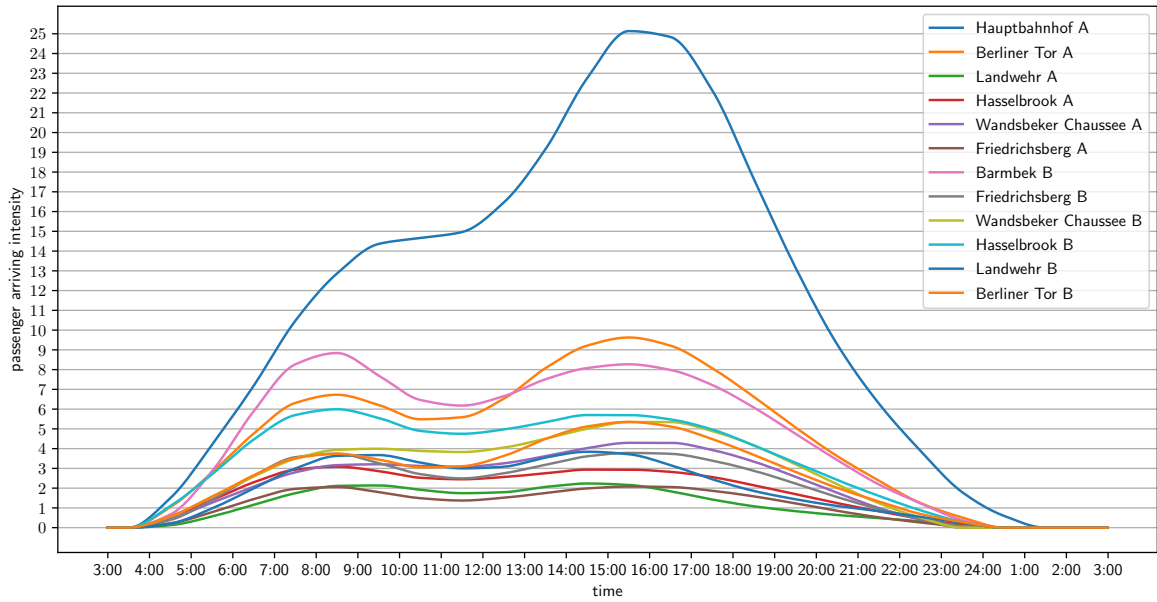


Figure A.2.: Estimated passenger arrival intensity for the stop Barmbek on Mondays

estimate the arrival intensity per stop and day as shown in Figure 2.3. To smoothen the passenger arrival rates, we additionally interpolate the data by computing the piecewise cubic hermite interpolating polynomial (PCHIP), which is exemplified in orange in Figure A.2. If we accumulate the the original or interpolated intensity over all periods we gain the average number of boarding passengers as observed by Hamburger Verkehrsbund GmbH (2020). Figure A.3a shows the resulting estimated passenger arrivals after interpolating the data. The shape of the curve of the central station, i.e., *Hauptbahnhof A*, notably deviates from the remainders. This is most likely because Google Maps not exclusively tracks passenger for the line *S1*, but instead tracks every person at the central station. To fit the curve to the rest, we weight the corresponding values with the average overall stops with a factor of 75%. Figure A.3b shows the final results.

(a) Original data.



(b) Central station (Hauptbahnhof A) adjusted.

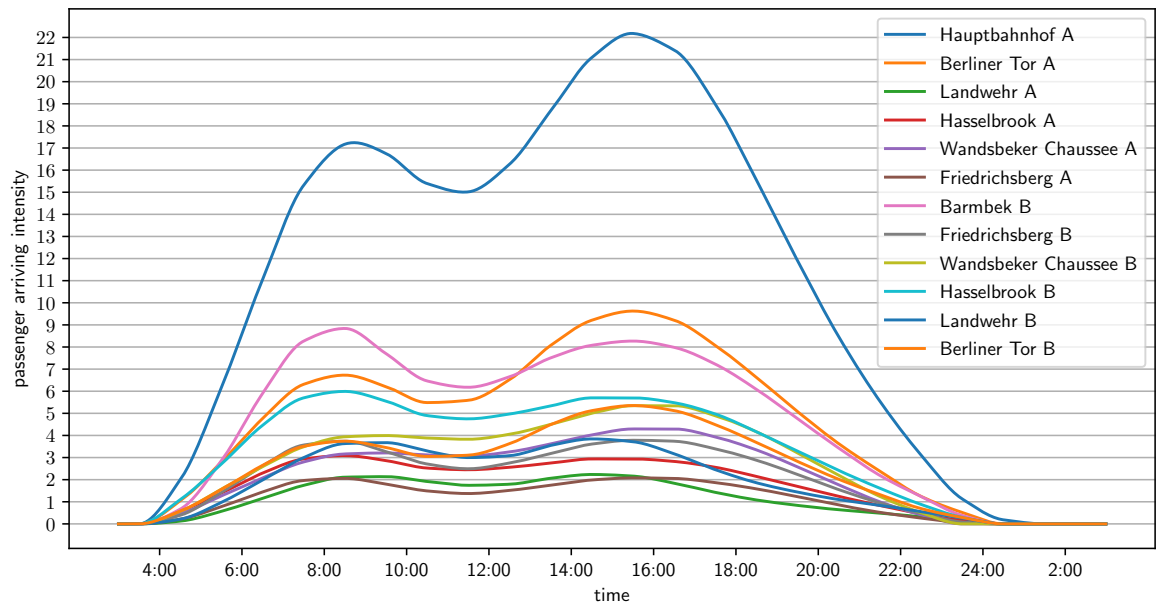


Figure A.3.: Estimated passenger arrival intensity on Mondays

**B.**

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**Appendix to Essay 4**

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## B.1. Lists of parameter values

Parameter	Value
Days	60
Days (Warmup)	7
Days (Strategical)	365
Days (Tactical)	30
Days (Operational)	1

Table B.1.: List of global parameters

Parameter	Value
LEZ Policy Ban	[False, True]
LEZ Policy Fee	[€0.00, €10.00, €20.00, €30.00]

Table B.2.: List of municipality parameters

Parameter	Value
Number of LSPs	3
Number of transporters (per LSP)	100
Transporter capacity	300 shipments
Average transporter speed	25 km/h
Last-mile costs (distance)	0.86 €/km
Last-mile costs (time)	21 €/h
Costs for failed delivery	100 €/shipment
Routing Heuristic - Time Limit	3 Sec.

Table B.3.: List of LSP parameters

Parameter	Value
Rail transport mode	[Shared trains, Dedicated trains]
Number of trains	78
Shared train capacity (passengers)	100% accessible, max. 500 passengers
Shared train capacity (freight)	20% accessible, max. 25 freight containers
Capacity freight container	60 shipments
Number of dedicated passenger trains	78
Passenger train capacity	500 passengers
Number of dedicated freight trains	14
Freight train capacity	3600 shipments
Contract fare	[€0.10, €0.20, €0.30, €0.40, €0.50]
Spot fare	[€0.10, €0.20, €0.30, €0.40, €0.50]
Passenger Fare	€2.80
Number circular lines	min. 3, max. 6 (random)
Frequency circular lines, 6am - 9am	30 Min.
Frequency circular lines, 9am - 3pm	60 Min.
Frequency circular lines, 3pm - 6pm	30 Min.
Frequency circular lines, 6pm - 8pm	60 Min.
Frequency circular lines, 8pm - 12pm	180 Min.
Number radial lines	min. 11, max. 15 (random)
Frequency radial lines, 6am - 9am	120 Min.
Frequency radial lines, 9am - 3pm	180 Min.
Frequency radial lines, 3pm - 6pm	120 Min.
Frequency radial lines, 6pm - 10pm	180 Min.

Table B.4.: List of PTSP parameters

Parameter	Value
Expected shipments (daily)	[550 (LSP 1), 1650 (LSP 2), 4400 (LSP 3)]
Urban Ratio	0.56
Suburban Ratio	0.44

Table B.5.: List of receiver parameters

Parameter	Value
Expected number of passengers (daily)	10000
Arrival intensity per hour, 12am - 5am (normalized)	0.0455
Arrival intensity per hour, 5am - 6am (normalized)	0.0182
Arrival intensity per hour, 6am - 9am (normalized)	0.2727
Arrival intensity per hour, 9am - 10am (normalized)	0.0545
Arrival intensity per hour, 10am - 3pm (normalized)	0.2273
Arrival intensity per hour, 3pm - 4pm (normalized)	0.0545
Arrival intensity per hour, 4pm - 6pm (normalized)	0.1818
Arrival intensity per hour, 6pm - 8pm (normalized)	0.0909
Arrival intensity per hour, 8pm - 10pm (normalized)	0.0364
Arrival intensity per hour, 10pm - 12am (normalized)	0.0182

Table B.6.: List of passenger parameters

## B.2. Urban transit prices in Western Europe

Municipality	Price	Ticket	Source
Paris, France	€2.15	One-way	RATP
Berlin, Germany	€3.50	One-way (Zone A, B)	BVG
Amsterdam, Netherlands	€3.40	1-hour	GVB
London, United Kingdom	€3.20 (£2.80)	One-way (Zone 1-2)	TfL
Brussels, Belgium	€2.60	One-way	STIB-MIVB
Zurich, Switzerland	€4.90 (CHF 4.60)	One-way (1–2 zones)	ZVV
Barcelona, Spain	€2.55	One-way	TMB
Rome, Italy	€1.50	One-way	ATAC
Lisbon, Portugal	€1.80	1-hour	Carris
Stockholm, Sweden	€3.70 (SEK 42)	75-minute	SL
Dublin, Ireland	€2.60	One-way	Dublin Bus
Oslo, Norway	€3.60 (42 kr)	One-way (1 Zone)	Ruter
Luxembourg City, Luxembourg	Free	Unlimited	ATP
Copenhagen, Denmark	€3.20 (24 DKK)	75-minute (2 zones)	DOT
Vienna, Austria	€2.40	One-way	WL
Helsinki, Finland	€2.95	80-minute (Zone AB)	HSL
Valletta, Malta	€2.50	2-hour	MPT
Reykjavik, Iceland	€4.30 (650 kr.)	One-way	Strætó
Monaco, Monaco	€2.00	One-way	CAM

Table B.7.: Urban Transit Prices in Western European Cities (2024) - Data accessed with GPT-4o (OpenAI, 2024) in September 2024 and manually corrected.

### B.3. Confidence intervals for main and interaction effects

Scenario	Costs Small LSP	Costs Medium LSP	Costs Large LSP	Revenue PTSP
Flexible (€0.1)	<b>-0.979 ± 0.018</b>	<b>-0.791 ± 0.009</b>	<b>-0.662 ± 0.024</b>	<b>0.026 ± 0.001</b>
Flexible (€0.2)	<b>-0.760 ± 0.018</b>	<b>-0.399 ± 0.013</b>	<b>-0.194 ± 0.036</b>	<b>0.028 ± 0.005</b>
Flexible (€0.3)	<b>-0.543 ± 0.028</b>	<b>-0.164 ± 0.009</b>	<b>-0.047 ± 0.011</b>	<b>0.017 ± 0.002</b>
Flexible (€0.4)	<b>-0.351 ± 0.031</b>	<b>-0.070 ± 0.011</b>	<b>-0.003 ± 0.003</b>	<b>0.011 ± 0.002</b>
Flexible (€0.5)	<b>-0.206 ± 0.025</b>	<b>-0.022 ± 0.011</b>	-0.000 ± 0.000	<b>0.008 ± 0.002</b>
Static (€0.1)	<b>-0.917 ± 0.021</b>	<b>-0.735 ± 0.011</b>	<b>-0.611 ± 0.054</b>	<b>0.024 ± 0.002</b>
Static (€0.2)	<b>-0.660 ± 0.024</b>	<b>-0.230 ± 0.050</b>	-0.038 ± 0.049	<b>0.011 ± 0.004</b>
Static (€0.3)	<b>-0.398 ± 0.041</b>	-0.010 ± 0.020	-0.001 ± 0.002	<b>0.006 ± 0.001</b>
Static (€0.4)	<b>-0.145 ± 0.078</b>	-0.003 ± 0.007	-0.000 ± 0.000	<b>0.003 ± 0.001</b>
Static (€0.5)	-0.025 ± 0.033	-0.000 ± 0.001	-0.000 ± 0.000	0.001 ± 0.001
LEZ (€10.0)	<b>0.140 ± 0.019</b>	<b>0.239 ± 0.030</b>	<b>0.398 ± 0.065</b>	<b>0.007 ± 0.003</b>
LEZ (€20.0)	<b>0.179 ± 0.028</b>	<b>0.332 ± 0.053</b>	<b>0.620 ± 0.126</b>	<b>0.011 ± 0.003</b>
LEZ (€30.0)	<b>0.218 ± 0.032</b>	<b>0.406 ± 0.077</b>	<b>0.780 ± 0.177</b>	<b>0.016 ± 0.005</b>
LEZ (€10.0) x Flexible (€0.3)	<b>-0.195 ± 0.027</b>	<b>-0.102 ± 0.016</b>	<b>-0.042 ± 0.008</b>	<b>0.005 ± 0.001</b>
LEZ (€20.0) x Flexible (€0.3)	<b>-0.248 ± 0.036</b>	<b>-0.137 ± 0.018</b>	<b>-0.052 ± 0.010</b>	<b>0.006 ± 0.001</b>
LEZ (€30.0) x Flexible (€0.3)	<b>-0.295 ± 0.048</b>	<b>-0.188 ± 0.034</b>	<b>-0.072 ± 0.027</b>	<b>0.009 ± 0.003</b>
LEZ (ban) x Flexible (€0.3)	<b>0.177 ± 0.021</b>	<b>0.191 ± 0.014</b>	<b>0.302 ± 0.053</b>	<b>0.021 ± 0.002</b>
LEZ (€10.0) x Static (€0.2)	<b>-0.191 ± 0.029</b>	<b>-0.172 ± 0.052</b>	-0.035 ± 0.045	<b>0.005 ± 0.004</b>
LEZ (€20.0) x Static (€0.2)	<b>-0.238 ± 0.036</b>	<b>-0.284 ± 0.073</b>	<b>-0.102 ± 0.081</b>	<b>0.010 ± 0.004</b>
LEZ (€30.0) x Static (€0.2)	<b>-0.272 ± 0.053</b>	<b>-0.370 ± 0.088</b>	<b>-0.229 ± 0.123</b>	<b>0.014 ± 0.005</b>

Table B.8.: Overview of the 95 percent confidence intervals for the financial main and interaction effects. Bold print indicates statistical significance.

Scenario	Number Transporters	Traveled Distance	Unused Capacity
Flexible (€0.1)	<b>-0.994 ± 0.007</b>	<b>-1.057 ± 0.008</b>	<b>-0.962 ± 0.055</b>
Flexible (€0.2)	<b>-0.547 ± 0.090</b>	<b>-0.739 ± 0.063</b>	<b>-0.696 ± 0.076</b>
Flexible (€0.3)	<b>-0.224 ± 0.015</b>	<b>-0.418 ± 0.025</b>	<b>-0.386 ± 0.036</b>
Flexible (€0.4)	<b>-0.110 ± 0.014</b>	<b>-0.251 ± 0.032</b>	<b>-0.216 ± 0.034</b>
Flexible (€0.5)	<b>-0.062 ± 0.011</b>	<b>-0.161 ± 0.029</b>	<b>-0.130 ± 0.023</b>
Static (€0.1)	<b>-0.893 ± 0.078</b>	<b>-0.987 ± 0.057</b>	<b>-0.116 ± 0.093</b>
Static (€0.2)	<b>-0.189 ± 0.063</b>	<b>-0.348 ± 0.058</b>	<b>0.194 ± 0.053</b>
Static (€0.3)	<b>-0.054 ± 0.006</b>	<b>-0.163 ± 0.021</b>	<b>0.327 ± 0.071</b>
Static (€0.4)	<b>-0.017 ± 0.009</b>	<b>-0.070 ± 0.035</b>	<b>0.170 ± 0.098</b>
Static (€0.5)	-0.003 ± 0.005	-0.014 ± 0.017	0.050 ± 0.052
LEZ (€10.0)	<b>-0.108 ± 0.044</b>	<b>-0.061 ± 0.048</b>	<b>-0.089 ± 0.034</b>
LEZ (€20.0)	<b>-0.178 ± 0.050</b>	<b>-0.109 ± 0.057</b>	<b>-0.100 ± 0.037</b>
LEZ (€30.0)	<b>-0.256 ± 0.070</b>	<b>-0.166 ± 0.077</b>	<b>-0.144 ± 0.031</b>
LEZ (ban)	<b>-0.813 ± 0.047</b>	<b>-0.733 ± 0.054</b>	<b>-0.686 ± 0.093</b>
LEZ (€10.0) x Flexible (€0.3)	<b>-0.061 ± 0.009</b>	<b>-0.121 ± 0.016</b>	<b>-0.086 ± 0.018</b>
LEZ (€20.0) x Flexible (€0.3)	<b>-0.079 ± 0.015</b>	<b>-0.160 ± 0.017</b>	<b>-0.137 ± 0.027</b>
LEZ (€30.0) x Flexible (€0.3)	<b>-0.120 ± 0.039</b>	<b>-0.207 ± 0.035</b>	<b>-0.178 ± 0.039</b>
LEZ (ban) x Flexible (€0.3)	<b>-0.257 ± 0.025</b>	<b>-0.125 ± 0.033</b>	-0.028 ± 0.069
LEZ (€10.0) x Static (€0.2)	<b>-0.100 ± 0.064</b>	<b>-0.148 ± 0.067</b>	-0.018 ± 0.037
LEZ (€20.0) x Static (€0.2)	<b>-0.188 ± 0.066</b>	<b>-0.256 ± 0.065</b>	-0.016 ± 0.040
LEZ (€30.0) x Static (€0.2)	<b>-0.265 ± 0.083</b>	<b>-0.332 ± 0.079</b>	<b>-0.064 ± 0.036</b>
LEZ (ban) x Static (€0.2)	<b>-0.387 ± 0.038</b>	<b>-0.277 ± 0.058</b>	<b>-0.600 ± 0.085</b>

Table B.9.: Overview of the 95 percent confidence intervals for the traffic main and interaction effects. Bold print indicates statistical significance.

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## Authors' Contribution Statements

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This chapter describes the authors' contributions to the essays by using the CRediT taxonomy (Contributor Roles Taxonomy). CRediT is an established taxonomy of in total 14 roles, that can be used to represent each contributor's specific contribution to the scientific research outputs. Not all of the roles are of significant importance to the essays and only the following roles are used (in alphabetical order): conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, software, supervision, validation, visualization, writing (original draft), and writing (review & editing). The name of the roles is self-explaining and a detailed explanation of them can be found on the CRediT website (<https://credit.niso.org/>). If the same role applies to multiple authors, CRediT's suggestion to specify each author's degree of contribution as 'lead', 'equal', or 'supporting' is followed. The following pages comprise the contribution statements for each distinct author-pairing.

## Essay 1 - Authors' Contribution Statement

### Roles

Lena Hörsting and Catherine Cleophas are co-authors of Essay 1. The breakdown of each authors' contributions to the essay 'Scheduling Shared Passenger and Freight Transport on a Fixed Infrastructure?' is as follows

Role	Hörsting	Cleophas
Conceptualization	lead	supporting
Data curation	lead	-
Formal analysis	lead	-
Funding acquisition	-	lead
Investigation	lead	supporting
Methodology	lead	supporting
Project administration	-	lead
Resources	-	lead
Software	lead	-
Supervision	-	lead
Validation	lead	-
Visualization	lead	-
Writing (original draft)	lead	-
Writing (review & editing)	equal	equal

### Confirmation

The authors confirm that the above statement of contribution is accurate and true.

03.04.2025



Date

Lena Hörsting

15.04.2025



Date

Catherine Cleophas

## Essay 2 - Authors' Contribution Statement

### Roles

Lena Hörsting and Catherine Cleophas are co-authors of Essay 2. The breakdown of each authors' contributions to the essay 'Integrating Micro-Depot Freight Transport in Existing Public Transport Services' is as follows

Role	Hörsting	Cleophas
Conceptualization	lead	supporting
Data curation	lead	-
Formal analysis	lead	-
Funding acquisition	-	lead
Investigation	lead	supporting
Methodology	lead	supporting
Project administration	-	lead
Resources	-	lead
Software	lead	-
Supervision	-	lead
Validation	lead	-
Visualization	lead	-
Writing (original draft)	lead	supporting
Writing (review & editing)	equal	equal

### Published Author Contribution Statement

Lena Hörsting created the mathematical model, implemented the code, ran the experiments, prepared the figures, and wrote the methodological parts of the manuscript. Catherine Cleophas supervised and advised on the research and modelling and wrote the introduction. Both authors contributed to writing the literature review and the conclusion and reviewed and edited the manuscript.

### Confirmation

The authors confirm that the above statement of contribution is accurate and true.

03.04.2025

Date



Lena Hörsting

15.04.2025

Date



Catherine Cleophas

## Essay 4 - Authors' Contribution Statement

### Roles

Lena Hörsting and Catherine Cleophas are co-authors of Essay 4. The breakdown of each authors' contributions to the essay 'Two sides of shared passenger and freight transport? An agent-based perspective' is as follows

Role	Hörsting	Cleophas
Conceptualization	lead	supporting
Data curation	lead	-
Formal analysis	lead	-
Funding acquisition	-	lead
Investigation	lead	-
Methodology	lead	supporting
Project administration	-	lead
Resources	-	lead
Software	lead	-
Supervision	-	lead
Validation	lead	-
Visualization	lead	-
Writing (original draft)	lead	-
Writing (review & editing)	equal	equal

### Confirmation

The authors confirm that the above statement of contribution is accurate and true.

10.05.2025

Date



Lena Hörsting

10.05.2025

Date



Catherine Cleophas

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## **Erklärung zum selbständigen Verfassen der Arbeit**

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Ich erkläre hiermit, dass ich meine Doktorarbeit „*Decision Support for Integrated Urban Passenger and Freight Transport on Rail*“ selbstständig und ohne fremde Hilfe angefertigt habe und dass ich als Koautorin maßgeblich zu den weiteren Fachartikeln beigetragen habe. Alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehnenden Ausführungen der aufgeführten Beiträge wurden besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert.

Kiel, der 14.05.2025

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(Lena Hörsting)