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Simulation-based Investigation of Decarbonization Strategies for Urban Freight Transport

vorlegt von

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Abstract

This thesis examines the decarbonization of urban road freight transport. Based on case studies, the conversion of the vehicle fleet from conventional (Internal Combustion Engine Vehicle (ICEV)) to Battery Electric Vehicle (BEV) is examined using the agent-based traffic simulation software MATSim. The investigations are carried out from the perspective of the transport companies as economic agents and the companies each carry out route planning with the available vehicle fleet. The objective function of the route planning algorithm is to minimize the total costs, which include costs for the vehicles, the distance traveled and the time taken as well as any additional costs (e.g., tolls). For the central investigations in this thesis, the already existing scenario of Schröder and Liedtke (2014) for the delivery of food markets in Berlin is further developed and used.

The thesis consists of three parts:

The first part of the work presents the basics, methods, the software used, and the scenarios used in the various studies.

The second part of the thesis deals with the direct conversion of the existing vehicle fleet from ICEVs to BEVs. The logistics network of the carriers remains unchanged. Customers (supermarkets) will therefore continue to be supplied directly from the depot. One study assumes that the carriers now only have BEVs at their disposal. The limited range of the BEVs is considered in an ex-post analysis. Another study deals with the transformation phase from fossil to battery-electric powered vehicle fleets. The carriers have both ICEVs and BEVs. The effects of different levels of CO_2 taxes on the fleet composition, in particular on the proportion of ICEVs to BEVs, are investigated. The range limitation of BEVs is already included in the route planning.

In the third part of the thesis, a change in the logistics network is also considered. The transportation problem is now shifted one level further up: As a higher-level unit, there is the Logistics Service Provider (LSP), which maintains other resources, such as hubs for goods handling, in addition to the transporters. The LSP has several options to choose from: i) direct delivery, as before, or ii) the use of a two-stage network with the main leg from the depot to the hub, transshipment in the hub and delivery from the hub to the customer. This enables completely new, more extensive investigations into the effects of local entry bans for, e.g., a) ICEVs or b) all large vehicles regardless of their engine technology. In addition to the respective costs and fleet compositions, the various studies also evaluate traffic effects such as the number of kilometers driven. The consideration of global CO_2 reductions is based on a Well-to-Wheel (W2W) analysis. In

addition to the values from the energy conversion in the vehicle, this also includes the determination of all direct and indirect CO_2 emissions over the entire path to the provision of the energy source.

In summary, this work helps to show, 1) to what extent a direct conversion of the vehicle fleet to BEVs is already possible today; 2) the extent to which political framework conditions, such as a CO_2 tax, support this; 3) further measures such as bans on certain types of vehicles entering city center areas have an impact on the logistics network and what role the concept of city hubs plays in the successful implementation of such measures.

Zusammenfassung

Die vorliegende Arbeit untersucht die Dekarbonisierung des städtischen Straßengüterverkehrs. Anhand von Fallstudien wird mittels der agentenbasierten Verkehrssimulationssoftware MATSim die Umstellung des Fuhrparks von konventionellen Verbrennungs Lkw (Internal Combustion Engine Vehicle (ICEV)) auf batterieelektrische Lkw (Battery Electric Vehicle (BEV)) untersucht. Die Untersuchungen erfolgen aus Sicht der Transportunternehmen als wirtschaftliche agierende Agenten. Die Unternehmen führen jeweils eine Tourenplanung mit dem jeweils zur Verfügung stehenden Fuhrpark durch. Die Zielfunktion des Tourenplanungsalgorithmus ist die Minimierung der Gesamtkosten, welche sowohl Kosten für die Fahrzeuge, die zurückgelegte Entfernung als auch die Zeitdauern sowie eventuell Zusatzkosten (z. B. Maut) enthalten. Für die zentralen Untersuchungen im Rahmen dieser Arbeit wird das bereits existierende Szenario von Schröder and Liedtke (2014) zur Belieferung der Lebensmittelmärkte in Berlin weiterentwickelt und verwendet.

Die Arbeit besteht aus drei Teilen:

Im ersten Teil der Arbeit werden die Grundlagen, Methoden, die verwendete Software und die in den verschiedenen Studien verwendeten Szenarien vorgestellt.

Im zweiten Teil der Arbeit geht es um die direkte Umstellung des vorhandenen Fuhrparks von ICEVs auf BEVs. Hierbei bleibt das Logistiknetzwerk der Transporteure unverändert. Die Kunden (Supermärkte) werden also weiterhin direkt vom Depot aus beliefert. In einer Studie wird davon ausgegangen, dass den Transporteuren nunmehr ausschließlich BEVs zur Verfügung stehen. Die limitierte Reichweite der BEVs wird im Rahmen einer ex-post-Analyse betrachtet. Eine weitere Studie beschäftigt sich mit der Transformationsphase von der fossilen zur batterieelektrisch angetriebenen Fahrzeugflotte. Die Transporteure verfügen dazu sowohl über ICEVs als auch über BEVs. Es wird die Wirkung von unterschiedlich hohen CO_2-Steuern auf die Flottenzusammensetzung, insbesondere auf den Anteil von ICEVs zu BEVs, untersucht. Die Reichweitenbegrenzung der BEVs ist in der Tourenplanung bereits enthalten.

Im dritten Teil der Arbeit wird darüber hinaus eine Änderung des Logistiknetzwerkes in Betracht gezogen. Das Transportproblem wird nun eine Ebene weiter nach oben verlagert: Als übergeordnete Einheit gibt es den Logistics Service Provider (LSP), welcher neben den Transporteuren auch weitere Ressourcen, wie Hubs zum Güterumschlag, unterhält. Der LSP hat mehrere Optionen, zwischen denen er entscheidet: i) die direkte Lieferung, wie bisher, oder ii) die Verwendung eines zweistufigen Netzwerks mit Hauptlauf vom Depot zum Hub, Umschlag im Hub und Auslieferung vom Hub zum Kunden. Dies ermöglicht ganz neue, weitergehende Untersuchungen bezüglich der Wirkungen

lokaler Einfahrtverbote für beispielsweise a) ICEVs oder b) alle großen Fahrzeuge unabhängig von ihrer Antriebstechnologie. In den unterschiedlichen Studien werden neben den jeweiligen Kosten und der Flottenzusammensetzung auch verkehrliche Wirkungen, wie die Anzahl der gefahrenen Kilometer, ausgewertet. Die Betrachtung der globalen CO_2-Reduktionen erfolgt auf Basis einer Well-to-Wheel (W2W)-Analyse. Diese umfasst neben den Werten aus der Energieumwandlung im Fahrzeug auch die Ermittlung aller direkten und indirekten CO_2-Emissionen über den kompletten Pfad zur Bereitstellung des Energieträgers.

Zusammenfassend trägt diese Arbeit dazu bei, darzustellen, 1) bis zu welchem Teil bereits heute eine direkte Umstellung des Fuhrparks auf BEVs möglich ist; 2) inwiefern politische Rahmenbedingungen, wie eine CO_2-Steuer hierauf unterstützend wirken; 3) weiterführende Maßnahmen wie Einfahrtverbote für bestimmte Fahrzeugtypen in Innenstadtbereiche sich auf das Logistiknetzwerk auswirken bzw. welche Rolle das Konzept von City-Hubs für die erfolgreiche Implementierung solcher Maßnahmen spielt.

CHAPTER 1

Introduction

1.1 Motivation

Reducing greenhouse gas (GHG) emissions is one major objective to limit global warming to below 2 °C above the pre-industrial level and go towards a (more) sustainable future (United Nations, 2015a). One relevant sector is the transportation sector, which is responsible for approx. 21 % of the global greenhouse gas (GHG) emissions and approx. 24 % of the German GHG emissions (Crippa et al., 2024). Within the German transportation sector, approx. 35 % of carbon dioxide (CO_2) emissions are currently emitted by road freight transport (BMUB, 2018).

The policy to address this challenge is set, e.g., by the **European Green Deal**, which calls for a 90 % reduction of transport emissions by 2050 (EC, 2019), and by national climate strategies such as Germany's Climate Action Plan 2050 (BMUB, 2016). Moreover, the United Nations (UN) Sustainable Development Goals (SDGs) explicitly call for *"sustainable transport systems for all"* (Goal 11.2) and *"universal access to safe, green and public spaces"* (Goal 11.7) (United Nations, 2015b).

At the same time, a growing number of European cities have introduced diesel vehicle bans or Low Emission Zone (LEZ) to protect public health (Wikipedia, 2019; Senatsverwaltung für Stadtentwicklung und Umwelt (SenStadt), 2013). These developments create an urgent need to understand how urban freight transport can be decarbonized.

Battery Electric Vehicles (BEVs), however, face two major technical constraints: limited driving range and comparatively long charging times (Liimatainen, van Vliet, and Aplyn, 2019). Ignoring these constraints in routing models leads to overly optimistic solutions that cannot be executed in practice (Martins-Turner et al., 2020). The transition will not be instantaneous; carriers are likely to operate mixed fleets of Internal Combustion Engine Vehicles (ICEVs) and BEVs for a considerable period (Ewert et al., 2021a). In addition, policy instruments such as CO_2 taxes, LEZs, and outright bans on diesel trucks create a complex regulatory environment that directly influences fleet composition and network design (Transport for London (TfL), 2022c,a; Senatsverwaltung für Umwelt, Verkehr und Klimaschutz Berlin (SenUVK), 2017).

Beyond vehicle-level considerations, the structure of the urban logistics network itself comes into focus. This is forced either by environmental or safety reasons, as also stated by the UN SDGs mentioned above. On the environmental side, e.g., LEZs are introduced, either banning or tolling vehicles that do not match certain emission standards (see, e.g., Senatsverwaltung für Umwelt, Verkehr und Klimaschutz Berlin (SenUVK), 2017; Ministère de la transition écologique et de la cohésion des territoires, 2022; Transport for London (TfL), 2022c). The same concept is applied analogously as so-called safety zones, where some large vehicle types are not welcome (Transport for London (TfL), 2022c). This has led to a growing interest in two-echelon distribution systems, where goods are first transported from a central depot to local hubs using larger vehicles, and then delivered to the final customers using smaller, often electric, vehicles (see, e.g., Oliveira, Ramos, and de Sousa, 2022).

The present dissertation addresses these topics by using an agent-based simulation framework. Freight carriers are modeled as economic agents that optimize daily routes under a cost-minimization objective that includes vehicle acquisition, distance-related operating costs, travel-time costs, and any additional charges such as tolls. For the studies related to the network design, an agent representing a Logistics Service Provider (LSP) is introduced, which assigns customer orders to different carriers and decides on the use of one- or two-echelon delivery systems. By systematically varying fleet composition, CO_2-tax levels, and logistics-network topology (direct delivery versus two-stage hub-and-spoke), the study provides a comprehensive assessment of the economic, operational, and environmental consequences of urban-freight decarbonization.

This motivation leads directly to the research questions presented in the following Section 1.2 and the research approach described in Section 1.3, which will guide the investigation in this thesis.

1.2 Research Questions

Before going into the research regarding the electrification of the truck fleet, a more general question regarding tour planning algorithm is investigated: When using last-mile delivery systems, is it possible that a driver can reload goods at the depot and run several (sub-) tours during their shift? This is in contrast to the Vehicle Routing Problem (VRP) setup, where each vehicle / driver is planned for only a single tour. After that, the shift is over and another vehicle with its own fixed costs is planned. This leads to the following questions:

RQ 1 *When changing the setup of the VRP to allow reloading and running multiple tours during the day, how does this influence the solution of the Vehicle Routing Problem and what are the advantages and disadvantages?*

For the decarbonization of the truck fleet, one endpoint would be that all ICEVs are replaced by BEVs. This leads to the following research question:

RQ 2 *What changes to the vehicle-fleet composition will result from the switch to an all-electric vehicle fleet?*

Since this simulation will give at least one possible solution:

RQ 3 *What is the maximum increase in cost for the carrier based on that change to an all-electric fleet?*

As an ex-post analysis from this simulation, the additional question regarding the limited range of BEVs can be investigated:

RQ 4 *How many tours planned under cost-minimizing aspects can be driven with a fleet of currently available BEVs?*

Another approach to deal with the limited range of the BEVs is to incorporate this restriction into the tour planning algorithm. To ensure the fulfillment of all customer requests, does the carrier have the possibility to choose ICEVs as a fallback option? This possible mixture of electric and non-electric vehicles is a good representation for the transition phase.

RQ 5 *To which extent will a cost-minimizing carrier switch to BEVs as long as ICEVs are available?*

To reduce CO_2 emissions and move forward to achieve the goal of net-zero GHG emissions, the carrier needs motivation for a decision to change its fleet. This could either be something like banning ICEVs, or using market mechanisms like reducing the costs for the new technology (for example, subsidizing the BEV) or increasing the costs for the no longer acceptable technology. The latter can be done, for example, by introducing a tax on GHG emissions.

The easiest way is to add this tax as an additional cost on the fuel price. This leads to the general question:

RQ 6 *How does the simulation model react to the increased fuel prices by introducing a tax on GHG emissions?*

This is followed by the more specific questions:

RQ 7 *What value of a GHG emission tax is needed to achieve a significant change of the carrier's decision regarding the fleet composition?*

and

RQ 8 *What are the effects on the tours and the resulting emissions?*

In this study, the focus is on the driving of the vehicles and the resulting emissions. But the electrification of the truck fleet will also have an impact on the required charging infrastructure. This is not part of this thesis, but other studies are using the results from chapters of the thesis to investigate this question (see, e.g., Miranda Jahn et al., 2021; Göhlich et al., 2021).

While all the previous questions are regarding the electrification of the truck fleet *without* changes to the logistics network, the following research questions will address the simulation of LSPs to investigate the reactions *with* changes in the logistics network. The need came from the overall idea, to avoid certain vehicle types entering specific areas. The main drivers behind this are: i) the idea of banning ICEVs from city centers, e.g., by introducing a Zero Emissions Zone (ZEZ), together with the limited range of BEVs, and ii) the idea of introducing a ban of large vehicles from city centers, e.g., by introducing a safety zone.

Once we are interested in the reactions in the logistics network, a new agent is needed — the LSP. The LSP now assigns the customer orders to the different carriers (on the different stages of the logistics chain), who then plan their tours to fulfill these orders.

This leads to the following research question:

RQ 9 *How to apply the concept of an LSP to an agent-based simulation framework?*

After testing the implementation of the LSP in a proof-of-concept scenario, the next step is to apply it to an existing case study. Later, it is applied to an existing case study, first without using the two-echelon network and later with it.

RQ 10 *What are the effects of introducing the higher-level LSP agent?*

RQ 11 *How does the use of a mix of two-echelon and one-echelon (direct) delivery lead to a change in costs, vehicle kilometers (vkm), and emissions?*

Now, it is possible to investigate the effects of introducing the policies for the use case:

RQ 12 *What are the effects of the introduction of a ZEZ in the inner-city on the supply chain of supermarkets in Berlin, and what effects can be observed on costs, tours, and emissions?*

RQ 13 *What are the effects of the introduction of a safety-zone in the inner-city on the supply chain of supermarkets in Berlin, and what effects can be observed on costs, tours, and emissions?*

Table 1.1 gives an overview of the chapters addressing the research questions. The embedding of the research topics and questions based on the literature takes place in the respective chapters. Some general topics are also addressed in Sections 2.1 and 2.2 and Chapters 3 to 5 in Part I.

Table 1.1: Overview of the chapters of the thesis addressing the research questions.

Part	Chapter	Research Question(s)
Part II: Electrification without changing the Logistic Network	Chapter 6: How Driving Multiple Tours Affects the Results of Last-Mile Delivery Vehicle Routing Problems	RQ 1
	Chapter 7: Replacement of the fleet's vehicles by electric vehicles	RQs 2 to 4
	Chapter 8: Effects of a GHG emission tax on the fleet composition	RQs 5 to 8
Part III: Reactions on Restrictions including Changes in the Logistics Network	Chapter 9: Modeling the Two-Echelon Vehicle Routing Problem	RQ 9
	Chapter 10: Applying the Two-Echelon Distribution Concept to an Urban Food Retail Case Study	RQs 10 and 11
	Chapter 11: Reactions to Zero-Emission and Safety Zone Restrictions in Urban Food Retail Logistics	RQs 12 and 13

1.3 Research Approach

In order to answer the research questions above, several simulation studies are done. For these simulations an agent-based, open-source transport simulation software is used: Multi-Agent Transport Simulation (MATSim) (Section 3.2). To investigate the reactions of the transport companies (carriers), the solving of VRPs (Section 3.3) for the carriers is included in the simulation. This based on the road network and vehicle-type-specific cost values, as well as vehicle-type specific tolls. Later (in Part III, the Logistics Service Provider (LSP) is introduced as an agent above the carriers. The LSP can have multiple logistic chains consisting of one or several carriers, and hubs. It has to assign the customer orders to the different carriers and decide on the use of one- or two-echelon delivery systems.

As usual when running simulations, it is a standard approach to have a so-called *base case*, simulating the current situation without any changes. Then changes to the scenario are made in the *policy case(s)*, e.g., by introducing other vehicle types to the scenario, adding tolls, changing prices or even providing other logistic chains in order to solve the transport problem. Afterward some key values are analyzed for these policy cases and compared to the base case.

In this thesis, this analysis will not only include vkm, time, and costs, but also two kinds of emission analysis: i) based on the driving (air) emissions derived from the Handbook on Emission Factors for Road Transport (HBEFA) (INFRAS (2019), Section 2.2.2.3), and ii) based on the Well-to-Wheel (W2W) emissions (Section 2.2.3). Most simulation studies are based on an existing case study by Schröder and Liedtke (2014). There is also a proof-of concept study for the simulation, including changes in the logistics network, before again applying it in a case study. All scenarios used in this thesis are described in Chapter 4.

Some main advantages and therefore the reasons to use this approach are:

- solving VRPs based on a network,
- including time-dependent networks, taking congestion into account,
- routing based on vehicle-type-specific tolling schemes,
- tracking of vehicles,
- tracking of shipments,
- calculating emissions from each vehicle based on vehicle type, link-specific attributes, traffic state, . . . ,
- having the LSP as an acting agent.

1.4 Outline

The thesis is structured as follows:

Part I addresses the basics of commercial transport and its environmental impacts (Chapter 2), agent-based modeling and simulation, including VRP solving, (Chapter 3) and gives a brief overview of the different scenarios used (Chapter 4).

Part II addresses the electrification of trucks *without* changes to the logistics network. It describes the different vehicle parameters for ICEVs and BEVs (Chapter 5), the effects of driving multiple tours with the same vehicle (Chapter 6), the replacement of the whole fleet (Chapter 7) and the effects of a tax on GHG during the transition phase from ICEVs to BEVs fleets (Chapter 8).

Part III addresses the simulation of LSPs to investigate the reactions *including* changes to the logistics network. It covers modeling the Two-Echelon Vehicle Routing Problem (2E-VRP) demonstrated as a proof-of-concept study (Chapter 9), its application in an existing case study (Chapter 10), and the investigation of measures such as a ZEZ (Chapter 10) or a safety zone, where large vehicles are not allowed to enter (Chapter 11).

Finally, Chapter 12 provides the overall conclusion and outlook.

Part I

Basics and Methodology

CHAPTER 2

Freight Transport and Emissions

This chapter presents some general information on the two core topics of this thesis: freight transport (see Section 2.1) and emissions (see Section 2.2).

2.1 Freight Transport

This section starts with the differentiation between freight and commercial transport (Section 2.1.1), followed by an overview of logistics networks (Section 2.1.2), and concludes with an overview of road freight transport in Germany (Section 2.1.3).

2.1.1 Freight Transport vs. Commercial Transport

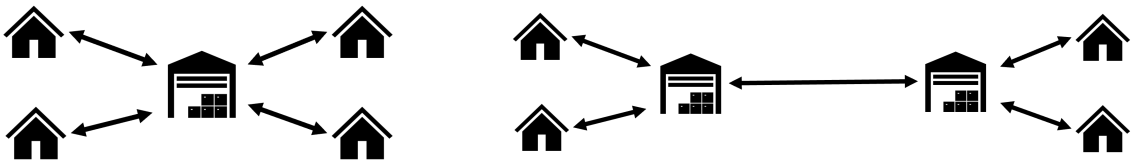
Freight transport is *not* a synonym for commercial transport and vice versa. Commercial transport is caused by the economic (= commercial) purpose on which the transport is based. According to Steinmeyer (2017); Göhlich et al. (2021), commercial transport has two main parts: commercial person transport and commercial goods (freight) transport. Commercial person transport is defined as "that part of commercial transport in which the main purpose of the transport is to carry passengers, as opposed to goods transport" (Wermuth, 2007). The commercial person transport includes, for example, the transportation of manual workers or nursing staff on their way to their next place of work. Freight transport involves everything related to the transportation of goods for commercial reasons. This can be, for example, the transport within a company (e.g., from a production site to a warehouse) or the transport between companies (e.g., from a wholesaler to a retailer), or to a customer or consumer. Summarizing, freight transport is a subset of commercial transport (Hesse, 2019; McKinnon, 2018). Commercial person transport and freight transport share common optimization challenges in routing and scheduling, though the underlying objectives and constraints may differ (Schneidewind, 2020).

2.1.2 Logistics Networks

To transport goods from A to B, a logistics network is needed. Logistics networks can be modeled as graphs where nodes represent locations and edges represent transport links with associated

costs, capacities, and travel times (Ballou, 2004). Nodes are, e.g., production sites, warehouses, distribution centers, or customers. Edges are the connections between the nodes (Domschke et al., 2017), e.g. roads, railways, or shipping routes. In network theory, the efficiency of a logistics network is often measured by metrics such as total distance, number of transshipments, and service level (Simchi-Levi, Kaminsky, and Simchi-Levi, 2008).

Figure 2.1 shows some simple designs of logistics networks. The simplest design of a logistics chain is the *direct link*, connecting two nodes by one direct link, building a point-to-point connection (Jakara and Brnjac, 2023; Woxenius, 2007). According to Jakara and Brnjac (2023); Woxenius (2007), the *hub-and-spoke* design consists of one single hub handling all transports between origin and destination (see Figure 2.1a). As soon as there are several interconnected hubs (see Figure 2.1b), it is called a *connected-hub* design (Jakara and Brnjac, 2023; Woxenius, 2007). Other authors, e.g., Gleißner and Femerling (2016), are still using the term hub-and spoke and name it a *two-stage hub-and-spoke* network. In larger networks, this is not limited to two hubs. Moreover, there exist hybrid designs, using direct connections as well as connections via hubs (Gleißner and Femerling, 2016).



(a) Hub and spoke

(b) Connected hubs or two-stage hub-and-spoke

Figure 2.1: Example of network designs. (Own visualisation based on Jakara and Brnjac (2023); Woxenius (2007); Gleißner and Femerling (2016))

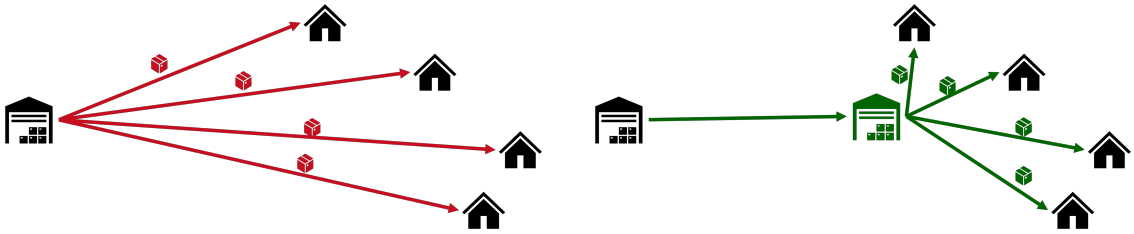
The main idea behind all the hub approaches is that goods are consolidated at the hub, which allows for economies of scale and more efficient routing (Jakara and Brnjac, 2023). The different segments of transport route along the edges (or links) are named as follows (see Gleißner and Femerling, 2016; Ehmke, 2012): The *collection run* (or pre-haul) refers to the collection of goods from the origin (sender) and their transport to a transshipment point (hub). From there, the *main run* (or main leg) takes place, bringing the goods to the hub near the destination. The final distribution to the destination (recipient) is done by the *distribution run* (or post-haul, last-mile).

In this thesis, the focus is on freight delivery. As the origin, a depot is assumed, so the goods are already in the region of the recipient and no collection is considered. The recipient is a customer, which can be either a consumer receiving a parcel (see Section 4.2), or — in most of the studies of this thesis — supermarkets receiving goods from the depot (see Section 4.1).

In Part II, the focus is on the electrification of the vehicles without changing the logistics network. Here, the distribution is usually a direct link delivery from the depot to the recipient. Part III focuses on changes in the logistics network caused by introduced policies. Therefore, the Logistics Service Provider (LSP) is introduced as a new agent[1], having a logistics network with several resources: carriers for the transport on the edges and hubs as nodes of the logistics network. The LSP has the option, to choose for each shipment, the logistics chain, e.g., direct link delivery from the depot to the recipient or using a hub as an intermediate stop (Crainic, Perboli, and Ricciardi, 2012). Such multi-echelon distribution systems are increasingly common in urban freight transport (Wiedemann, 2021).

[1]Please refer to Section 3.2.2.2 for more information about the LSP agent.

Figure 2.2 shows a simple version of such logistics networks used in this thesis. The direct link delivery from the depot to the recipient is shown in Figure 2.2a, while Figure 2.2b shows a two-echelon delivery via a hub. The hybrid version, consisting of both of them, is used in this thesis as well.



(a) Direct one-echelon chain. **(b)** Two-echelon logistics chain

Figure 2.2: Logistics network structure: One- vs. two-echelon delivery network (Own visualisation)

2.1.3 Road Freight Transport in Germany

The German road freight sector represents a critical focus for decarbonization research.

Road freight transport accounts for almost three-quarters of total land goods transport in Germany, and this share is expected to increase despite political efforts to strengthen rail as an alternative mode (Kerriou, 2023). In 2025, 3′340 million tons (t), were transported on the road, including German and foreign trucks (Statistisches Bundesamt, 2025). In Germany, there are about 35′000 road freight companies, with an average workforce of 11.3 people per company (Kerriou, 2023) According to Biemann et al. (2024), the traffic volume of Germany's road freight transport has been increasing over the years. While bulk-goods transports are declining, the rise of road-oriented goods such as parcel or consolidated shipments and mail generates increasing demand for road transport (Intraplan and Trimode, 2023).

Light commercial vehicles (Gross Vehicle Weight Rating (GVWR) < 3.5 t), which are used, among other things, by tradespeople or for Courier, Express, and Parcel (CEP) traffic, have a share of 45 % regarding the vehicle types (Biemann et al., 2024). For heavy commercial vehicles, vehicles with a GVWR over 28 t dominate, primarily truck units with trailers. Moreover, the majority of freight transport occurs on highway and rural road categories, while the share on urban roads is still significant at 27 % (Biemann et al., 2024).

2.2 Emissions

After a brief overview of emissions in general and in the transport sector (see Section 2.2.1), the calculation approaches for emissions while driving (see Section 2.2.2) are presented as well as the Well-to-Wheel (W2W) approach (see Section 2.2.3). The implementation of the emission calculation for driving emissions in Multi-Agent Transport Simulation (MATSim) is presented in Section 3.2.3.

This section is an edited and extended version of previously published material: Martins-Turner et al. (2020); Ewert et al. (2021a); Kaddoura, Ewert, and Martins-Turner (2022); Gable, Martins-Turner, and Nagel (2022).

2.2.1 Overview

Transport-related emissions comprise a heterogeneous set of stressors that affect air quality, climate, and human health. According to the European Environment Agency (2023), the main categories related to transport are:

- greenhouse gas (GHG),
- air pollution (non-GHG),
- noise, and
- impacts on ecosystems and biodiversity.

GHGs (e.g., carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O)) drive global warming, whereas the non-GHG air pollutants (e.g., nitrogen oxides (NO_x), sulfur dioxide (SO_2), particulate matter $< 10\,\mu m$ (PM_{10}), particulate matter $< 2.5\,\mu m$ ($PM_{2.5}$), carbon monoxide (CO), non-methane volatile organic compounds ($NMVOC$)) primarily affect local and regional air quality and have well-documented health effects (Intergovernmental Panel on Climate Change (IPCC), 2023). Environmental noise — not only from transport — has negative impacts on health and the environment and is thus regulated under the EU Noise Directive (see European Parliament and Council of the European Union, 2021). The impacts on ecosystems and biodiversity are caused, e.g., by affecting quality and connectivity of habitats or the growth of plants (European Environment Agency, 2023).

In this thesis, the focus lies on the effects of different transport related measures and their effects on air pollutants and GHG emissions. Therefore, other emission types such as noise or the impacts on ecosystems and biodiversity are excluded.

Relevance of the Transport Sector As already stated in the overall Motivation (Section 1.1), reducing GHG emissions is a major objective to limit global warming and move towards a (more) sustainable future (United Nations, 2015a). According to Crippa et al. (2024), the transportation sector is responsible for approximately 21 % of global GHG emissions and approximately 24 % of Germany's GHG emissions. For Germany, the share has increased from 13 % in 1990, mainly caused by the increase in road freight transport, motorized individual transport, and an increase in diesel consumption (Umweltbundesamt, 2026). While the absolute GHG emissions of the transport sector remained relatively stable over the years (165 million t CO_2 equivalents (CO_2eq) p.a. in 1990; 145 mio t CO_2eq p.a. in 2024), the sum of all non-transport sectors decreased in the same time period significantly (from 1088 to 504 mio t CO_2eq p.a.) (Umweltbundesamt, 2026). In Germany the road freight transport is responsible for about a third of the transport sector's CO_2 emissions (BMUB, 2018), highlighting the relevance of integrating freight transport in emission reduction strategies. According to Umweltbundesamt (2026), the technically driven emission reductions per kilometer (km) have been partially offset by the increased mileage. For emissions, the savings were even overcompensated. Despite the technical improvements, the absolute CO_2 emissions from operating road freight transport increased by 12.7 % between 1995 and 2024 (Umweltbundesamt, 2026). To address this challenge, strategies are set on different levels, e.g., the European Green Deal (EC, 2019) or Germany's Climate Action Plan 2050 (BMUB, 2016).

The transport sector is not only a major contributor to GHG emissions but also to other air pollution. Road transport is responsible for 40 % of all NO_x emissions by the EU member states in 2024, while non-road transport contributes an additional 13 %, leading to a total share of about 53 % originating from the transport sector (European Environment Agency, 2026). Regarding particulate matter (PM), the transport sector is responsible for a share of 13 % (road: 10 %;

non-road: 3 %) for PM_{10} and 14 % (road: 10 %; non-road: 4 %) for $PM_{2.5}$ emissions from all EU member states in 2024 (European Environment Agency, 2026).

Emission Calculation Approaches In the different studies of this thesis, different approaches are used to calculate the GHG and air pollutant emissions:

1. emissions emitted while driving (see Section 2.2.2) and
2. W2W emissions, including the production of diesel and electricity and from their use in the vehicles (see Section 2.2.3).

Another approach is the Life Cycle Assessment (LCA), which includes the whole life cycle of a vehicle, including its production and disposal (DIN EN ISO 14040, 2021; DIN EN ISO 14044, 2021). MATSim scenarios enable realistic LCAs. For long-haul heavy-duty truck transport, reference is made to Syré and Göhlich (2025) as an example. However, LCA is not part of this thesis.

2.2.2 Emissions while driving

The different pollutants emitted while driving are divided into two categories: *exhaust* emissions (see Section 2.2.2.1) and *non-exhaust* emissions (see Section 2.2.2.2). To calculate these emissions, the emission factors from the Handbook on Emission Factors for Road Transport (HBEFA) database (see Section 2.2.2.3) are used. The calculation itself is done using MATSim's *emissions* contrib (see Section 3.2.3).

2.2.2.1 exhaust emissions

When discussing the reduction of transport-related emissions in general, and GHG reduction in particular, the focus is usually on the reduction of *exhaust* emissions. Exhaust emissions are, as the name says, the emissions that come from the engine and are emitted through the exhaust. They are highly relevant for all Internal Combustion Engine Vehicles (ICEVs). The most common exhaust emissions are CO_2, CO, NO_x, PM_{10}, $PM_{2.5}$, and black carbon (BC).

There are several studies to quantify transport-related emissions for today's situation or for policy cases (see e.g., Hülsmann et al., 2011; Ghafghazi and Hatzopoulou, 2014; Fernandes et al., 2014; Guzman, de la Hoz, and Monzón, 2015; Washburn, Frey, and Rouphail, 2016; Garcia-Castro et al., 2016; Kickhöfer and Nagel, 2016). Most of these studies do not explicitly consider the shift from ICEVs to Battery Electric Vehicles (BEVs) or treat BEVs as zero-emission vehicles.

When calculating emissions for "zero-emission-vehicles", e.g., BEVs, these exhaust emissions are zero, as there is no engine with a combustion process and therefore no exhaust gases. Thus, a growing share of BEVs will not only reduce GHG emissions but also reduce local exhaust air pollutants.

2.2.2.2 non-exhaust emissions

Even a fully decarbonized transport sector continues to generate so-called *non-exhaust* emissions (see e.g. Kaddoura, Ewert, and Martins-Turner, 2022). Non-exhaust emissions arise from the abrasion of brakes, tires, and road surfaces, as well as from the (re)suspension of road dust (Grigoratos and Martini, 2014; INFRAS, 2019). For certain pollutants, such as PM_{10}, $PM_{2.5}$, and BC, a significant share of emissions originates from so-called *non-exhaust* sources, such as road and tire wear or the resuspension of dust (Kaddoura, Ewert, and Martins-Turner, 2022). Therefore, even vehicles often referred to as "zero-emission" are *not* free from producing air pollutants.

2.2.2.3 HBEFA: Handbook Emission Factors for Road Transport

The Handbook on Emission Factors for Road Transport (HBEFA) (INFRAS, 2019) is a widely recognized tool for estimating traffic-related emissions in Europe. HBEFA provides detailed emission factors and energy consumption for a broad range of vehicle categories, fuel types, road types, and traffic situations, focusing on emissions while driving. As vehicle categories, HBEFA differentiates between e.g., passenger cars, Light Commercial Vehicles (LCVs), Heavy Goods Vehicles (HGVs), buses, and motorcycles. For each vehicle category, HBEFA provides emission factors for different engine technologies (e.g., diesel, gasoline, electric, hybrid), vehicle sizes (e.g., weight classes for trucks), and emission standards (e.g., Euro 3, Euro 4, Euro 5, Euro 6). Road types are classified into urban, rural, and highway roads, each with specific traffic conditions and speed profiles. Traffic situations are categorized based on average speeds, ranging from free-flowing traffic to heavily congested conditions. Using these emission factors makes it easy to quantify emissions of key pollutants, including exhaust (see Section 2.2.2.1) and non-exhaust emissions (see Section 2.2.2.2). Besides the emission factors for driving once the engine has reached its normal operating temperature, HBEFA also includes additional emission factors for the first km of driving after engine start. This reflects how vehicle emissions vary depending on engine temperature and operating conditions after starting, and depend on the distance driven after starting as well as on the parking duration before starting. In the currently used version 4.1 of HBEFA, cold start emissions are only provided for passenger cars and LCVs, but not for HGVs. Thus, in our studies, additional cold start emissions are not considered. This is not a major limitation, as HGVs typically drive longer distances once used, so their (additional) cold start emissions are less significant compared to passenger cars.

For this thesis, HBEFA version 4.1 with the data for Germany is used (see INFRAS, 2019). However, HBEFA does not provide sufficiently detailed emission factors for HGVs at the level we need in our study, where a differentiation between various truck sizes is essential, but we do not know anything about the emission standard of each truck. To address this limitation, Gable, Martins-Turner, and Nagel (2022) refined the set of emission factors specifically for HGV. It uses the detailed emission factors available in HBEFA for different truck sizes, including the emission standard of each truck. Then, it averages them according to their share as given in the database. As a result, we now have size-specific emission factors for HGV without needing to know the emission standard of each truck. These enhanced emission factors are used for the vehicle-specific emission calculations presented in the different studies.

Nevertheless, HBEFA is a good fit to be used together with MATSim because it can pick up much of the information that is available in the MATSim simulation. Since MATSim is a mesoscopic simulation tool, we have detailed trajectories of each vehicle during the whole simulation. The situation on each link is not known in detail, but we know the time when a vehicle enters and leaves a link. This allows us to derive the traffic state by comparing the calculated speed on the link with the free-flow speed of the link. More details on the (driving) emissions calculation using HBEFA in MATSim can be found in the corresponding section addressing MATSim's *emissions* contrib (see Section 3.2.3).

This level is sufficient as long as we do not need the exact position and time of each emitted pollutant, as it is necessary for dispersion models. However, Laudan et al. (2024) solved this issue and subsequently determined the emission distribution on the link. This made it possible to feed the traffic emissions determined using HBEFA from a MATSim simulation into the PALM urban climate model[2].

[2] see https://palm.muk.uni-hannover.de/trac

2.2.3 Well–to–Wheel Analysis

To analyze the environmental impact of the simulated scenarios, GHG emissions from the production of diesel and electricity, as well as from their use in the vehicles, are estimated following the Well-to-Wheel (W2W) methodology (JRC et al., 2014).

Unfortunately, HBEFA does not (yet) provide differentiated energy consumption values for BEVs above 12 t GVWR. In this study, three out of four used vehicle sizes are larger than that. Therefore, it is not yet possible to base a meaningful W2W analysis on this data. Instead, the energy consumption per vehicle type is calculated by multiplying the vehicle kilometer (vkm) driven with an average diesel or electricity consumption. The resulting energy consumption is then multiplied by the W2W emission factors.

The diesel consumption for the ICEVs was extracted from Planco, ITP, and TUBS (2015) and ranges from 13.57 liter (l)/100 km for trucks with a GVWR of 7.5 t up to 37.45 l/100 km for the trucks with a GVWR of 40 t. The vehicle type-specific energy consumption for the BEVs is between 61 and 180 kilowatt hours (kWh)/100 km as mentioned in Section 7.2. Three different emission factors were used to show the effects of electrification depending on the electricity production. For calculating the annual emissions, 250 workdays per year are assumed (Planco, ITP, and TUBS, 2015).

The following factors are assumed to calculate the W2W GHG emissions from *electricity* production:

- 518 gram (g) CO_2eq/kWh in 2018 (Icha and Kuhs, 2019),
- 347 g CO_2eq/kWh in 2030 (Wietschel, Kühnbach, and Rüdiger, 2019), and
- 25 g CO_2eq/kWh for renewable energies (Wietschel, Kühnbach, and Rüdiger, 2019).

For *diesel*, 3′170 g CO_2eq/l of diesel are assumed (DIN EN 16258:2012, 2013).

Combining these factors leads to the vehicle type-specific W2W emission factors per vkm provided in Table 2.1. It also shows that the footprint of a BEV fleet changes over time, along with changes in energy production, while for ICEVs it remains stable as long as there is no significant amount of synthetic diesel available for trucks.

Table 2.1: Well-to-Wheel (W2W) emission factors per 100 vehicle kilometer (vkm). For BEVs, three different values are computed, based on the (assumed) electricity production in 2018, 2030, and from full renewable electricity production.

vehicle size (GVWR)	W2W factor (kg CO_2eq/100 vkm) ICEV	BEV 2018	BEV 2030	BEV renewable
7.5 t	43.02	31.60	21.17	1.53
18 t	105.24	54.91	36.78	2.65
26 t	105.24	77.70	52.05	3.75
40 t	118.72	93.24	62.46	4.50

CHAPTER 3

Modeling and Simulation

This chapter is dedicated to the modeling and simulation of (freight) traffic. This includes a short general introduction to agent-based modeling and simulation (see Section 3.1). Section 3.2 introduces the agent-based transport simulation software MATSim together with those extensions — out of a large pool of options — that are actually used in this thesis. This chapter concludes with the topic of (solving) Vehicle Routing Problems (VRPs) in Section 3.3, including the introduction of the VRP-solving software jsprit.

3.1 Agent-based Modeling and Simulation

Agent-Based Modeling (ABM) has emerged as a powerful computational approach for understanding and simulating complex transportation systems (Huang et al., 2022). It offers a bottom-up methodology that represents transportation systems with a fine level of detail through autonomous decision-making entities —*agents*— whose individual behaviors and interactions produce emergent system-level outcomes (Karolemeas et al., 2024). Unlike traditional transportation modeling approaches relying on aggregate-level assumptions, Agent-Based Simulation (ABS) allows the explicit simulation of heterogeneous agents, e.g., individual vehicles, drivers, or passengers and their dynamic interactions within transportation networks (Huang et al., 2022). This granular representation allows for the capture of behavioral complexity, adaptation, and learning that characterize real-world transportation systems. The application of agent-based approaches to transportation has experienced remarkable growth in recent years (Domenteanu et al., 2023).

As many other simulation approaches, they are suitable for exploring "what-if" scenarios in urban transport simulation. In a meso- or microscopic simulation scope, it is possible to keep track of each agent's activity (e.g., loading, unloading, waiting) and vehicle movement. This is an implementation of the Activity-based Approach, described by McNally and Rindt (2007), using travel-activity patterns over a specific time period. This allows for a detailed analysis of the impact of different policies, infrastructure changes, or operational strategies on traffic flow, congestion, emissions, and overall system performance. For a general overview on transport simulation, including the

differentiation between macro-, meso-, and microscopic simulations, please also refer to Moltenbrey (2020).

Agent-based transport modeling has evolved to include considerations of individual-level learning, decision-making under uncertainty, and feedback mechanisms that shape travel behavior over time. Furthermore, ABM applications extend beyond traffic simulation, e.g., to answer questions of urban land-use patterns, accessibility, social equity, and the integration of emerging technologies such as shared autonomous vehicles (Karolemeas et al., 2024; Ziemke, 2022; Bischoff, 2019; Kaddoura, 2019) into transportation systems.

Over a long time, ABS were used in person transport simulations, but they are also increasingly applied to freight transport modeling (Zilske and Joubert, 2016). Moreover, the application of ABM is relevant for urban freight transport simulations, where heterogeneity in vehicle types, routing strategies, and operational constraints strongly influence the single tours, and thus in the end the overall outcomes (Iwan and Małecki, 2017). Moreover, Bean and Joubert (2021) implemented an agent-based approach for freight receiver and carrier collaboration. Other developments go into the direction of implementing Logistics Service Providers (LSPs) as their own agents (Matteis, Wisetjindawat, and Liedtke, 2019).

In this thesis, the mesoscopic ABS software MATSim is used. It will be introduced in detail in the following Section 3.2.

3.2 The Multi-Agent Transport Simulation Software MATSim

This section gives a brief overview of the Multi-Agent Transport Simulation software MATSim that is used in this thesis for all simulations. It is an edited summary of descriptions in previously published articles (see, e.g., Martins-Turner and Nagel, 2019; Martins-Turner et al., 2020; Ewert et al., 2021a; Kaddoura, Ewert, and Martins-Turner, 2022; Martins-Turner and Nagel, 2025). It focuses on the most important aspects of Multi-Agent Transport Simulation (MATSim) for this thesis.

The section is structured as follows: it starts with a short, general description of MATSim (Section 3.2.1). After that, the most important extensions of MATSim, which are used for the different studies in this thesis, are introduced: these are the freight contrib (Section 3.2.2), the emissions contrib (Section 3.2.3), and the roadpricing contrib (Section 3.2.4).

3.2.1 MATSim

MATSim is an open-source software for agent-based transport simulation. It is an activity-based and extensible framework implemented in Java, designed to handle large-scale scenarios. MATSim is built in a modular way, with a common core and several optional extensions[1]. Please also refer to the code database available on GitHub[2], as well as to the MATSim book (see Horni, Nagel, and Axhausen, 2016) and the MATSim user guide[3], as an up-to-date extract of the first chapters of the MATSim book.

[1] https://matsim.org/extensions
[2] https://github.com/matsim-org/matsim-libs
[3] https://matsim.org/docs/userguide/

MATSim relies on a co-evolutionary algorithm, where each iteration follows three main steps: traffic simulation (mobsim), scoring, and replanning. This approach is shown in Figure 3.1. While the mobsim step represents the agents' physical behavior, the replanning and scoring steps describe the agents' mental behavior (Kaddoura, 2019).

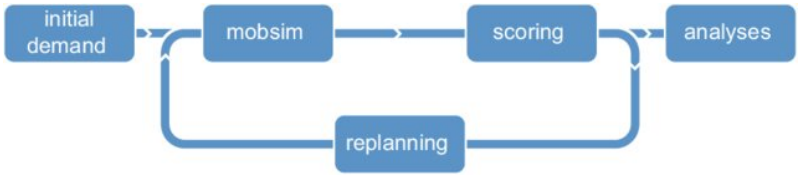


Figure 3.1: The MATSim loop. (Source: Horni, Nagel, and Axhausen (2016))

In MATSim, agents — typically persons — are simulated with daily plans consisting of activities such as home or work and the trips between these activity locations. These plans are executed in the mobility simulation (*mobsim*) and then evaluated (*scored*) based on the agents' experienced performance. During the *replanning* step, some agents attempt to modify their plans, while other agents only choose another existing plan from their plan set for the next iteration. The different strategies can be combined and weighted, so that in each iteration a certain percentage of agents use a specific strategy. The replanning strategies can be categorized as either innovative (modifying existing plans or creating new ones) or non-innovative (selecting from existing plans). The number of plans per agent is limited, so the plan with the worst score is removed from the choice set. To avoid that an agent only has very similar plans, it is possible to add a so-called *plan type* to the plan. During the removal of the worst plan, it will be checked, that at least one plan of each type remains. To relax the simulation results and come to a stable situation, the innovative strategies are switched off for the last iterations, so that the agents can only select another plan from their plan set (Horni and Nagel, 2016). Once the re-planning step is completed, the next iteration begins with the updated plans. After the predefined number of iterations has been completed, MATSim terminates with a final scoring step (Horni, Nagel, and Axhausen, 2016). The simulation output can be *analyzed*, e.g., based on the event log, which records the trajectories of individual agents and their vehicles, allowing for detailed examination of routes taken, activity times and durations, and vehicle utilization.

In the studies in Part II of this thesis, the re-planning step is not needed and thus only the initial MATSim iteration is run. The freight driver's plans are results from the tour planning and would not change or be innovated during the MATSim iteration.

Congestion, e.g., due to passenger traffic, can be taken into account without simulating these agents by using a *time-dependent network*. In this network the (free speed) travel time is changed for different time-bins in such a way that it represents the travel time during the same time-bin from an existing passenger transport simulation. Technically, this is done by using the network change events (NCEs), which modify the properties of the network, when the event is thrown (Rieser, Nagel, and Horni, 2016).

Later, in Part III, a new agent is introduced, having its own plans: the LSP. Since the LSP has different plans, so many MATSim iterations are needed that all plans are run at least once. In the latest studies the LSP gets the ability to modify (replan) its plans, as usual MATSim agents do, and thus requiring more MATSim iterations.

It is possible to simulate different modes of transport, e.g., car, walk, bicycle, taxi, and freight vehicles. The router will take into account the available modes of transport for each agent, as well as

the allowed modes on each link of the network. The network itself consists of nodes and links (Rieser, Horni, and Nagel, 2016). The nodes are described by their x and y (optional z) coordinates. They are connected by links, which derive their locations from the two nodes (from, to). The links have more properties, such as, the length, the flow capacity, the free-speed, and the allowed modes. They are one-way; a second link in the opposite direction must be defined.

In some studies of this thesis policies are investigated, that restrict the access of certain vehicle types to parts of the network, e.g., a Zero Emissions Zone (ZEZ) or a safety zone (see Chapters 9 and 11). One way to do this is to remove the network mode for the restricted vehicle types on the affected links. This has some issues, e.g., if a vehicle is already on a link and the next link is not allowed, the router vehicle will get stuck. The same occurs if the restricted vehicle starts outside the restricted area, but its destination is inside. Also, we need a different mode for each vehicle type that should be restricted and another mode for the unrestricted vehicles. Another approach is to significantly slow down these vehicle types on the affected links. This makes the router avoid these links, but if there is no alternative route, the vehicle will still be able to reach its destination. The downside of this approach is that this will also affect other vehicles on the same link. To overcome all these issues and keep the network as simple as possible, the *roadpricing contrib* (see Section 3.2.4) can be used. All the policies in this thesis that restrict the access of certain vehicle types to parts of the network (see Chapters 9 and 11) use this approach. This approach affects the routing of the vehicles as well as the scoring if the vehicle still needs to drive on the tolled links, but it neither affects the traffic dynamics on the affected links directly nor makes areas unreachable.

3.2.2 MATSim-contrib: freight

The following is a summarizing and edited version of descriptions in previously published articles: Martins-Turner and Nagel (2019); Martins-Turner et al. (2020); Ewert et al. (2021a); Richter, Martins-Turner, and Nagel (2024); Martins-Turner and Nagel (2025, 2026).

The `freight contrib` is an extension of MATSim for simulating freight transport. It now consists of two parts (packages)[4]:

1. The `Carriers` package (see Section 3.2.2.1), which contains the long-time existing *freight contrib*. It deals with solving the VRP and generating the agents' plans based on the results of the VRP solving based on the carriers.
2. The `Logistics` package (see Section 3.2.2.2), which is a new package, containing the *Logistics Service Provider (LSP)*. Its focus is on the transport of goods through a logistics network, consisting of different resources for collecting, transporting, and delivering goods. This includes the existence of hubs for reloading goods between different carriers.

3.2.2.1 Carriers package

Simulating freight transport in agent-based transport simulations is often done similarly to usual passenger transport. The drivers of the vehicles are the individual agents with fixed plans of their tours. Typically, they can only optimize their own route between the various destinations. An adjustment of the sequence within the tour is rarely performed, and moving pickups or deliveries from one agent/vehicle to another is not possible (Zilske and Joubert, 2016). Because of this, the

[4]Please note: Before adding the *logistics* package to the freight contrib, the freight contrib consists only of everything that can be found now in the *carriers* package. Thus, when talking only of the *freight contrib*, it usually means the carriers package of the freight contrib, as it had been there for many years.

tour plans are generated in advance. Depending on the available data and the research objective, there are at least two different approaches for doing this:

1. Creating the final agent's plan
2. Creating and solving a Vehicle Routing Problem (VRP)

The *first* of these approaches is used, e.g., by Lu, Martins-Turner, and Nagel (2022), setting up a long distance freight model for Germany. Starting with the demand of goods transport between different regions and an average load per truck, the number of trucks needed is calculated. The tour for each truck is a fixed origin-destination relation. The (driver) agents'plan is very short with two activities (start and end) and one leg in between. Possible replanning strategies or changes between simulation setups/iterations are therefore mainly *ReRoute* or *TimeAllocation*, allowing changes to the route between origin and destination or to the departure time. This approach can be used especially for long-distance transport and/or if no behavioral changes are needed, e.g., for the transport between two sites of one company or other fixed direct transportation relations. Such an approach was also used for an early integration of freight traffic into the MATSim Open Berlin Scenario (see Ziemke, Kaddoura, and Nagel, 2019).

The *second* approach creates and solves a VRP[5]. This VRP will contain information about the transport jobs (quantity of goods, origin and/or destination), the depot location, and the available fleet for fulfilling the requested jobs. Solving such VRPs will solve two interdependent sub-problems (Prockl, 2010; Scheuerer, 2004):

i Assignment of the transport orders to the different tours/vehicles (clustering) and

ii defining the optimal sequence of transport orders inside each tour (routing).

In the simulations, the fleet mix is left open as well, so that it is also an output of the VRP-solving process. The results also depend on the transport system, e.g., if there is congestion and/or toll(s)[6].

MATSim has a so-called component, dealing with that: the `freight contrib`. In this, *carriers* have *vehicles* as *resources*, for which they plan *tours* to fulfill their jobs. The jobs can be defined either as *services* or as *shipments*. Having services means that only the job's location needs to be reached, while shipments stand for transporting goods from a location (origin) to another (destination). More details about the different job types can be found in Section 3.3.2. Their implication on the simulation results is investigated in Chapter 6.

The main objective of MATSim freight contrib is the integration of the open source VRP-solver jsprit into MATSim (Zilske and Joubert, 2016). Thus, it is possible to start with MATSim input data, solve the VRP based on the MATSim road network with jsprit, and create the agents for the MATSim simulation. The analysis of the simulation output can be done as usual in MATSim based on the events. The event log allows analyzing the trajectories of the individual freight agents and their vehicles, e.g., to examine the routes taken, the times and durations of pickups and deliveries, or the utilization of the vehicles. Figure 3.2 shows the interaction between MATSim and jsprit.

Within the `freight` contrib of MATSim, a *carrier* represents a freight operator responsible for organizing and executing transport jobs. For each carrier, one VRP is created and independently solved. Each carrier has a set of *vehicles* with defined properties such as capacity, operating costs, and time constraints. These vehicles are assigned to *tours*, which specify the sequence of locations to visit in order to fulfill the assigned jobs. The execution of these tours is carried out by so-called *carrier agents*, which act as the drivers of the respective vehicles. These agents operate similarly to regular MATSim agents but follow pre-defined, fixed plans that originate from solving a VRP prior

[5] For an general overview please refer to Section 3.3.

[6] Tolling in MATSim is described in Section 3.2.4

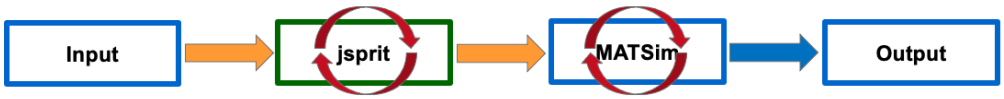


Figure 3.2: Integration of jsprit into MATSim: The input and output are in MATSim format. The MATSim freight contrib (orange arrows) is used for converting these data to and from the jsprit data. The VRP-solving is done by jsprit.

to the simulation. Their daily plan typically includes driving and freight activities, such as loading or unloading at customer locations. While route choice and departure times may still be adjusted during the simulation, the assignment of jobs to vehicles and the sequence of visits within a tour remain unchanged.

The score of a carrier agent bases on the sum of the scores of the individual activities and legs in its plan, which are calculated based on the defined scoring function. Usually, it consists of the vehicle's fixed costs (per day), the variable costs per distance, and the variable costs per time. The time for loading and unloading of goods is also part of the vehicles and drivers executed plan, and thus included. Additionally, costs , e.g., for paid tolls will be included. Since the carrier's score represents the costs for fulfilling the jobs, the score has a negative value. This is in line with the co-evolutionary algorithm of MATSim, which aims to maximize the score of all agents in the simulation, because an higher score means lower costs for the carriers.

For more detailed information about Vehicle Routing Problems (VRPs) and the open-source VRP-solver jsprit, see Section 3.3. The long-time existing *freight* contrib[7] is mainly used for the studies in Part II of this thesis. The carrier's core functionality is also included in the freight contribs (new) *logistics* packages (Section 3.2.2.2), which is the basis for the studies in Part III.

3.2.2.2 Logistics and Logistics Service Providers

As mentioned in the previous Section 3.2.2.1, one central limitation of the *carriers package* is, that each *carrier* stands for one independent VRP. So each (solved) VRP only represents one tier of a logistics network. The functionality of planning along the complete transportation chain, including hubs, is missing. Because of this, an integrated solving of, e.g., the Two-Echelon Vehicle Routing Problem (2E-VRP) is not possible.

The *logistics package*[8] addresses this. While the overall ontology and prototypical implementation of the LSPs stems from Matteis, Wisetjindawat, and Liedtke (2019), this thesis uses that framework to address practical problems. Its central agent is the LSP, which has *hubs* as resources and can recruit *carriers* to transport the goods along the complete chain from the *sender* to the *receiver*. LSPs and carriers can be vertically integrated, but do not have to.

In this thesis (see Part III), the focus is on the distribution of goods to the customers. Therefore, the (last) depot is set as origin and all the upstream logistics chain is ignored. Besides the direct transportation from the depot, the transport via a transshipment hub is also of interest. A small example of such a 2-echelon delivery is shown in Figure 3.3. In this example a large vehicle (red) transports the goods on the main run from the depot (black) to the hub (green) and returns empty. From the hub, another (e.g., smaller) vehicle (green) distributes the goods to their destination.

[7] Due to the extension of the freight contrib by including the logistics functionality, it has become the *carrier* package within the freight contrib.

[8] It was fist set up as own `logistics` contrib and has been integrated as an own package in the existing `freight` contrib.

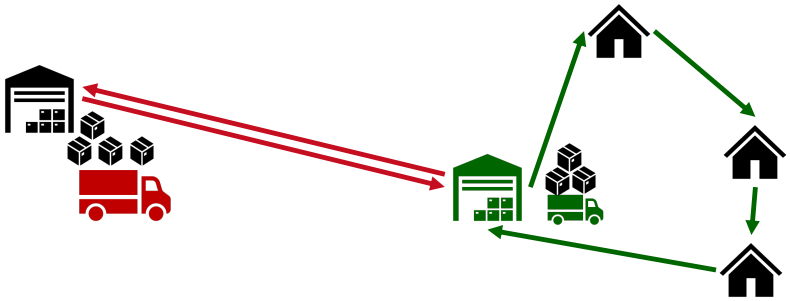


Figure 3.3: Example of a two-echelon distribution network: The large vehicle (red) transports the goods from the depot (left) to the hub (center). From there, the last-mile / distribution run is done by a smaller vehicle (green). (Source: Martins-Turner and Nagel (2025))

In earlier studies, e.g., Turner (2015), such a problem was solved by splitting it into two different sub-problems, which are solved sequentially: i) the last part from the hubs to the customer is solved as VRP or Multi-Depot Vehicle Routing Problem (MDVRP). This gives the information on the goods that are needed at each hub; ii) setting up and solving a VRP from the originating depot(s) to the hub(s), based on the result from i). This approach lacks the higher authority that is responsible for an integrated planning of the transport along the entire logistics chain: the LSP.

Logistics Service Provider (LSP) The LSP agent extends the MATSim freight contrib by introducing a higher planning level that coordinates multiple carriers and hubs along a complete transport chain (Schröder et al., 2012). While a *carrier* solves a single VRP for direct deliveries from its depot to customers, the LSP organizes multi-stage logistics networks, including transshipment at hubs (Schröder et al., 2012). This enables the simulation of 2E-VRP and other complex freight distribution concepts within the agent-based simulation framework.

In order to fulfill the job(s)[9], the LSP can select between one or more different options (*plans*). One LSP plan consists of one or more *logistics chains*, which define the path of the goods from the origin to the destination. This could be, for example, the direct delivery, the use of a more or less complex hub-and-spoke network, or a combination of both. The data structure of an LSP is shown in Figure A.1 (see Appendix A).

In the present agent-based simulation framework, the LSP is the owner of these *plans* (Matteis, Wisetjindawat, and Liedtke, 2019). The LSP's behavior is analogous to MATSim's standard person agents: it selects, executes, and scores one plan per iteration (see also Section 3.2.1 for the general MATSim approach). As in the general MATSim approach, it is also possible to have strategies to modify (replan) the LSP-plan between the iterations. This is implemented, e.g., by Richter, Martins-Turner, and Nagel (2024).

Logistics Chains A *logistics chain* defines the abstract path of a shipment from its origin to its destination, comprising the sequence of carriers and hubs involved. In this thesis, different types of logistics chains are used:

- **Direct chain**: A single carrier transports the goods directly from the depot to the customer.

[9] In the technical implementation of the LSP, a job is an `LspShipments`, which is technical close to the `CarrierShipment`, which is one job type in the carriers package (see Section 3.2.2.1. In the following the terms *job* and *shipment* are used simultaneously.

- **Two-echelon chain**: Two carriers are involved with an intermediate hub. The first carrier (main run) transports the goods from the depot to the hub, where they are unloaded and handled. The second carrier (distribution run) then delivers the goods from the hub to the customer.

These logistics chains are the representatives of the *direct link* or *hub-and-spoke* network chain as defined in Section 2.1.2. In addition to this sole type, the hybrid version (*mixed chain*) is also used in this thesis, where some goods are delivered directly and others via a hub. Other logistics chains, representing, e.g., a connected hub logistics network, can be created with this simulation framework as well, but are not part of this thesis. Each logistics chain is associated with specific carrier(s) and, if applicable, hub(s). The carrier(s) solve(s) their respective VRPs independently for the jobs assigned to them by the LSP.

LSP Plans Each LSP maintains a set of *plans*, analogous to the person agents in MATSim. A plan represents a complete strategy for fulfilling all assigned shipments using a specific configuration of logistics chains. Each plan contains at least one *logistics chain*, which defines the abstract path of the goods from the origin to the destination. The LSP can be initialized with one or multiple plans. In each MATSim iteration, the LSP executes one plan. As long as an LSP plan only consists of one logistics chain, the assignment of all shipments to this logistics chain is fixed and cannot be changed over the iteration. In the case of a mixed chain, each shipment is assigned to one of the available logistics chains of this plan. For the initial assignment to the logistics chain, different `InitialAssignmentStrategies` exist, e.g., `RandomLogisticChainShipmentAssigner`, `RoundRobinLogisticChainShipmentAssigner`, or `PrimaryLogisticChainShipmentAssigner` (see Richter, Martins-Turner, and Nagel, 2024). During the simulation, each logistics chain of the current plan is scheduled, resulting in a specific transportation schedule for each shipment. This schedule is then executed in the mobility simulation on the transportation network and logged in the events log.

Scoring To evaluate the plan, it is scored in the next step. The score of an LSP plan represents the total cost of the logistics operations scheduled and executed in this plan. It is calculated as the sum of the *carrier*'s score and the costs for using *hubs*. The *carrier*'s score includes fixed costs for all vehicles used by the carriers, variable costs per distance for all vehicle kilometers traveled, variable costs per time for driver time and vehicle operation time, and any applicable tolls or driving charges (see Section 3.2.2.1). The costs of the hubs may include hub operation costs and handling fees. In the current setup, a fixed value per day is assumed.

Replanning The LSP aims to maximize its score (= minimize its costs). This can be achieved by selecting another plan out of its plan set, by creating new, or modifying existing plans. All this is part of the *replanning* phase. This means that each LSP agent chooses in each iteration one of its replanning strategies. While non-innovative strategies only select a plan out of the existing plan set, innovative strategies create new plans, usually by copying the currently selected plan and modifying it. This plan is then selected for execution in the next MATSim iteration. The following are examples for strategies used in this thesis:

- `BestPlanSelector`: Selects the best-scoring plan from the existing plan set. This is a non-innovative strategy, used, e.g., when plan modification is not needed, because the plan consists only of one logistics chain. Additionally this strategy is used with a small probability to make

the currently best plan the selected one for execution and / or for the relaxion phase after switching off the innovative strategies.

- `RandomShipmentShiftingModule`: The innovative strategy in this module creates a copy of the current plan and shifts one randomly selected shipment from one logistics chain to another logistics chain within the same plan. This allows the LSP to explore different assignments of shipments to the different logistics chains.

There are other strategies implemented in the `logistics` package and in MATSim's core functionality. Moreover, it is possible to create own StrategyModules and add them to the LSP.

Since the size of each agent's plan set is limited (typically to 5 plans), the worst-scoring[10] plan is removed when the limit is exceeded. To preserve at least structurally different plans, the *plan types* are used to ensure that at least one plan of each type is kept in the plan set. This refers, e.g., to plans representing either a direct link, a hub-and-spoke, or a hybrid logistics network, by implementing a direct chain, a 2-echelon chain, or a mixed chain as described above.

Now, after replanning, the carriers associated with the modified plan re-solve their VRPs to schedule their tours based on the current job assignments, leading to a new schedule for each vehicle and each shipment. The LSP then executes the plan and updates its plan set based on the scores obtained. This co-evolutionary approach allows the LSP to iteratively improve the use of its logistics chains for fulfilling the transportation jobs.

3.2.3 MATSim-contrib: emissions

The *emissions contrib* enables the calculation of exhaust and non-exhaust emissions while driving (see Section 2.2.2) within the agent-based traffic simulation framework MATSim.

Emission factors are derived from the Handbook on Emission Factors for Road Transport (HBEFA) database (INFRAS, 2019, see Section 2.2.2.3), which provides pollutant-specific data for a wide range of vehicle and traffic conditions. These pollutants include carbon dioxide (CO_2), nitrogen oxides (NO_x), particulate matter $< 10\,\mu m$ (PM_{10}), particulate matter $< 2.5\,\mu m$ ($PM_{2.5}$), black carbon (BC), among others. The emission factors are differentiated by the following criteria:

- vehicle category and engine technology,
- road type,
- allowed free-flow speed,
- traffic state (e.g., free-flow, congested),
- and, optionally, engine temperature states (cold start vs. warm start).

In MATSim, each vehicle's trajectory is fully tracked through the transport network, including precise timestamps for entering and leaving a link. Because of the agent-based simulation approach, traffic congestion emerges from interactions among agents, allowing the model to capture time-dependent traffic states on each network link. This is done by comparing the actual speed of the vehicle on the link with the link's free-flow speed defined in the network. The network links are also classified into different road types, such as motorways, urban roads, etc., that can be used to map the link to the corresponding road type in the HBEFA database. Consequently, the emissions module computes emissions dynamically based on the actual speed and traffic conditions experienced by each vehicle on each specific link. These conditions are mapped to the speed conditions defined in the HBEFA database (INFRAS, 2019, see also Section 2.2.2.3).

[10] There are also other selection strategies available

The modular design of the *emissions contrib* allows for integration with various MATSim scenarios and datasets, supporting detailed environmental impact assessments in both passenger and freight transport simulations.

A comprehensive description of the emissions modeling methodology implemented in MATSim is given in Kickhöfer (2016); Hülsmann et al. (2011).

In this dissertation, all calculations of the driving emissions, using the HBEFA database, are done with HBEFA version 4.1 for Germany (see INFRAS, 2019). For all situations where the vehicle's speed is between two traffic state conditions, the emissions are calculated as a mix of the two traffic states, assuming a part of the link is driven with one state and the other part with the other state. This approach is described in (Hülsmann et al., 2011)[11].

For Heavy Goods Vehicles (HGVs), this database only provides *average* emission factors for different vehicle categories. These are not sufficient for detailed modeling of freight transport because they do not differentiate between different vehicle sizes. This is okay for small vehicles like cars or Light Commercial Vehicle (LCV), but for HGVs with a Gross Vehicle Weight Rating (GVWR) between 7.5 ton (t) and 40 t, it is not sufficient. On the other hand, the HBEFA database provides detailed emission factors for the different size classes, but this also requires defining the vehicle's emission concept, e.g., Euro 6, Euro 5, etc. This level of detail from the database is not included in our simulation because we only define the vehicle's size class. Everything beyond that is not known, so an average vehicle of this size class is assumed.

To deal with that, a refined set of emission factors is calculated for our simulation context. These modifications are described in detail in Gable, Martins-Turner, and Nagel (2022), presenting the methodology and resulting database extensions used to improve emission modeling for freight scenarios in MATSim. The approach can be summarized as follows: The detailed values of the HBEFA database are used to calculate weighted average emission factors for each vehicle size class, considering the shares of different engine technologies and emission standards included in the HBEFA database. This results in a new set of emission factors that better represent the average emissions of vehicles within each size class, while still accounting for the diversity of technologies and standards present in the real-world vehicle fleet. These enhanced emission factors are used for the vehicle-specific emission calculations presented in the different studies in this thesis (see Chapters 7, 8, and 11).

3.2.4 MATSim-contrib: roadpricing

For this thesis another MATSim extension is used: the *roadpricing contrib*. With this contrib, it is possible to add tolling schemes to a MATSim scenario. The following is a short description of the relevant parts for the thesis. It is based on the corresponding chapter by Nagel (2016) in the MATSim book (Horni, Nagel, and Axhausen, 2016), as well as on the codebase on GitHub[12]. Please look there for more information.

A road-pricing scheme contains a list of *links* in the road network that are tolled, allowing only certain parts of the network to be tolled. Moreover, one or more time-windows can be defined in which the tolling is active. The tolled value can be set specifically for each time-window.

A main setting controls the calculation method of the toll:

[11] Current and ongoing investigations at out department indicate that this approach may lead to an overestimation of emissions when driving at higher speeds on motorways (Papis and Nagel, 2025).

[12] see https://github.com/matsim-org/matsim-libs/tree/main/contribs/roadpricing

- link-based: The toll value is charged every time a vehicle enters a tolled link. If a vehicle drives on the same tolled link multiple times during the day, it is charged every time (again).
- distance-based: The toll value is multiplied by the length of the link. This calculation gives the amount charged for driving on that link.

To implement a *cordon* toll, all (usual) *inbound* links creating the cordon must be defined in the (link-based) tolling scheme. All links inside the cordon *must not* be part of the tolling scheme, to avoid multiple tolling when driving inside the cordon. For the *distance-based* approach, *all* links on which the vehicles should be tolled must be defined. This may be an area or several, connected links.

It is possible to apply the tolling schemes in a *vehicle-type specific* manner. The easiest way is to use a toll factor for each vehicle type. A factor of one means that the vehicle is charged the full toll value, a factor of zero means that the vehicle is not charged at all. The factor is not limited to the range between zero and one, but it should be a positive value.

As already mentioned above (see Section 3.2.1), this road-pricing approach makes it is very easy to introduce, e.g., a Low Emission Zone (LEZ) or ZEZ, by charging, e.g., all Internal Combustion Engine Vehicles (ICEVs), or to implement a ban on certain vehicle type(s). For a ban or access restriction, the toll value for this vehicle type needs to be set to a prohibitively high value. This approach is used, e.g., for the studies in Chapters 9 and 11.

3.3 Solving Vehicle Routing Problems

Planning tours is an important step for commercial transport simulations. It will answer the questions which job(s) will be on which tour, with which vehicle (type), and in which sequence the jobs of each tour will be served.

This section gives a brief overview of Vehicle Routing Problems (VRPs) (see Section 3.3.1) and the VRP solving software jsprit (see Section 3.3.2). This overview is an edited summary of descriptions in previously published articles, see, e.g., Martins-Turner and Nagel (2019); Martins-Turner et al. (2020); Ewert et al. (2021a); Martins-Turner and Nagel (2025). For more information about the integration of jsprit into MATSim, please refer to Section 3.2.2.1.

3.3.1 Vehicle Routing Problems

Vehicle Routing Problem The VRP, as defined by Irnich, Toth, and Vigo (2014), involves formulating a plan to "determine a set of vehicle routes to perform [...] transportation jobs with the given vehicle fleet at minimum costs" (Irnich, Toth, and Vigo, 2014). Solving the VRP addresses two principal sub-problems: i) job allocation to tours (clustering) and ii) optimal job sequencing within each tour (routing) (Prockl, 2010; Scheuerer, 2004).

Developing optimal vehicle routing solutions for transportation companies relies on internal and external factors. Internally, critical considerations include depot locations and fleet resources, with each vehicle type having distinct attributes like carrying capacity and cost structures (jsprit, 2024). Externally, crucial specifications revolve around customer requisites such as cargo volume, type, delivery locations, and temporal constraints (Cerwenka, 2007). Additionally, external constraints like road networks, traffic patterns, tolls, and regulations significantly influence route optimization strategies (Cerwenka, 2007). Congestion can decrease service quality and increase the transportation costs for the carrier(s). Nevertheless, congestion is usually not considered in urban tour planning (Ehmke, 2012).

Types of Vehicle Routing Problems The following briefly summarizes some of the various (sub-)types of VRPs that emerged over time. Besides the following summary, more detailed information regarding different types of VRPs can be found, e.g., in the work by Irnich, Toth, and Vigo (2014) — included in Toth and Vigo (2014) — or by Scheuerer (2004); jsprit (2024). A more detailed overview of related literature regarding the 2E-VRP can also be found in Section 9.2.

Among the foundational variants, the Capacitated Vehicle Routing Problem (CVRP) enforces vehicle capacity limits (see, e.g., Semet, Toth, and Vigo, 2014). Adding service time restrictions leads to Vehicle Routing Problem with Time Windows (VRPTW), coupling routing and scheduling of jobs (Desaulniers, Madsen, and Ropke, 2014). The Multi-Depot Vehicle Routing Problem (MDVRP) extends the classical setting to several geographically distributed depots, reflecting, e.g., large-scale distribution networks (Jayarathna, 2024). Combining the delivery and pickup of jobs leads to the Vehicle Routing Problem with Pickup and Delivery (VRPPD), which introduces additional complexity in terms of route planning and resource allocation, especially when considering time windows and vehicle capacities (Battarra, Cordeau, and Iori, 2014). Considering different available vehicle types leads to Mixed Fleet Vehicle Routing Problem (MFVRP) (also called Heterogeneous VRP), introduced by Golden et al. (1984). Once an unlimited number of vehicles is available, the Fleet Size and Mix Vehicle Routing Problem (FSMVRP) is obtained, which allows optimizing the fleet size and composition (Golden et al., 1984; Baldacci, Battarra, and Vigo, 2008). Combining this with electric vehicles and their recharging needs leads to a VRP described as Electric Fleet Size and Mix Vehicle Routing Problem with Time Windows and Recharging Stations (E-FSMFTW) (Hiermann et al., 2016).

Hierarchical distribution structures are captured by the 2E-VRP, in which first-tier vehicles move goods from a central depot to an intermediate hub and second-tier vehicles execute the final-mile deliveries. Relevant 2E-VRP types and their history in the context of city logistics are summarized by Oliveira, Ramos, and de Sousa (2022). According to them, Perboli, Tadei, and Vigo (2008) give the first formal definition of a Two-Echelon Capacitated Vehicle Routing Problem (2E-CVRP), while Crainic, Ricciardi, and Storchi (2004, 2009) are said to be the first to address the application of the two-echelon distribution systems in the context of city logistics. Many extensions have been proposed, e.g., the 2E-VRP with simultaneous pickup-delivery (2E-VRPSDP) (Dethloff, 2001; Liu and Jiang, 2021) or the Two-Echelon Vehicle Routing Problem with Time Windows (2E-VRPTW). Caggiani et al. (2020) solve the Two-Echelon Electric Vehicle Routing Problem with Time Windows and Partial Recharging (2E-EVRPTW-PR), considering electric vehicles on both the first and second tier. The usage of delivery robots or unmanned vehicles on the second tier has been explored, e.g., by Bakach, Campbell, and Ehmke (2021) and Yu, Puchinger, and Sun (2020).

3.3.2 The Vehicle Routing Problem Solver jsprit

One toolkit for solving VRPs is jsprit. It is an open-source library written in Java and available on GitHub (jsprit, 2024). Jsprit can solve many VRP variants, e.g., MDVRP, time restrictions, capacity constraints, infinite fleets, including the FSMVRP. The algorithm of jsprit is based on an iterative approach using the ruin-and-recreate principle from Schrimpf et al. (2000). The aim of jsprit is to reduce the costs for the carrier. Costs can be, e.g., fixed costs for the vehicle, including depreciation, insurance, and maintenance; variable cost for distance and time a vehicle is on tour; or other costs such as tolls or penalties for missed time windows (jsprit, 2024). Jsprit can be integrated into MATSim to solve VRPs on time-dependent road networks with vehicle type specific

cost values (see, for example, Martins-Turner et al., 2020; Ewert et al., 2021b). This integration is done via MATSim's *freight contrib*, as described in Section 3.2.2.1.

There are two different types of jobs that can be defined in jsprit:

- *service*: This job has only one location where it takes place. The other location is (one of) the depot(s).
- *shipment*: This job has two locations: one for the pickup and one for the delivery.

For more results and consequences of changing the two job types, please refer to Chapter 6.

Service The huge advantages of *services* are i) the possibility to solve Multi-Depot Vehicle Routing Problems (MDVRPs), letting the algorithm decide from which depot a job gets done; ii) fast computation because the capacity constraint only needs to check the sum of all job sizes and whether it satisfies the vehicle's capacity restriction. The main disadvantage is that there is no reloading of goods during a single (delivery) tour[13]. As a consequence, a tour is limited by the vehicle's capacity. Even if there are more open jobs and enough time left for the vehicle, it cannot go out for a second (sub-)tour. The algorithm will create another tour with another vehicle, leading to higher costs (due to the fixed-cost components) and a solution where too many tours are driven in parallel instead of sequentially. Another missing aspect is that it is not possible to define any duration for handling the goods at the depots.

Shipment Shipments have the huge advantage that they define a VRPPD. This allows for intermediate un-/reloading of goods during the tour and therefore also for a return of the vehicle to the depot, and starting another (sub-)tour with the same vehicle (and driver). Because both locations are set in the job, it is *not* possible to solve MDVRPs. Furthermore, due to the reloading option, it is necessary to check that the capacity restriction is met for each point of the tour, leading to a much longer computation time of the algorithm.

[13] or vice versa: unloading of goods during a collection tour

CHAPTER 4

Scenarios

For the various (case) studies in this thesis, different scenarios are used. This chapter gives an overview of each of these scenarios and their usage in the following studies. Depending on the study, more detailed information can be found in the corresponding chapter. The scenarios mainly used in this thesis are:

- Supplying shops of the food retailing industry in Berlin, Germany (Section 4.1): Chapters 6 to 8, 10, and 11,
- Parcel delivery in the Wilmersdorf district of Berlin, Germany (Section 4.2): Chapter 6,
- Grid scenario (Section 4.3): Chapter 9.

The first two scenarios originate from other authors and are used in an adapted version. The grid scenario is an academic example of proof-of-concept studies.

4.1 Berlin Food Retailing scenario

The Berlin food retailing scenario deals with supplying food retailing shops with the goods they need. It is located in Berlin, the capital and largest city in Germany. It includes 1′928 jobs at 867 food retailing shops. The shops belong to 15 retailing companies in Berlin, with 17 distribution centers in and around Berlin. The original scenario was developed and published by Schröder and Liedtke (2014). This scenario is based on the model of Schröder and Liedtke (2014).

Figure 4.1 shows the location of the shops and distribution centers (depots).

The scenario was originally used to investigate various measures, such as tolling heavy trucks for entering the environmental zone. The shops' demand is the demand of an average day. Each shop offers various heterogeneous products to their consumers, which require different transport conditions. The products are grouped into three categories: fresh, frozen, and dry. This results in $15\ companies \cdot 3\ product\ groups = 45\ carriers$ in the model. That is, "fresh", "frozen", and "dry" are transported by different carriers (Schröder and Liedtke, 2014). As mentioned in Section 3.3.2, each carrier defines its own, independent Vehicle Routing Problem (VRP), with its own fleet available. The available vehicle types in the fleet of a carrier depend on the product group and the business

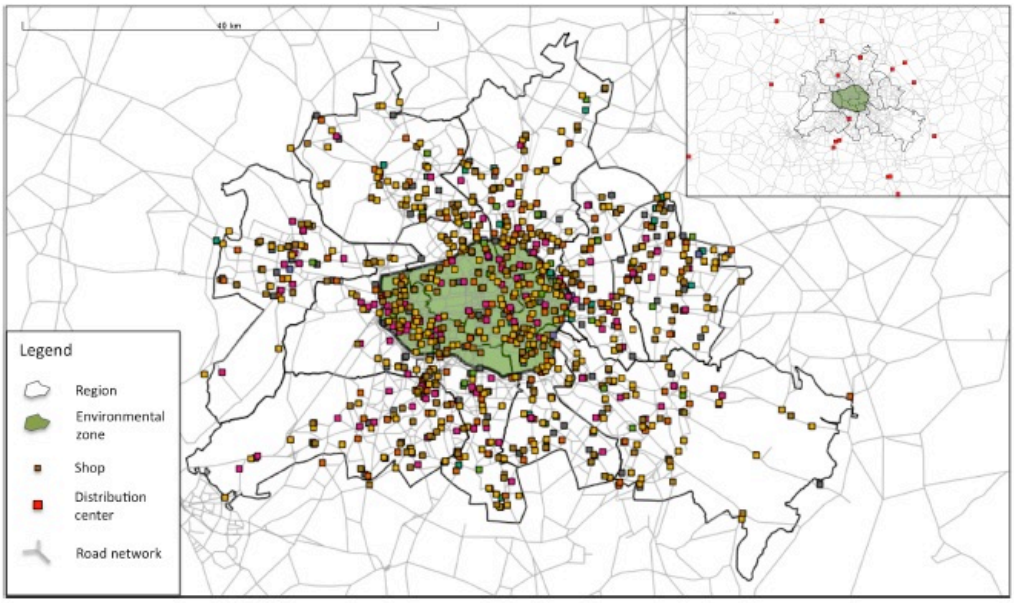


Figure 4.1: The original Berlin food retailing scenario by Schröder and Liedtke (2014): Location of shops and distribution centers.

type of the company. In total, there are four different vehicle sizes available: 7.5 ton (t), 18 t, 26 t, and 40 t Gross Vehicle Weight Rating (GVWR). Furthermore, some retail companies have more than one depot for supplying their shops (Schröder and Liedtke, 2014).

In the original Berlin food retailing scenario, the time-windows for delivering the goods to the shops are defined depending on the type of product (Schröder and Liedtke, 2014):

- **Fresh** products are delivered in a time-window of [4am – 9am].
- **Frozen** and dry products are delivered either in a time-window of [9am – 2pm] ("morning") or [2pm – 7pm] ("afternoon"). For each delivery, the time-window is randomly assigned.

In this model, the demand of the different shops is represented by the activity type "service". As mentioned in Section 3.3.2, it is possible to model it as a Multi-Depot Vehicle Routing Problem (MDVRP). As a consequence, each vehicle only drives one tour from the depot to the assigned shops and returns to the depot. Since the vehicles cannot reload goods, they cannot be "reused", e.g., a vehicle that was used for dry products between 9am and 2pm can neither be used for another tour in the same (morning) time-window, nor for a tour in the afternoon. As a result, many more vehicles are needed than necessary for supplying all shops. Due to the underlying cost model with fixed costs for each employed vehicle, this leads to an inefficient solution with too high costs (Martins-Turner and Nagel, 2019).

In the context of this thesis and for further investigations, the original scenario by Schröder and Liedtke (2014) has been updated. Besides some minor changes like updating the road network, there were some major updates. This includes solving the issue with the missing "reusability" of vehicles during a day (see Chapter 6). After that change, it was possible to ease that separation into a morning and an afternoon delivery time-window. As a result, the delivery time-windows for dry and frozen goods are set to [9am – 7pm], for fresh goods it is set to [4am – 9am].

Other updates regarding the cost structure of the vehicle types (see Chapter 5) and, e.g., the introduction of Battery Electric Vehicles (BEVs) are part of the further investigations:

- Replacement of Internal Combustion Engine Vehicles (ICEVs) by BEVs (Chapter 7),

- Introducing taxes on greenhouse gas (GHG) emissions (Chapter 8),
- Converting it into a 2-echelon delivery system in combination with access restrictions (Chapters 10 and 11).

In all the studies, there was no change in the location of the depots or the demand (location and quantity) of the shops. The assignment of depots and shops to the different carriers remains unchanged, too.

For these studies, the network was updated to the network of the MATSim Open Berlin scenario[1] version 5.5 (Ziemke, Kaddoura, and Nagel, 2019). In the studies, the focus is on the freight transport, so the passenger traffic is not considered. Nevertheless, it is possible to use a time-dependent network for the tour planning, representing the travel times as they were observed in the simulation output of the MATSim Open Berlin scenario. This is done using so-called *network change event (NCE)* (Rieser, Nagel, and Horni, 2016).

4.2 Parcel delivery scenario Berlin-Wilmersdorf

Another scenario used in this thesis is a scenario dealing with the Courier, Express, and Parcel (CEP) field. It deals with the last-mile parcel delivery on an average day in one district of Berlin. The district of Wilmersdorf is located next to the city center. The main data for this scenario were taken from Zhang et al. (2018). The scenario consists of 1′217 jobs, with a demand of 1–12 parcel(s) each. In total there are approximately 3′700 parcels to be delivered — either to private or commercial customers. The private customers should receive their parcels between 9am and 5pm, while the commercial customers have a delivery time-window between 9am and 6pm. Figure 4.2 shows the location of the jobs and the distribution center (depot).

This scenario is used for the study in Chapter 6, regarding the "reusability" of vehicles. For that study, the following two cases are considered:

- Base case (A): Distribution of all parcels directly from the (one) distribution center (DC) by light parcel delivery trucks, and
- Policy case (B): Commercial parcels are first delivered from the DC to given micro depots by light parcel delivery trucks, and from there delivered to the customers by cargo bicycles. Parcels to private recipients are still directly delivered by cargo vehicles from the DC.

The key values of the vehicles used in this scenario are summarized in Section 5.2

For both cases, two simulations are run. One *service*-based (reference scenarios: only one tour per vehicle per day), and one *shipment*-based (policy scenarios: vehicles can reload within the tour). In contrast to the food retailing scenario (see Section 4.1), no adjustment of delivery time windows or vehicle availability was required, as the original study by Zhang et al. (2018) did not define any manual shifts.

4.3 Grid scenario

The grid scenario is a small scenario for proof-of-concept studies. It is openly available in matsim-examples.[2] This section provides only the relevant information on the network configuration. Further

[1] https://github.com/matsim-scenarios/matsim-berlin

[2] https://github.com/matsim-org/matsim-libs/tree/master/examples/scenarios/freight-chessboard-9x9

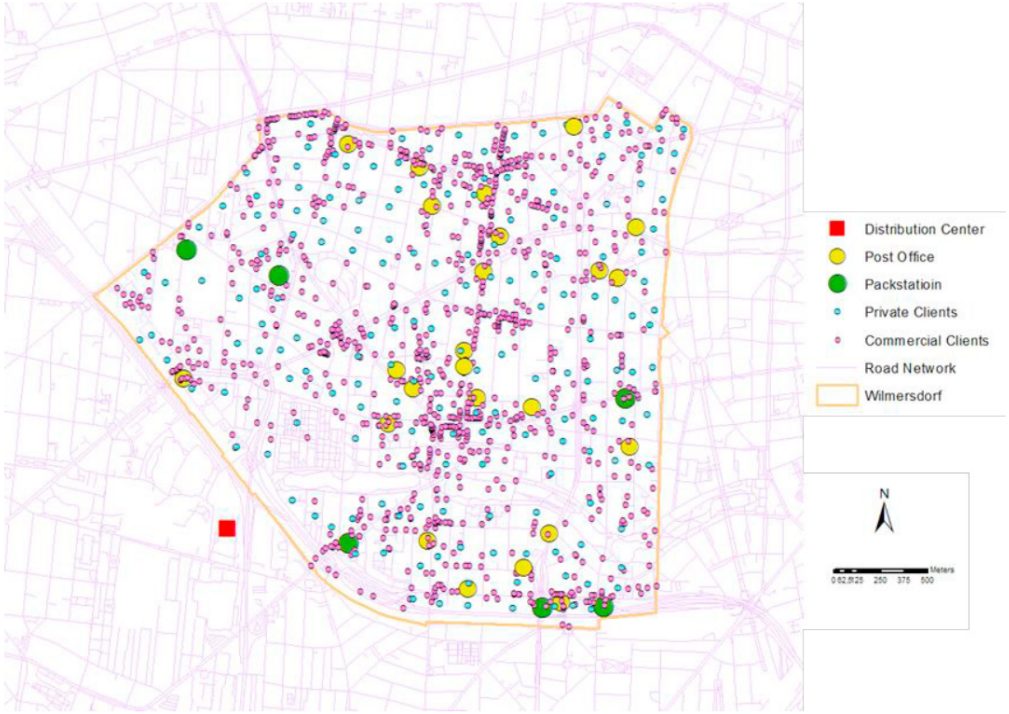


Figure 4.2: The original Parcel delivery scenario (Berlin-Wilmersdorf) by Zhang et al. (2018): Road network and locations of jobs and distribution center.

details are presented in the application case in Chapter 9. The following description is adapted with minor changes from Martins-Turner and Nagel (2025).

The network (see Figure 4.3) consists of 9×9 links. Each link has a length of $\ell = 1\,\text{km}$ and is one-way. As one can see, each link is a continuous connection with alternating directions. The free speed on each link is constant at $v = 30\,\text{km/h} = 8.333\,\text{m/s}$, resulting in a free speed travel time of $tt_{\text{free}} = \ell/v = \frac{1\,\text{km}}{30\,\text{km/h}} = 120\,\text{s}$.

This scenario is used in Chapter 9 to model the Two-Echelon Vehicle Routing Problem (2E-VRP). The locations of the depot, the hub, and the customers are described there in more detail, since they depend on the specific study.

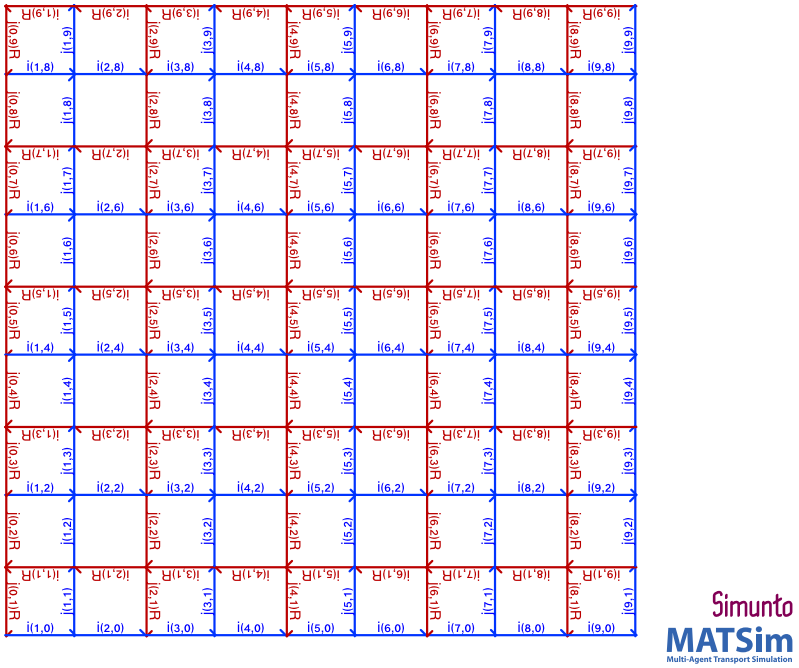


Figure 4.3: Road network of the 9 × 9 grid scenario. All roads are one-way. Blue indicates positive direction; red indicates negative (return) direction.

CHAPTER 5

Vehicle Parameters

Solving Vehicle Routing Problems (VRPs) is an important step in the studies of this thesis. For solving such VRPs, different parameters for the vehicle type are necessary (see also Sections 3.2.2.1 and 3.3). These are the *capacity* and the *cost parameters*. For the majority of the studies, these cost parameters have been recalculated using a transport cost calculation (TCC) based on the methodology of the German Bundesverkehrswegeplan (BVWP). In this chapter, the TCC methodology is presented and applied in Section 5.1. For the first study in this thesis, vehicle parameters *without* a self-conducted TCC are used. They are listed in Section 5.2. Finally, Section 5.3 gives an overview of the vehicle types and their usage in the different studies of this thesis.

5.1 Calculation of cost parameters

As an overview, this chapter is based on and summarizes the descriptions presented in Martins-Turner et al. (2020); Ewert et al. (2021a) (see also Chapters 7 and 8).

For the first electrification study in this thesis (see Chapter 7) based on the food retailing scenario (see Section 4.1) by Schröder and Liedtke (2014), the cost calculation for the vehicle types has been updated. This was done, among other things, to achieve comparability between the base case with Internal Combustion Engine Vehicles (ICEVs) and the updated Battery Electric Vehicles (BEVs).

To obtain values for the variable (distance-dependent), the fixed, and the personnel (time-dependent) cost parameters, a TCC is carried out. The methodology for the TCC itself and many input values are (now) based on the German BVWP (BMVI, 2016). One assumption is that the purchase cost of the vehicles is depreciated half by time and half by driven distance. Data for representative vehicle types are given in Planco, ITP, and TUBS (2015); the numbers include driver wages. Since the BVWP has a national economic perspective, taxes and insurance are not included in the cost calculation (PTV, TCI, and Mann, 2016). For calculating the time-dependent transport costs, the driver wages for representative vehicle types are also given in Planco, ITP, and TUBS (2015). In contrast to the national assessment of the BVWP, taxes (except the Value Added Tax (VAT)) and insurances are relevant for the carrier. For this reason, we have to consider

these cost components in our TCC. Therefore, we use the data provided by Eurotransport (2017). Furthermore, we are assuming 250 workdays per year (Planco, ITP, and TUBS, 2015) and a use phase of 11 years (Planco, ITP, and TUBS, 2015) for the vehicles.

For the energy costs, we started with the values from PTV, TCI, and Mann (2016). They assume a diesel price of 0.71 €/liter (l) and an electricity price of 0.1816 €/kilowatt hour (kWh). As stated before, the BVWP does not include taxes. Adding these values (without VAT), as well as other components such as a profit margin, follows the data given in (PTV, TCI, and Mann, 2016). This results in a price of 1.23 €/l for diesel and 0.22 €/kWh for electricity.

5.1.1 Internal Combustion Engine Vehicles (ICEV)

We use the following vehicle types from Planco, ITP, and TUBS (2015) for the base scenario with ICEVs:

- **light − 7.5 ton (t)**: Mercedes Atego 818L / MAN TGL 12.220 BL
- **medium − 18 t**: MAN TGX 18.440 XLX
- **heavy − 26 t**: Mercedes Actros 2544 LL
- **heavy (with trailer) − 40 t**: MAN TGM 18.340 BL + Trailer 7.75 meter (m)

As stated above, some minor adaptations of the cost calculation are made to consider taxes and insurance, while most values are taken from the corresponding tables in Planco, ITP, and TUBS (2015). The calculation tables for the different vehicle types are given in Appendix B. The resulting cost structure for all ICEV types used as input for the VRP is summarized in Table 5.1.

In Chapter 8, the impact of a carbon dioxide (CO_2) tax on the vehicle costs is analyzed. For this, the variable costs per distance are adapted to include the additional costs from the CO_2 tax. The resulting changes of the variable costs per distance are described in the corresponding study (see Section 8.3.2).

5.1.2 Battery Electric Vehicles (BEV)

We introduce BEVs of the same GVWR as the already existing ICEVs to all carriers. The battery size is chosen in a way that the maximum payload is equal for the ICEVs and BEVs.

It has to be taken into account that, according to the European Parliament and Council (2015), within the European Union (EU) an additional t on the GVWR is allowed for medium and heavy trucks and up to two additional t for heavy trucks with a trailer when using a clean propulsion system. We assume that only 70 % (e.g., from 10 % to 80 %) of the theoretical battery capacity is used in order to ensure an adequate battery life. According to Rehman et al. (2016), this is rather conservative.

To calculate the possible ranges, consumption data for electric trucks currently available on the market are chosen. This leads to consumption specifications of 61 kWh/100 km for the light truck, 106 kWh/100 km for the medium truck, 150 kWh/100 km for the heavy truck, and 180 kWh/100 km for the heavy truck with trailer. These specifications are supported by findings of current publications such as Gao, Lin, and Franzese (2017). With these specifications, we calculate possible distance ranges of 100 km for the 7.5 t truck, 80 km (18 t), 133 km (26 t), and 172 km (40 t).

Table 5.1: Characteristics for the different ICEV types used in the food retailing scenario studies. The cost parameters are used as inputs for the tour planning. The average energy consumption, the energy costs per 100 kilometer (km), the range, and the payload capacity are provided as additional information. Vehicles with a Gross Vehicle Weight Rating (GVWR) of 7.5 t and 26 t are used for frozen goods.

vehicle type	parameter	Base: ICEV
7.5 t	fixed costs (€ /day)	63.49
	variable costs per distance[1] (€ /m)	0.00040
	variable costs per time[2] (€ /s)	0.00490
	energy consumption (per 100 km)	13.57 l
	energy costs (€ /100 km)	16.69
	range (km)	(unlimited)
	payload capacity (pallets)	10
	payload capacity frozen goods (boxes)	70
18 t	fixed costs (€ /day)	80.47
	variable costs per distance[1] (€ /m)	0.00065
	variable costs per time[2] (€ /s)	0.00490
	energy consumption (per 100 km)	33.12 l
	energy costs (€ /100 km)	40.74
	range (km)	(unlimited)
	payload capacity (pallets)	16
26 t	fixed costs (€ /day)	82.60
	variable costs per distance[1] (€ /m)	0.00067
	variable costs per time[2] (€ /s)	0.00490
	energy consumption (per 100 km)	33.12 l
	energy costs (€ /100 km)	40.74
	range (km)	(unlimited)
	payload capacity (pallets)	24
	payload capacity frozen goods (boxes)	160
40 t	fixed costs (€ /day)	126.58
	variable costs per distance[1] (€ /m)	0.00069
	variable costs per time[2] (€ /s)	0.00559
	energy consumption (per 100 km)	37.45 l
	energy costs (€ /100 km)	46.06
	range (km)	(unlimited)
	payload capacity (pallets)	33

[1] The variable costs per distance include the energy costs.
[2] The variable costs per time are the personnel costs.

The costs for electric vehicles are strongly driven by the battery. Therefore, we consider the prices for the chassis and for the battery separately. For the chassis, market analysis shows that current electric chassis are about 1.6 times as expensive as ICEV chassis. According to Fuessel (2017), the prices for a BEV chassis will approach the prices for ICEV as soon as mass production picks up pace. Therefore, we will consider

i) the current situation[1] with a 60 % price increase from ICEV to BEV chassis (case A: BEV 160) and

ii) the possible future situation with equal chassis prices as a sensitivity analysis (case B: BEV 100).

The cost of commercial vehicle batteries is significantly higher than that of batteries for private vehicles (IKT für Elektromobilität, 2015). Following IKT für Elektromobilität (2015) and our own analysis of the current market for commercial BEVs, we choose a battery price of 600 €/kWh. Furthermore, we set the possible lifetime charging cycles to 4′000 and specific energy density to 0.15 kWh/kilogram (kg) at pack level according to Göhlich, Fay, and Park (2019). Due to the possible charging cycles, no battery change is required in the presumed use phase of the vehicles

[1] The original study and thus the calculation are from 2019.

(11 years, 250 days of use per year), even with an average of more than one charging event per day. Thus, the battery costs are considered as fixed costs.

We use the following vehicle types for the BEV in the electrification scenario:

- **light – 7.5 t**: Orten E75 TL – 87 kWh
- **medium – 18 t**: Orten E 180 AX – 122 kWh
- **heavy – 26 t**: FE electric – 286 kWh
- **heavy (with trailer) – 40 t**: EForce – 443 kWh + Trailer 7.75 m

The resulting cost structure for all BEV types used as input for the VRP is summarized in Table 5.2.

Table 5.2: Characteristics of the different BEV types used in the food retailing scenario studies. The cost parameters are used as inputs for the tour planning. The average energy consumption, the energy costs per 100 km, the range, and the payload capacity are provided as additional information. Vehicles with a GVWR of 7.5 t and 26 t are used for frozen goods. The two cases, A and B, represent different assumptions for the chassis costs: BEV 160 means that the chassis is 60 % more expensive than the chassis of same-size ICEV, while BEV assumes equal chassis prices as for the ICEV.

vehicle type	parameter	A: BEV 160	B: BEV 100
7.5 t	fixed costs (€ /day)	81.04	74.76
	variable costs per distance[1] (€ /m)	0.00051	0.00046
	variable costs per time[2] (€ /s)	0.00490	0.00490
	energy consumption (per 100 km)	61 kWh	
	energy costs (€ /100 km)	13.52	
	range (km)	100	
	payload capacity (pallets)	10	
	payload capacity frozen goods (boxes)	70	
18 t	fixed costs (€ /day)	107.43	96.26
	variable costs per distance[1] (€ /m)	0.00061	0.00055
	variable costs per time[2] (€ /s)	0.00490	0.00490
	energy consumption (per 100 km)	106 kWh	
	energy costs (€ /100 km)	23.49	
	range (km)	80	
	payload capacity (pallets)	16	
26 t	fixed costs (€ /day)	132.14	111.90
	variable costs per distance[1] (€ /m)	0.00076	0.00072
	variable costs per time[2] (€ /s)	0.00490	0.00490
	energy consumption (per 100 km)	150 kWh	
	energy costs (€ /100 km)	33.24	
	range (km)	133	
	payload capacity (pallets)	24	
	payload capacity frozen goods (boxes)	160	
40 t	fixed costs (€ /day)	192.80	183.93
	variable costs per distance[1] (€ /m)	0.00080	0.00078
	variable costs per time[2] (€ /s)	0.00559	0.00559
	energy consumption (per 100 km)	180 kWh	
	energy costs (€ /100 km)	39.89	
	range (km)	172	
	payload capacity (pallets)	33	

[1] The variable costs per distance include the energy costs.
[2] The variable costs per time are the personnel costs.

Table 5.3: Characteristics for the different vehicle types used in the original food retailing scenario studies by Schröder and Liedtke (2014); Gabler et al. (2013). The cost parameters are used as inputs for the tour planning.

vehicle type	parameter	ICEV	BEV
7.5 t	fixed costs (€ /day)	80.00	89.00
	variable costs per distance (€ /m)	0.00047	0.0005
	variable costs per time (€ /s)	0.008	
	energy consumption (per 100 km)	20 l	—
18 t	fixed costs (€ /day)	107.00	112.00
	variable costs per distance (€ /m)	0.00061	0.00055
	variable costs per time (€ /s)	0.008	
	energy consumption (per 100 km)	25 l	—
26 t	fixed costs (€ /day)	130.00	n.a.
	variable costs per distance (€ /m)	0.00077	
	variable costs per time (€ /s)	0.008	
	energy consumption (per 100 km)	30 l	
40 t	fixed costs (€ /day)	140.00	n.a.
	variable costs per distance (€ /m)	0.00086	
	variable costs per time (€ /s)	0.008	
	energy consumption (per 100 km)	35 l	

5.2 Vehicle types from other studies

The first study of this thesis (see Chapter 6) uses the original vehicle types and their cost parameters from the food retailing scenario by Schröder and Liedtke (2014); Gabler et al. (2013). This study was done before the electrification studies based on the updated cost calculation. The values are summarized in Table 5.3[2]. In this dataset only vehicles with a GVWR of up to 18 t are available as BEVs. The range of the vehicles, as well as the energy consumption of the BEV were not reported.

For the parcel delivery scenario (see Section 4.2) used in the study in Section 6.4, the vehicle types from the original scenario by Zhang et al. (2018) are used. These values were neither recalculated nor updated. They are summarized in Table 5.4.

Table 5.4: Characteristics for the different vehicle types used in the parcel delivery scenario. The values are taken from Zhang et al. (2018). The cost parameters are used as inputs for the tour planning.

Parameter	Parcel Truck	Cargo Bike
fixed costs (€ /day)	48.7869	3.2673
variable costs per distance[1] (€ /m)	0.000370807	0.000103
variable costs per time[2] (€ /s)	0.00627778	0.003333
permissible total weight	3.5 t	370 kg
energy consumption (l per 100 km)	11.2	–
maximum capacity (parcels)	230	23

[1] The variable costs per distance include the energy costs.
[2] The variable costs per time are the personnel costs.

Furthermore, for the proof-of-concept study in Chapter 9, we use a simplified vehicle type, allowing only for a differentiation between small and large vehicles. The values (see Table 5.5) are set manually and are not based on real values.

[2]Please note that the values of the BEVs were not published in the original studies. They are part of the dataset kindly provided by Gernot Liedtke and were then used and reported by Turner (2015).

Table 5.5: Cost parameters for the small and large vehicle types used in the proof-of-concept study in Chapter 9. These values are set manually and not based on real values.

Parameter	small vehicle	large vehicle
fixed costs (€ /day)	25	150
variable costs per distance (€ /m)	0.001	0.01
variable costs per time (€ /s)	0.005	0.01
maximum capacity (units)	5	50

5.3 Overview of vehicle types and their cost parameters

Table 5.6 summarizes the cost parameters of the different vehicle types, together with their associated scenarios (see Chapter 4) and the studies in which they are used in this thesis.

Table 5.6: Overview of vehicle types with their cost parameters, associated scenarios, and the studies in which they are used in this thesis.

vehicle type	associated scenario	€/day	€/m	€/s	used in
7.5 t ICEV orig.[1]	Food (Section 4.1)	80.00	0.00047	0.008	Chapter 6
7.5 t ICEV	Food (Section 4.1)	63.49	0.00040	0.00490	Chapters 7, 8, 10, and 11
7.5 t BEV orig.[1]	Food (Section 4.1)	89.00	0.00050	0.008	Chapter 6
7.5 t BEV 160	Food (Section 4.1)	81.04	0.00051	0.00490	Chapter 7
7.5 t BEV 100	Food (Section 4.1)	74.76	0.00046	0.00490	Chapters 7, 8, 10, and 11
18 t ICEV orig.[1]	Food (Section 4.1)	107.00	0.00061	0.008	Chapter 6
18 t ICEV	Food (Section 4.1)	80.47	0.00065	0.00490	Chapters 7, 8, 10, and 11
18 t BEV orig.[1]	Food (Section 4.1)	112.00	0.00055	0.008	Chapter 6
18 t BEV 160	Food (Section 4.1)	107.43	0.00061	0.00490	Chapter 7
18 t BEV 100	Food (Section 4.1)	96.26	0.00055	0.00490	Chapters 7, 8, 10, and 11
26 t ICEV orig.[1]	Food (Section 4.1)	130.00	0.00077	0.008	Chapter 6
26 t ICEV	Food (Section 4.1)	82.60	0.00067	0.00490	Chapters 7, 8, 10, and 11
26 t BEV 160	Food (Section 4.1)	132.14	0.00076	0.00490	Chapter 7
26 t BEV 100	Food (Section 4.1)	111.90	0.00072	0.00490	Chapters 7, 8, 10, and 11
40 t ICEV orig.[1]	Food (Section 4.1)	140.00	0.00086	0.008	Chapter 6
40 t ICEV	Food (Section 4.1)	126.58	0.00069	0.00559	Chapters 7, 8, 10, and 11
40 t BEV 160	Food (Section 4.1)	192.80	0.00080	0.00559	Chapter 7
40 t BEV 100	Food (Section 4.1)	183.93	0.00078	0.00559	Chapters 7, 8, 10, and 11
Parcel truck	Parcel (Section 4.2)	48.7869	0.000370807	0.00627778	Chapter 6
Cargo bike	Parcel (Section 4.2)	3.2673	0.000103	0.003333	Chapter 6
small vehicle	grid (Section 4.3)	25	0.001	0.005	Chapter 9
large vehicle	grid (Section 4.3)	1550	0.01	0.01	Chapter 9

[1] These values are from the original scenario by Schröder and Liedtke (2014), based on Gabler et al. (2013).

Part II

Electrification without changing the Logistic Network

CHAPTER 6

How Driving Multiple Tours Affects the Results of Last-Mile Delivery Vehicle Routing Problems

This chapter is an edited version of a paper that has been previously published: Martins-Turner and Nagel (2019).

6.1 Introduction and Problem Statement

Urban freight transportation and last-mile delivery are two major aspects of the growing e-commerce business. At the same time, trucks are responsible for 35 % of carbon dioxide (CO_2) emissions in Germany (BMUB, 2018). Recently, various courts have issued bans on diesel vehicles in several cities to protect the population from harmful emissions (Wikipedia, 2019). Additionally, environmentally motivated measures to increase the quality of life are being discussed in society and politics (Senatsverwaltung für Stadtentwicklung und Umwelt (SenStadt), 2013). For investigating the effects of different measures, it is important to have good simulation tools. Goods for a city typically arrive at distribution centers ("hubs") at the periphery of the city, from where they need to be distributed further. This implies solving a fleet assignment and Vehicle Routing Problem (VRP) so that each customer is included in a tour. Jsprit (see Section 3.3.2) is an open-source toolkit for solving such VRPs. It has been developed to work in conjunction with the transport planning software Multi-Agent Transport Simulation (MATSim) (see Section 3.2), by using MATSim's freight contrib (see Section 3.2.2.1), but can also be used separately. Jsprit can solve Multi-Depot Vehicle Routing Problems (MDVRPs), i.e., it does not only construct tours, but also assigns each destination to one of several hubs. The approach in its current implementation is, however, not able to have the same vehicle perform multiple tours on the same day.

In this paper, this is modified in a way that the vehicles can reload goods within their (daily) tours. This makes it possible to reduce the number of vehicles needed for solving the VRP, leading to lower costs, as fixed costs for no longer needed vehicles can be saved. It also brings the solution closer to reality, as companies aim for high fleet utilization. Moreover, it is relevant for last-mile delivery using smaller vehicles, where vehicle use is restricted by capacity rather than the driver's

shift duration. The investigation looks at the effects of reloading (and therefore running a second tour) compared to the previous situation, where each vehicle operates only one tour per day. For this, two different scenarios from two different sectors of urban commercial transport are investigated: supplying supermarkets in Berlin (see Section 6.3) and parcel delivery in a district of Berlin (see Section 6.4).

Vehicle Routing Problem (VRP) Irnich, Toth, and Vigo (2014) define a Vehicle Routing Problem (VRP) (see also Section 3.3.1) as follows: Finding a plan to "determine a set of vehicle routes to perform [...] transportation requests with the given vehicle fleet at minimum costs" (Irnich, Toth, and Vigo, 2014). A VRP solves two interdependent main subproblems: (i) assigning requests to tours (clustering) and (ii) determining the optimal sequence in which the requests are served within a tour (routing) (Prockl, 2010; Scheuerer, 2004).

The decision regarding optimal vehicle routing made by transport companies depends on various factors. Internal restrictions influencing the carrier can include the location of depot(s) and the available vehicle fleet at the depot(s). Each vehicle type has its own properties, e.g., capacity, fixed and variable costs, and fuel consumption. External restrictions and specifications offer a framework within which carriers have to operate. Customer requests (quantity, type of goods, location, and time window to bring goods) are key specifications for generating tour plans (jsprit, 2024). Further constraints such as driving restrictions and tolls can exist due to political or court decisions (Cerwenka, 2007). The (expected) traffic situation has a direct impact on travel times. As a result, congestion can reduce service quality and increase the delivery costs for the carrier(s). Nevertheless, congestion is usually not considered in urban tour planning (Ehmke, 2012). For more information about different types of vehicle routing problems, see, e.g., Toth and Vigo (2014); Scheuerer (2004); jsprit (2024).

jsprit Jsprit (see also Section 3.3.2) is an open-source toolkit for solving VRPs. For each VRP there is a carrier with a given fleet and a list of requests. The fleet is located at the depot(s) from where they start and where they return after completing their tour. The fleet can either be defined explicitly by listing all available vehicles or implicitly by assuming an infinite number of vehicles of given types. When using the infinite fleet size option, the fleet composition is part of the VRP solution. The requests (or demand) can be defined in several ways: either as *service*s or as *shipment*s. While services have only one location — either a delivery or pickup point — with the depot as another location, a shipment has two defined locations: the origin (from) and the destination (to). When applied to services, jsprit can also solve Multi-Depot Vehicle Routing Problems (MDVRPs), which means that the algorithm also decides from which depot each request is served. Jsprit iteratively optimizes the solution by ruining some parts of the solution and recreating a new one. The aim of jsprit is to reduce the costs for the carrier. These costs may include, for example, fixed vehicle costs (e.g., depreciation, insurance), variable costs (e.g., distance- and time-based costs during the tour), and other costs such as tolls or penalties for missed time windows (jsprit, 2024).

Multi Agent-based Transport Simulation (MATSim) The Multi-Agent Transport Simulation (MATSim) (see also Section 3.2.1) is an open-source software for agent-based transport simulation. It is an activity-based and extendable framework implemented in Java, which is designed for large-scale scenarios. In addition to a common base, several optional extensions are available[1] (Horni, Nagel, and Axhausen, 2016). MATSim is based on a co-evolutionary algorithm,

[1] see https://matsim.org/extensions

where each iteration consists of the following three steps: traffic simulation, scoring, and replanning. MATSim simulates agents — normally persons — and their daily plans, which consist of activities like home or work and trips between their activity locations. These plans are simulated and then evaluated (scored) based on the agents' experienced performance. After scoring, some agents try to improve their plans, for example by selecting a different route or modifying activity start and end times. For this, several strategies are available to generate new or modified plans. After this replanning step, a new iteration of the simulation starts with the modified plans. After running the specified number of iterations, MATSim terminates after the scoring step (Horni, Nagel, and Axhausen, 2016).

Freight traffic in MATSim Simulating freight traffic in agent-based traffic simulations is often done similarly to passenger traffic. The drivers of the vehicles are represented as individual agents with fixed plans for their tours. Typically, they can only optimize their route between the various destinations. An adjustment of the sequence within the tour is rarely performed, and moving pickups or deliveries from one agent/vehicle to another is not possible (Zilske and Joubert, 2016). For this reason, one needs to generate the tour plans in advance.[2] The already mentioned toolkit jsprit (see above) is a VRP solver that is integrated into MATSim. That integration is enabled via the MATSim freight contrib (Zilske and Joubert, 2016, see also Section 3.2.2.1).

6.2 Methodology

In jsprit, the (delivery) requests can be defined as either *service*s or *shipment*s (see Section 3.3.2). Shipments have two locations (from and to) while services only have one location (either to or from — depending on the direction of the transport: pickup or delivery) and the other one is always the depot. For enabling jsprit to use vehicles for more than one tour and to allow them to reload goods at the depot, the definition of the request is changed from service to shipment. With shipments, vehicles can load or unload during their tour, while with services the vehicles either start empty at the depot, pickup the request and return full to the depot or start full at the depot, deliver the requested goods and return empty. Solving service-based VRPs requires significantly less computational time as vehicle capacity constraints only need to be checked once per tour. Converting a service-based VRP to a shipment-based-VRP is straightforward for VRPs with only one depot: One only needs to add the depot as a second location. For Multi-Depot Vehicle Routing Problem (MDVRP), however, it is not clear which depot the goods should originate from, because this decision is part of the MDVRP solving.

Due to this, the service-based MDVRP is solved first — which we also used here as a reference scenario. In a second step, the shipments were created by looking up in the solution of the MDVRP where the tours with a certain request start, and set that as the pickup location for the shipment. As a consequence, the new shipment-based VRP is no longer an MDVRP because the origin is now defined in the request and no longer open for the solver.

[2] There are other approaches for an "online" planning during the day, similar to personal transport with Demand Responsive Transport (DRT). There are also approaches to combine both online and offline planning: assigning pre-planned short tours "online" to idle vehicles (e.g., Schlenther et al., 2020; Meinhardt et al., 2022).

The analysis of the effects of multiple tours is investigated in two different delivery scenarios located in the city of Berlin, Germany:

- Food retailing in Berlin (Section 6.3)
- Parcel delivery in Berlin-Wilmersdorf (Section 6.4)

They focus on entirely different sectors of commercial traffic. As a consequence, the underlying VRPs differ in the type and quantity of goods, the vehicles used, etc. They were also originally set up by different teams and can therefore be used to get a better overview of the effects when enabling vehicles to run more than one tour.

6.3 Scenario 1: Food retailing in Berlin

6.3.1 Scenario description

This scenario is based on Schröder and Liedtke (2014). It is described in more detail in Section 4.1. The Berlin food retailing scenario includes 1′928 requests from 867 food retailing shops. The shops belong to 15 retail companies in Berlin, with 17 distribution centers in and around Berlin. The shops'demand is the demand of an average day.

Each shop has various heterogeneous products it offers to its consumers. They require different transport conditions for supplying the shops and are aggregated into three different groups: fresh, frozen, and dry (Schröder and Liedtke, 2014). This leads to 15 $companies \cdot 3 \frac{groups}{company} = 45$ *carriers* in the model, that is, "fresh", "frozen", and "dry" are transported by different carriers. Each carrier has its own fleet available. The available vehicle types in the fleet of a carrier depend on the group of goods and the business type of the company. Some retail companies have more than one depot for supplying their shops.

In the *reference scenario (single tour per vehicle)*, the capabilities for the three different product groups were set as they were defined by Schröder and Liedtke (2014):

- **Fresh** products are delivered in a time-window of [4 a.m. – 9 a.m.].
- **Frozen** and dry products are delivered either in a time-window of [9 a.m. – 2 p.m.] ("morning") or [2 p.m. – 7 p.m.] ("afternoon"). For each delivery, the time-window is randomly assigned.

In this reference scenario, the demand of the different stores is represented by the activity type "service". As mentioned in Section 3.3.2, it is possible to model it as an MDVRP, but then each vehicle only drives one tour from the depot to its customers and returns to the depot. In consequence, there are more vehicles in the solution than necessary for supplying all shops. Please note that it is also not possible to "reuse" vehicles: vehicle that was used for dry products between 9am and 2pm cannot be reused between 2 p.m. and 7 p.m.. Because of the underlying cost model with fixed costs for each employed vehicle, this leads to an inefficient solution with too high costs.

Several policies are implemented as policy cases, which in part re-investigate previous results (Schröder and Liedtke, 2014), and by introducing city hubs (called Urban Consolidation Centers (UCCs)), went beyond. The policy cases regarding the existing Low Emission Zone (LEZ) of Berlin are:

- (A1) Cordon toll (20 €) for heavy Internal Combustion Engine Vehicles (ICEVs) (26 ton (t) or 40 t) for entering the Low Emission Zone (LEZ), but no alternative vehicle type available
- (A2) Cordon toll (20 €) for heavy ICEVs (26 t or 40 t) for entering the LEZ, Battery Electric Vehicles (BEVs) are available at depots

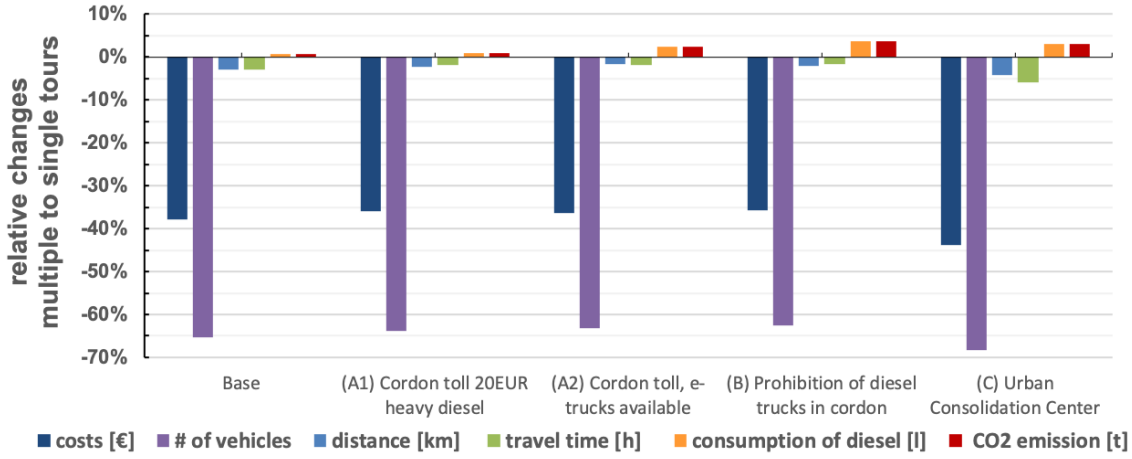


Figure 6.1: Comparison of results for all cases of the Berlin food retailing scenario; vehicle can run more than one tour (improved algorithm) instead of only one single tour.

- (B) Prohibition of ICEVs inside the LEZ; BEVs available at depots
- (C) Prohibition of ICEVs inside the LEZ; BEVs available at depots, and three UCCs located close to the LEZ to supply *all* shops within the LEZ using BEVs. The UCCs are supplied from the main depots. All shops outside the LEZ are supplied directly from the depot.[3]

For the *improved algorithm* (vehicles can run multiple tours, including reloading of goods), it is no longer necessary to have two separate shifts for having tours in the afternoon. As a consequence, the time windows for delivering as well as the availability of vehicles at the depots for frozen and dry goods were combined into a single time window of [9 a.m. – 7 p.m.]. The time window of [4 a.m. – 9 a.m.] for fresh goods remains unmodified because fresh goods should be available in the stores in the morning. Note that the "fresh goods" vehicles cannot be reused for "dry" or "frozen" goods, since they belong to a different carrier. Now the algorithm can choose which shops are supplied when. Once more, the same cases as in the reference (single-tour) scenario are used in the simulation.

6.3.2 Results

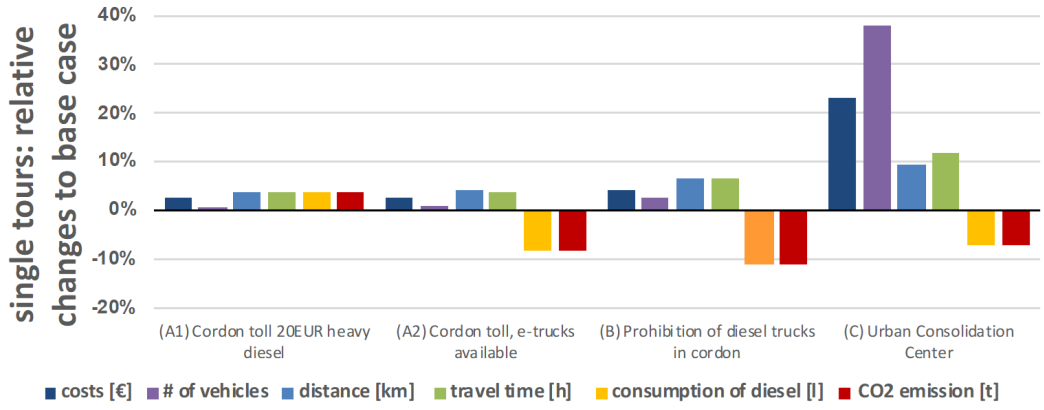
Comparing the results (single tour vs. multiple tours) for the different cases, one can see that allowing vehicles to drive several tours leads to the expected results (see Figure 6.1 and Table 6.1). The number of vehicles used decreases by approximately 62.5–68 % depending on the investigated policy. Due to the high influence of fixed cost savings, the total costs now decrease by 35–44 %. The distance traveled and travel time slightly decrease by up to 6 %. The consumption of diesel and therefore the CO_2 emissions increase by up to 3.8 %.

Figure 6.2 shows the relative changes of the different policy cases compared to their base case for both the single tour and multiple tour setup. The effects when using the new multiple tour setup (see Figure 6.2b) go in the same direction as in the previous single tour setup (see Figure 6.2a). The relative changes compared to its base case are — except for the changes in the number of vehicles used — approximately the same. An exception is the UCC case, where a significantly lower increase in costs and vehicles is observed when using the improved algorithm. This arises from the more efficient use of the vehicles, especially for the shorter trips on the last mile from the UCC.

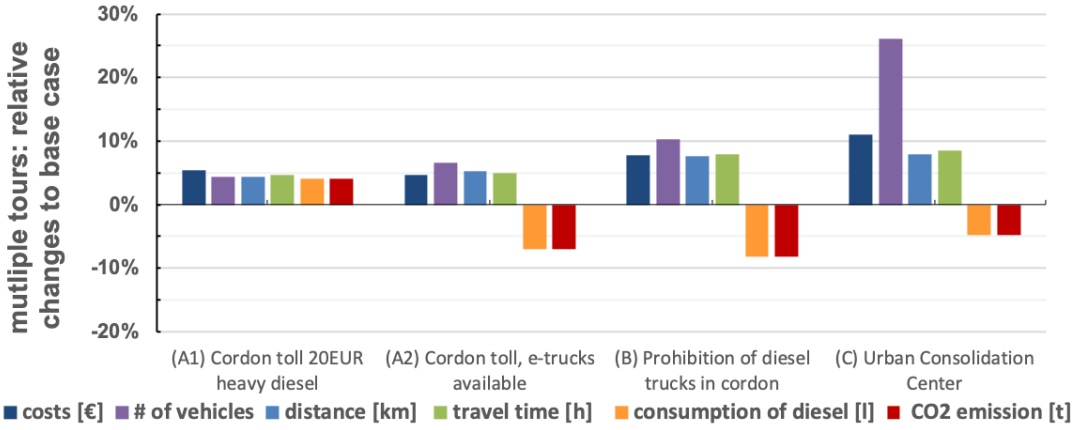
[3] Another, integrated, approach for using a Two-Echelon Vehicle Routing Problem (2E-VRP) in the Berlin food retailing scenario is presented in Chapters 10 and 11.

Table 6.1: Comparison of results vehicle can run *more than one tour* (m) instead of only one single tour (s) for the Berlin food retailing scenario.

policy	case	costs (€)	# veh. (veh)	distance (kilometer (km))	travel time (hour (h))	fuel (liter (l))	CO_2 (t)
Base	s	114′575	529	38′146	706.8	11′170	29.3
	m	71′263	184	37′072	686.4	11′254	29.5
	diff.	**−43′313**	**−345**	**−1′704**	**−20.4**	**+84**	**+0.2**
(A1) Cordon toll 20EUR on heavy ICEVs	s	117′391	532	39′614	732.5	11′612	30.4
	m	75′120	192	38′682	718.9	11′721	30.7
	diff.	**−42′271**	**−340**	**−932**	**−13.6**	**+109**	**+0.3**
(A2) Cordon toll, BEVs available	s	117′345	534	39′683	733.4	10′229	26.8
	m	74′637	196	39′051	720.4	10′470	27.4
	diff.	**−42′708**	**−338**	**−632**	**−13.0**	**+241**	**+0.6**
(B) No ICEVs in cordon, BEVs available	s	119′552	542	40′707	753.7	9′951	26.1
	m	76′842	203	39′907	741.3	10′328	27.1
	diff.	**−42′710**	**−339**	**−800**	**−12.4**	**+377**	**+1.0**
(C) UCC	s	140′891	731	41′805	791.7	10′401	27.3
	m	79′083	232	40′036	744.7	10′715	28.1
	diff.	**−61′808**	**−499**	**−1′769**	**−47.1**	**+314**	**+0.8**



(a) Vehicles can run one single tour.



(b) Vehicles can run more than one tour (improved algorithm).

Figure 6.2: Relative changes for all policy cases of the Berlin food retailing scenario compared to the base case.

6.4 Scenario 2: Parcel delivery Berlin-Wilmersdorf

This scenario comes from the Courier, Express, and Parcel (CEP) sector and its subject is the last-mile parcel delivery of an average day in one district of Berlin (see Section 4.2). The data are taken from Zhang et al. (2018). In total, 1′217 requests with a demand of 1–12 parcel(s) each are considered.

6.4.1 Scenario description

For our study, we are considering the following two scenarios from Zhang et al. (2018, see also Section 4.2) as follows:

- scenario A: Distribution of all parcels directly from the (one) distribution center (DC) by light parcel delivery trucks, and
- scenario B: Commercial parcels are first delivered from the DC to given micro depots by light parcel delivery trucks and from there delivered to the customers by cargo bicycles. Parcels to private recipients are still directly delivered by cargo vehicles from the DC.

For both CEP-scenarios, two simulations are run.

1. *service*-based (s): only a **s**ingle tour per vehicle per day (reference case), and
2. *shipment*-based (m): improved algorithm; vehicles can reload within the tour and thus drive **m**ultiple tours per day (policy case).

The adaptation of the time-windows for delivery as well as for vehicle availability was not necessary here as, in contrast to the food retailing scenario in Section 6.3, no shifts for the drivers were defined by Zhang et al. (2018).

6.4.2 Results

For *scenario A* (direct delivery with light parcel trucks), the improved algorithm (= multiple tours per vehicle) did not lead to a significantly different result in terms of costs, distance, time, ... (see Table 6.2a). Even with the improved algorithm, none of the 20 vehicles reload parcels at the DC during the day. This makes sense because the limitation for the VRP in this case was the time window ([9 a.m. – 5 p.m.] for private or [9 a.m. – 6 p.m.] for commercial recipients) and not the capacity of the vehicles. Because of this, enabling reloading and running multiple tours has no positive influence on the fleet size needed.

In addition to the stated results, a massive increase in computation time was observed for this scenario. Solving the service-based VRP took less than 1.5 h, while the shipment-based VRP ran for several days until the algorithm terminated. This is dramatically longer than observed in the food retailing scenario above and seems to be related to the significantly larger number of shipments.

For *scenario B* (with micro depots and cargo bicycle delivery for the last mile), the multiple tour algorithm significantly reduces the number of vehicles needed and therefore the costs (see Table 6.2b). This is expected: Because of the significantly lower capacity of the cargo bicycles, the tours in the single-run reference case were restricted by the capacity of the vehicles and not by their temporal availability or the drivers'shift duration. Using the improved algorithm, the vehicles can reload at the micro depots and therefore run multiple tours per day. In this scenario, the light parcel delivery trucks have shorter tours with higher demand to deliver the commercial parcels to the micro depots and the private parcels directly to the recipients. Thus, they are, in particular, no

Table 6.2: Comparison of results when vehicles can run *more than one tour* (m) instead of *only one tour* (s) for the different CEP scenarios.

(a) Scenario A: direct distribution

policy	case	costs (€)	# veh. (veh)	distance (km)	travel time (h)	fuel (l)	CO_2 (t)
scenario A:	s	6′066	21	237.3	10.75	26.58	7.12
direct	*m*	5′938	20	259.3	11.96	29.04	7.78
distribution	**diff.**	**−128**	**−1**	**+22.0**	**+1.21**	**+2.46**	**+0.66**

(b) Scenario B: micro depots and cargo bicycles for commercial parcels

policy	case	veh. type	costs (€)	# veh. (veh)	distance (km)	travel time (h)	fuel (l)	CO_2 (t)
scenario B: micro depots & cargo bikes	s	parcel truck		20	177.3	7.91	19.86	5.32
		cargo bike		121	473.2	21.79	0	0
		total	7′056	141	650.5	30.86	19.86	5.32
	m	*parcel truck*		12	178.7	7.91	20.01	5.36
		cargo bike		33	511.6	22.95	0	0
		total	6′396	45	690.3	30.86	20.01	5.36
	diff.	**parcel truck**		**−8**	**+1.4**	**0**	**+0.15**	**+0.04**
		cargo bike		**−88**	**+38.4**	**+1.16**	**0**	**0**
		total	**−660**	**−96**	**+39.8**	**+1.16**	**+0.15**	**+0.04**

longer limited by their temporal availability but instead by their capacity. This makes them able to run multiple tours per day as well. As a result, the number of light parcel delivery trucks used decreases as well.

6.5 Conclusion

In this article, an enhancement of solutions for tour planning problems has been presented. It demonstrates the high influence of eliminating tour planning restrictions on the solution of VRPs. Allowing the algorithm to use vehicles for more than one *depot* → *customer* → . . . → *customer* → *depot* tour per day reduces the fleet size by about 2/3 for the cases of food retailing and parcel delivery by cargo bicycles from micro hubs. The costs decrease, depending on the case, by about 9 % to 44 %.

If the vehicle capacity is not the main restriction for VRP, no significant reduction of the fleet size (and costs) can be observed. In all scenarios, only small changes in distance, time traveled, fuel consumption, and therefore the CO_2 emissions of the whole fleet were observed.

For our investigations, we improved the collaboration between the agent-based transport simulation software MATSim and the vehicle routing problem solver jsprit. Using *shipments* instead of *services* allows the algorithm to reload goods at the depot and continue with the current vehicle. Allowing the algorithm to use vehicles for more than one tour allows breaking up the implicitly given separation of delivery shifts. For evaluating the effects, two independent scenarios were used. The first is about supplying food retail shops in Berlin. The second scenario is about parcel delivery in one district of Berlin. Both scenarios have different designs and policy cases to see the effects under different situations.

Using the proposed approach for the Multi-Depot Vehicle Routing Problem (MDVRP) means that one has to run jsprit twice: First as an MDVRP with the computationally faster and multi-depot-able

activity type *service*. From the resulting tour plan, the "shipment"-based VRP is generated [4]. With this, one can go into the second, computationally slower but multiple-tour-capable *shipment*-based jsprit run. Running the VRP twice also affects the results. The assignment of requests to depots may be suboptimal for multiple tours, since the depot is fixed as the shipment's pickup point. The increase in computation time for the shipment-based VRPs is within an acceptable range for VRPs with up to approximately 200 shipments per carrier. In the CEP scenario A, with more than $1'200$ shipments for a single carrier, the computational time increases from less than 1.5 h to four days.

[4] We have done this once per scenario and started all of our further simulation runs directly using the converted "shipment"-based VRP.

CHAPTER 7

Replacement of the fleet's vehicles by electric vehicles

This chapter is an edited, updated and extended version of a previously published paper: Martins-Turner et al. (2020).

7.1 Introduction and Problem Statement

Reducing greenhouse gas (GHG) emissions to limit global warming and climate change with all its implications is one of the major global challenges of the 21st century. As a response to this challenge, the European Commission (EC) agreed on the "European Green Deal", which includes having net zero emissions of GHGs by 2050 and decoupling economic growth from resource use (EC, 2019). To achieve this goal, "a 90 % reduction in transport emissions is needed by 2050" (EC, 2019). Currently, 35 % of transport carbon dioxide (CO_2) emissions in Germany are emitted by trucks (BMUB, 2018). Besides reducing the transport system's impact on global climate, bans on diesel vehicles are being discussed in various cities to protect the population from harmful emissions (Senatsverwaltung für Stadtentwicklung und Umwelt (SenStadt), 2013; Wikipedia, 2019). In this paper, we investigate if and to what extent the current requirements for urban freight transport can be fulfilled when replacing the current Internal Combustion Engine Vehicles (ICEVs) by Battery Electric Vehicles (BEVs).

Goods for a city typically arrive at distribution centers ("hubs") at the periphery of the city. From these hubs, they are distributed throughout the city. Generating tours for a fleet to perform this distribution task can be done by solving the Vehicle Routing Problem (VRP).

An open source toolkit for solving VRPs is jsprit (jsprit, 2024), which can be used standalone as well as in conjunction with the agent-based transport planning software Multi-Agent Transport Simulation (MATSim) (Zilske and Joubert, 2016).

7.2 Methodology

This study uses the open source software Multi-Agent Transport Simulation (MATSim)[1]. It is an activity-based, extendable framework that is designed for agent-based transport simulations of large-scale scenarios. Several optional extensions are available[2] as well as open-access scenarios[3] (Horni, Nagel, and Axhausen, 2016). Investigating the effects of measures is a three-step approach:

1. Building a model of the base case,
2. Building a model of the policy case(s), and
3. Comparing the results, e.g., costs and benefits.

Simulation model The model of the base case is distributing goods to the food retailing shops with ICEVs, in this case diesel powered trucks. For this, a model of the daily demand is needed, as well as a method to generate plausible vehicle tours serving that demand. With some modifications, the demand is based on earlier studies. Section 4.1 provides detailed information about the simulation model and its development. The vehicle tour for each vehicle starts at a depot, goes back and forth between the depot and the delivery locations (shops), and finally returns to the depot.

These tours need to be generated in advance of the traffic simulation, because the agents (persons, drivers) in the traffic simulation have to follow their tour plan (Zilske and Joubert, 2016). For generating the tour plan, we are using the open source software jsprit (jsprit, 2024) as heuristic VRP solver. It is integrated into MATSim using the MATSim freight contrib (Zilske and Joubert, 2016) (see Section 3.2.2.1). Thanks to this integration we are, in contrast to Ehmke (2012), able to consider traffic congestion in our model (see Sections 3.2.1, 3.2.2.1, and 4.1).

For the policy cases, the same demand is assumed. However, now only BEV are allowed to transport the goods. Running the scenario means that we solve the VRP using jsprit with 10′000 iterations and afterward run a single MATSim iteration. From the output events, we can calculate the travel times and distances for each vehicle. In an ex-post analysis, we analyze the effects on the carriers in terms of fleet compositions and costs. We also evaluate the tours of the vehicles to see under which conditions it is possible to use BEVs as replacement for ICEVs.

In this study, the range of the BEVs is *not* limited in the tour planning – it is assumed that BEVs can recharge during the tour without additional time consumption. A study taken the range restriction into account is presented in Chapter 8.

Emission analysis Based on the simulation results, the impacts on emissions are analyzed. These are on the one hand the exhaust emissions (Section 2.2.2.1), non-exhaust emissions (Section 2.2.2.2), as well as the energy consumption, using MATSims emissions contrib (see Section 3.2.3), which uses the Handbook on Emission Factors for Road Transport (HBEFA) database (see Section 2.2.2.3). BEVs do not emit exhaust emissions during driving, but they do emit non-exhaust emissions, e.g. from tire and brake wear. On the other hand, we use a Well-to-Wheel (W2W) analysis (see Section 2.2.3). . It includes the GHG emissions from the production of diesel and electricity as well as from their use in the vehicles (JRC et al., 2014). Unfortunately, HBEFA does not (yet) provide differentiated energy consumption values for BEV with a Gross Vehicle Weight Rating (GVWR) above 12 ton (t). In this study, three out of four used vehicle sizes are larger than that.

[1] https://matsim.org, https://github.com/matsim-org/matsim-libs
[2] https://matsim.org/extensions
[3] https://matsim.org/open-scenario-data

Thus, it is not possible yet to base a meaningful W2W analysis on the fuel consumption data from HBEFA. As a consequence, the energy consumption per vehicle type is calculated by multiplying the vehicle kilometer (vkm) driven with an average diesel or electricity consumption. The resulting energy consumption is then multiplied with the W2W emission factors. The W2W GHG emissions of the simulation cases are calculated by multiplying the observed distance traveled (see Table 7.3, Figure 7.1) with the aggregated W2W emission factor per vkm as noted in Table 2.1 in Section 2.2.3.

7.3 Case Study

This case study is located in Berlin, the capital and largest city of Germany. It deals with transporting goods to the shops of the food retailing industry. It is based on the case study of Schröder and Liedtke (2014) and includes some modifications by Martins-Turner and Nagel (2019) (see Chapter 6). For more information about this scenario and its development, please have a look at Section 4.1.

Road Network The network is taken from the MATSim Open Berlin scenario[4], which is available publicly and free of charge (Ziemke, Kaddoura, and Nagel, 2019). Since we are only interested in the effects of changing the truck fleet from ICEVs to BEVs, we do not run a simulation that includes passenger transport. The time dependent travel times in the network were generated accordingly to the observed traffic in the simulation output of the MATSim Open Berlin Scenario, using so called NetworkChangeEvents (Rieser, Nagel, and Horni, 2016).

Freight Demand For this scenario we use the demand of Schröder and Liedtke (2014), together with modifications by Martins-Turner and Nagel (2019). The main modification is enabling vehicles to run more than one delivery tour from the depot. This implies that loading vehicles with goods at the depot becomes part of the VRP. We assume the same average loading time of three minutes per pallet at the depot as it is assumed by Schröder and Liedtke (2014) for unloading one pallet. In total, the demand of 15 food retailing companies in Berlin with 17 distribution centers located in and around Berlin is modelled. These companies serve 867 food retailing shops with 1′928 demand requests. The shops' demand is the demand of an average day.

As summarized in Section 4.1, Schröder and Liedtke (2014) aggregate the different products a shop offers to their consumers into three different groups: fresh, frozen, and dry. They are handled separately by different carriers, leading to a total of 45 independent carriers in the model. The delivery time-windows for dry and frozen goods are set to [9 am – 7 pm], for fresh goods they are set to [4 am – 9 am] (see also Section 4.1 and Chapter 6). The available vehicle types in the fleet of a carrier depend on the type of goods (fresh, dry, or frozen) and the business type of the retailing company (discount store, supermarket, hypermarket, or department store) (Schröder and Liedtke, 2014).

Vehicle Types and Costs Parameters Schröder and Liedtke (2014) made some assumptions about the available vehicle types. In total, four different vehicle types representing differently sized vehicles are defined: light 7.5 t, medium 18 t, heavy 26 t, and heavy 40 t. Not all vehicle types are available for all carriers (Schröder and Liedtke, 2014; Gabler et al., 2013).

In the simulation base case, all vehicles are ICEVs, while in the policy case only BEVs are available. To reach comparability between all cases, a new cost calculation is also done for the

[4] https://github.com/matsim-scenarios/matsim-berlin

ICEVs. The used methodology and many values for the calculation are based on the German Bundesverkehrswegeplan (BVWP) (BMVI, 2016). It is described in more detail in Section 5.1. The corresponding calculation tables are in Appendix B, the results are summarized in Section 5.3.

The BEVs are newly introduced in this study. Their size is selected in a way that the maximum payload is equal for the ICEVs and BEVs.

To calculate the possible ranges, consumption data for electric trucks currently[5] available on the market are chosen. The costs for BEVs are strongly driven by the battery. Therefore, we consider the prices for the chassis and for the battery separately. For the chassis, market analysis shows that current BEV chassis are about 1.6 times more expensive than ICEV chassis. According to Fuessel (2017), the prices for a BEV chassis will approach the prices for ICEV as soon as mass production pick up pace. Therefore, we will consider the current situation with a 60 % price increase from ICEV to BEV chassis (case A: BEV 160) and the possible future situation with equal chassis prices as a sensitivity analysis (case B: BEV 100).

The battery costs for the BEVs vary from 52′200 € for the small truck (7.5 t) to 265′714 € for the 40 t truck. The possible lifetime charging cycles are set to 4′000 and the specific energy density is set to 0.15 kilowatt hour (kWh)/kilogram (kg) at pack level according to Göhlich, Fay, and Park (2019). Because of the possible charging cycles, no battery change is required in the presumed use phase of the vehicles (11 years, 250 days of use per year), even with an average of more than one complete charging event per day. Thus, the battery costs are considered in the calculation in the same way as the costs for the chassis.

The cost structure for all vehicle types used in this study as input for the VRP is summarized in Table 7.1.

[5] Please note that is study was published in 2020. The market analysis was done in 2019. So “currently” in this study refers to these years if not stated otherwise.

Table 7.1: Characteristics for the different vehicle types. This table summarizes the results of the cost calculation and vehicle information provided in Chapter 5 and Appendix B. The costs parameters are used as inputs for the tour planning. The average energy consumption, the energy costs per 100 kilometer (km), and the range are provided as additional information.

vehicle type	parameter	Base: ICEV	A: BEV 160	B: BEV 100
7.5 t	fixed costs (€ /day)	63.49	81.04	74.76
	variable costs per distance[1] (€ /m)	0.00040	0.00051	0.00046
	variable costs per time[2] (€ /s)	0.00490	0.00490	0.00490
	energy consumption (per 100 km)	13.57 l	61 kWh	
	energy costs (€ /100 km)	16.69	13.52	
	range (km)	(unlimited)	100	
18 t	fixed costs (€ /day)	80.47	107.43	96.26
	variable costs per distance[1] (€ /m)	0.00065	0.00061	0.00055
	variable costs per time [2] [€ /s]	0.00490	0.00490	0.00490
	energy consumption (per 100 km)	33.12 l	106 kWh	
	energy costs (€ /100 km)	40.74	23.49	
	range (km)	(unlimited)	80	
26 t	fixed costs (€ /day)	82.60	132.14	111.90
	variable costs per distance [1] (€ /m)	0.00067	0.00076	0.00072
	variable costs per time[2] (€ /s)	0.00490	0.00490	0.00490
	energy consumption (per 100 km)	33.12 l	150 kWh	
	energy costs (€ /100 km)	40.74	33.24	
	range (km)	(unlimited)	133	
40 t	fixed costs (€ /day)	126.58	192.80	183.93
	variable costs per distance[1] (€ /m)	0.00069	0.00080	0.00078
	variable costs per time [2] [€ /s]	0.00559	0.00559	0.00559
	energy consumption (per 100 km)	37.45 l	180 kWh	
	energy costs (€ /100 km)	46.06	39.89	
	range (km)	(unlimited)	172	

[1] The variable costs per distance include the energy costs.
[2] The variable costs per time are the personnel costs.

7.4 Results

7.4.1 Tour characteristics and costs

As explained in Sections 7.2 and 7.3, the fleet and tour planning is run for the retail scenario and the three different vehicle configurations: ICEV, BEVs 160, and BEVs 100. It is possible that vehicles can reload goods at the depot and run one or more additional sub-tour(s). The resulting daily tours are analyzed ex-post after the traffic simulation.

Figure 7.1 shows the distance of the tours driven in the network for the three cases. The distances in both policy cases are, with few exceptions, comparable to the distances observed in the base case. The BEV tours are planned without range constraint (see Section 7.2). It is assumed that any necessary recharging could be done during pickup or drop-off activities without additional costs. However, 56 % of all tours could be driven without recharging during the day. Assuming one recharging during the tour and therefore doubling the vehicles' range would result in 90 % possible tours with BEVs (see Table 7.2).

Table 7.3 shows some results of the simulation for a typical workday. Figure 7.2 summarizes the cost breakdown of the different cases by cost type. In terms of total costs for the carriers, we observe an increase of approximately 15′800 €/day (23.5 %) when using BEVs compared to ICEVs in the case that the chassis prices of the BEVs will be 60 % higher than that for ICEVs (A). In the sensitivity case (B) with equal chassis prices for BEV and ICEV, the cost for the carrier will increase by 11′713 €/day (16.9 %). The reason why the total cost increases are not larger is that

personnel costs are a relevant portion of overall costs, and their cost rate does not change between the cases, and the time travelled remains almost constant over all cases.

Distance and time traveled increase by 1.5 to 2.7 %. This is presumably related to a small reduction of the fleet size. The decreasing fleet size is reasonable since higher costs for the BEVs compared to the ICEVs force jsprit to a more efficient solution regarding vehicle usage. Even if the changes in number of vehicles used and travel distance are small, the resulting cost changes are significant due to other cost rates per vehicle used (fixed costs) and vehicle mileage driven (variable costs per distance).

Table 7.2: Absolute number and relative share of tours that can be driven with BEVs according to the vehicles' range.

(a) *without* recharging

vehicle Type	range	A: BEV 160		B: BEV 100	
7.5 t	100 km	9 / 20	45 %	9 / 21	43 %
18 t	80 km	7 / 24	29 %	5 / 27	19 %
26 t	133 km	131 / 207	63 %	137 / 207	66 %
40 t	172 km	7 / 24	29 %	7 / 24	29 %
total		**154 / 275**	**56 %**	**158 / 279**	**57 %**

(b) *with* one-time recharging: range doubled

vehicle Type	range	A: BEV 160		B: BEV 100	
7.5 t	200 km	20 / 20	100 %	20 / 21	95 %
18 t	160 km	18 / 24	75 %	15 / 27	56 %
26 t	266 km	202 / 207	98 %	203 / 207	98 %
40 t	374 km	11 / 24	46 %	13 / 24	54 %
total		**251 / 275**	**91 %**	**251 / 279**	**90 %**

Table 7.3: Results of the simulation for a typical workday

Costs [€]		Base: ICEV 67′288	A: BEV 160 83′087	B: BEV 100 78′659
vehicles used	total	283	275	279
	light 7.5 t	17	20	21
	medium 18 t	16	24	27
	heavy 26 t	223	207	207
	heavy 40 t	27	24	24
Distance travelled [km]		36′783	37′368	37′761
Time travelled [h]		1′054	1′074	1′070



Figure 7.1: Observed daily tour distances (km) driven per vehicle type and simulation case: TOP: Base case with ICEV only; MIDDLE: Case A: BEV 160 with higher chassis prices; BOTTOM: Case B: BEV 100: equal chassis prices.

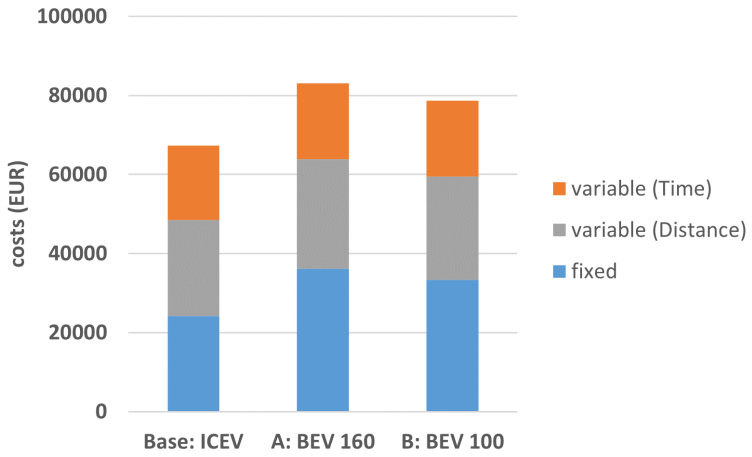


Figure 7.2: Cost breakdown (EUR) of the different cases by cost type for a typical workday.

7.4.2 Emissions during operations

In Table 7.4, aggregated emission values are given for selected emission components and the different simulation cases. They are calculated by using the HBEFA database, and thus only take into account the direct emissions from operating the vehicles. To calculate the annual values, 250 workdays per year are assumed (Planco, ITP, and TUBS, 2015). Switching to BEVs reduces all exhaust emissions (see Table 7.4a) to zero. In terms of CO_2 this is a reduction of 7′714 t per year.

As stated in Section 2.2.2.2, vehicles also emit other, so-called *non*-exhaust, emissions while driving. These are, e.g., particulate matter $< 10\,\mu m$ (PM_{10}), particulate matter $< 2.5\,\mu m$ ($PM_{2.5}$), or black carbon (BC) and will be emitted from *non*-combustion vehicles as well (see Table 7.4b). As a consequence, switching to BEVs will only save approximately 18 % of PM_{10}, approximately 38 % of $PM_{2.5}$, and approximately 76 % of BC emissions (exhaust + non-exhaust; see Table 7.4c).

7.4.3 Well-to-Wheel emissions

The above calculation takes into account the exhaust pollutants produced by the combustion of the fuel itself. To include the emissions from the production of the fuel/electricity itself, a supplementary Well-to-Wheel (W2W) analysis is carried out.

The W2W GHG emissions of the three different simulation cases are calculated by multiplying the observed distance traveled (see Table 7.3, Figure 7.1) with the aggregated W2W emission factor per vkm as noted in Table 2.1 in Section 2.2.3.

Again, to calculate the annual emissions, 250 workdays per year are assumed (Planco, ITP, and TUBS, 2015). We can observe a reduction of the W2W emissions from approximately 9′500 t CO_2 equivalents (CO_2eq)/year using ICEVs to approximately 7′000 t CO_2eq/year (−26 %) using BEVs and assuming electricity production in 2018. Assuming the expected German electricity production in 2030, approximately 4′700 t CO_2eq/year (−50 %) would be emitted with the BEVs. With renewable energy, the GHG emission would decrease to approximately 340 t CO_2eq/year (−96 %) (see Figure 7.3). As a consequence of the very similar travel distances for both BEV cases, the W2W emissions of both cases are very similar as well.

Table 7.4: Aggregated emissions of selected emission components (pollutants) from vehicle operations in t per year. All values are calculated, using the HBEFA database.

(a) exhaust emissions

pollutant	Base: ICEV	A: BEV 160	B: BEV 100
particulate matter $< 10\,\mu m$ (PM_{10})	0.43	0 (−100 %)	0 (−100 %)
particulate matter $< 2.5\,\mu m$ ($PM_{2.5}$)	0.43	0 (−100 %)	0 (−100 %)
black carbon (BC)	0.217	0 (−100 %)	0 (−100 %)
nitrogen oxides (NO_x)	22.48	0 (−100 %)	0 (−100 %)
carbon monoxide (CO)	8.23	0 (−100 %)	0 (−100 %)
carbon dioxide (CO_2)	7′714	0 (−100 %)	0 (−100 %)

(b) non-exhaust emissions (n.e.)

pollutant	Base: ICEV	A: BEV 160	B: BEV 100
particulate matter $< 10\,\mu m$ (PM_{10}) n.e.	1.47	1.54 (+4.8 %)	1.58 (+7.6 %)
particulate matter $< 2.5\,\mu m$ ($PM_{2.5}$) n.e.	0.62	0.65 (+4.6 %)	0.67 (+6.6 %)
black carbon (BC) n.e.	0.062	0.065 (+4.6 %)	0.067 (+6.6 %)

(c) total (exhaust + non-exhaust) emissions

pollutant	Base: ICEV	A: BEV 160	B: BEV 100
particulate matter $< 10\,\mu m$ (PM_{10})	1.90	1.54 (−19.0 %)	1.58 (−16.9 %)
particulate matter $< 2.5\,\mu m$ ($PM_{2.5}$)	1.06	0.65 (−38.2 %)	0.67 (−37.0 %)
black carbon (BC)	0.279	0.065 (−76.6 %)	0.067 (−76.1 %)
nitrogen oxides (NO_x)	22.48	0 (−100 %)	0 (−100 %)
carbon monoxide (CO)	8.23	0 (−100 %)	0 (−100 %)
carbon dioxide (CO_2)	7′714	0 (−100 %)	0 (−100 %)

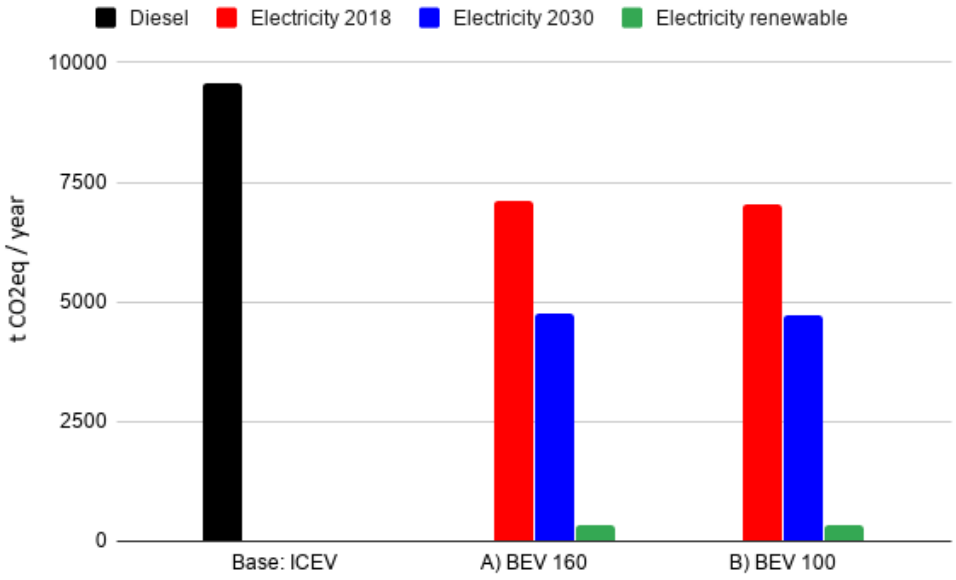


Figure 7.3: Calculated W2W emissions in t CO_2eq per year. For the BEVs, three different electricity mixes are assumed. Both policy cases show very similar results, because their fleet mix and their vkm driven are very similar.

7.5 Conclusion, Discussion and Outlook

In this study, we analyze whether electrification is suitable for the urban last mile supply of shops based on a case study in the city of Berlin. The BEVs are designed to have the same payload as ICEVs in the same weight class. In the selected scenarios we could show with an ex-post analysis that 56 % of the resulting tours can be driven with BEVs without recharging during the tour, another 34 % (≈ 90 % in total) with recharging once. In terms of costs, the change from ICEVs to BEVs will result in increasing costs by 23 % if the chassis of the BEVs are 60 % more expensive than the chassis of the ICEVs (case A). In the sensitivity case (B) with equal chassis cost, the total transportation costs will increase by 17 %. These costs include the costs for the battery as well as the costs for diesel and electric energy. An important reason why the relative cost increase is not larger is that personnel costs are a significant portion of the overall costs, and they remain approximately the same in all cases.

Regarding the fleet size and composition, no significant change is observed. Replacing the fleet by electric vehicles will avoid all exhaust emissions. This means an annual saving of 7′714 t CO_2, approximately 8 t carbon monoxide (CO), and approximately 22 t nitrogen oxides (NO_x). Other components which also originate as non-exhaust emissions are reduced when using BEVs instead of ICEVs, but they will not disappear completely; e.g., PM_{10} goes down by approximately 18 %, $PM_{2.5}$ decreases by approximately 38 %, and BC is reduced by approximately 76 %. From a W2W perspective, the usage of BEVs for all tours leads to a reduction of 2′500 to 9′200 t CO_2eq per year depending on the assumed electricity production. This is a reduction by 26 % to 96 % compared to the usage of ICEVs.

In this paper we evaluate the feasibility of using BEVs with an ex-post analysis. Including a vehicle type specific distance constraint into the VRP can force respecting this limitation already in the tour generation (see Chapter 8).

Including (re-)charging may be another useful further development. Miranda Jahn et al. (2021) show for the simulation output of this current study, that approximately 71 fast charging points (400 watt (W)) distributed over the depots are sufficient to complete 90 % of all tours with BEV. With additional 29 high performance opportunity chargers within the city, all tours can be operated with BEVs. Including recharging into the VRP solving may also force to a re-planing of the logistics network adding additional hubs between the depots and the shops. Providing additional variants of vehicles with larger battery capacity is another option, even though this leads to a reduction of the payload. Regardless of these improvement potentials for our method, we were able to show that even without major changes in carrier's operating strategies, and based on vehicle types available in 2019, a significant amount of urban freight delivery tours can be electrified with current technology. Because of technical and economic progress, there are now (in 2024) vehicles with a significantly greater range. An updated study has been published recently (Ewert et al., 2025, see also Section 12.2).

CHAPTER 8

Effects of a GHG emission tax on the fleet composition

The study on the effects of a tax on greenhouse gas (GHG) emissions is an edited excerpt from a previously published article: Ewert et al. (2021a). While the simulation output is taken from that original study, the analysis is extended and updated.

8.1 Introduction and Problem Statement

Reducing greenhouse gas (GHG) emissions is one major objective to limit the global warming to below 2°C above pre-industrial level and go toward a (more) sustainable future (United Nations, 2015a). At the European level, the European Commission (EC) agreed on the *European Green Deal* in 2019 which includes decoupling of economic growth from resource usage and having zero net GHG-emissions by 2050 (Europäische Kommission, 2019). Besides this, at the national level, different countries defined their plans for climate protection, e.g., the German "Climate Action Plan 2050" (BMUB, 2016). 35 % of carbon dioxide (CO_2) emissions in the German transportation sector are currently emitted by road freight transport (BMUB, 2018). This German action plan foresees reducing the GHG-emissions of the transport sector by 40 % until 2030, compared to 1990. The European Commission (EC) aims to reduce the transport emissions by 90 % until 2050. To achieve this goal, electrifying the transportation sector could be a suitable solution. Hence, the current Internal Combustion Engine Vehicles (ICEVs) have to be replaced by Battery Electric Vehicles (BEVs).

The range of BEVs is currently restricted, and recharging BEVs is still much more time-consuming compared to refueling ICEVs. Martins-Turner et al. (2020, see also Chapter 7) show that route planning without taking these limitations into account is too optimistic, and some of the planned routes are too long and cannot be carried out by BEVs. This is also in line with (Liimatainen, van Vliet, and Aplyn, 2019). Considering the limitations concerning battery capacity and energy consumption of BEVs already in the route planning could avoid this issue. Integrating the limited range of BEVs in an existing Vehicle Routing Problem (VRP) solving algorithm to consider the limited range of BEVs was done by Ewert et al. (2021a). As a consequence, the routes planned for range-restricted BEVs can be performed by them.

In this study, we will investigate the impacts of the limitations of BEVs on freight transport demand, road mileage performed, and the resulting transport costs and GHG-emissions. Because of the limitations of these vehicles, we expect that more BEVs will be required in comparison to ICEVs to fulfill the orders of the clients. Furthermore, we also find that some ICEVs are still needed to ensure that all orders can be fulfilled. While in the previous study (Martins-Turner et al., 2020, see Chapter 7) the BEVs were used as a full replacement of ICEVs, this study focuses on the economically driven decision of a carrier having both kinds of vehicles available: ICEVs and BEVs. To support the change from ICEVs to BEVs, an additional *tax on GHG-emissions for ICEVs* is introduced.

For generating the routes, the open-source VRP solver jsprit is used. It is linked to the microscopic Multi-Agent Transport Simulation (MATSim) as described in Section 3.2.2.1. The extended algorithm in combination with different cost values for the BEVs is applied (see Section 8.2) to the case study focusing on food retail distribution in Berlin, Germany (see Section 8.3). This is done for two different policy cases: i) with limited range of BEVs and ii) with unlimited range of BEVs. The simulation results are analyzed in terms of the tour characteristics including the costs, as well as in terms of emissions from driving and emissions on a Well-to-Wheel (W2W) basis (see Sections 8.4 and 8.5).

8.2 Methodology

In this study – in contrast to Martins-Turner et al. (2020, see Chapter 7) – the tour planning now considers the restricted range of the BEVs. This means that the planned tours are limited by the vehicle's range. The extended algorithm is developed by Ewert et al. (2021a) and will not be shown here in detail. Its general approach is to use an additional constraint in the recreation phase of jsprit's iterative ruin-and-recreate algorithm (see also Section 3.3.2):

> "Using the range constraint for a VRP, the constraint is checked at each part of changing the route. These changes could be the *usage of a different vehicle type* or *adding a new job to the tour*. Therefore, the method of the constraint is called which verifies whether all conditions for the route of the corresponding vehicle type are still fulfilled for the change made. If this is not the case, the examined change in the route is rejected. By this method, all suitable investigations for the range restriction of the electric vehicles are integrated." (Ewert et al., 2021a)

The solution is accepted if all conditions are (still) fulfilled. Everything else of the VRP solving algorithm is unmodified.

This study also uses the Berlin Food Retailing scenario as described in Section 4.1 and used, e.g., in the previous Chapter 7. As mentioned before, the (range) limitation is now also considered, which was not the case in the previous study. It is assumed that only the BEVs have a limited range, being relevant for the tour planning in the urban context of the scenario. In addition to the BEVs, ICEVs without range limitations are included to ensure that the VRP remains solvable, especially when certain locations are located outside the range of BEVs.

An additional *tax on GHG-emissions for ICEVs* is added to support the change from ICEVs to BEVs. By such a tax, the variable costs per distance for the ICEVs increase and thereby the BEVs become more attractive. This tax should internalize the external costs for emitting GHG-emissions. For this study, different tax values up to 300 €/ton (t) CO_2 are applied.

Each vehicle type is associated with different cost parameters (see Section 5.1, Appendix B, and for the current study, Table 8.1), which serve as input for the objective function of jsprit. For the policy cases, the tax on GHG emissions increases the variable costs per distance of the ICEVs (see Table 8.3 in Section 8.3.2). Jsprit's objective function aims to minimize the total costs of a given VRP solution. jsprit completes the route planning by selecting the most cost-effective solution within the given iterations. The output is then passed to Multi-Agent Transport Simulation (MATSim) to run the transport simulation.

The *base case* of the current study is the freight transport in urban food retail distribution carried out by ICEVs with a Gross Vehicle Weight Rating (GVWR) of 7.5 t, 18 t, 26 t, and 40 t, as used in the previous study (Martins-Turner et al., 2020, see Chapter 7). It is described in Section 8.3.1.

For the *policy cases*, the baseline scenario is extended by including BEVs with the same GVWR as the ICEVs. For the ICEVs, the GHG-emissions tax is applied, which increases the variable costs per distance. Two different sets of simulations are run: with a i) limited, and ii) unlimited range of the BEVs. Please refer to Section 8.3.2 for a detailed description of the policy cases.

8.3 Case study: Urban food distribution

In the framework of this case study, we investigate the food retail distribution in Berlin, Germany. This scenario was originally developed by Gabler et al. (2013); Schröder and Liedtke (2014). For the present study, some modifications are made (see e.g., Chapters 6 and 7). The scenario is also described in detail in Section 4.1.

In the baseline scenario (Section 8.3.1), we focus on the traditional freight transport in urban food retail distribution carried out by ICEV. In further scenarios (Section 8.3.2), the baseline scenario is extended by including BEVs with specific vehicle characteristics. The expected effects are the changed fleet composition, possibly an increased number of trips and mileage performed, and as a result, increased power consumption, transport costs, and GHG-emissions. MATSim (Horni, Nagel, and Axhausen, 2016, see also Section 3.2.1) and the connected VRP solver *jsprit* (jsprit, 2024, see also Section 3.3.2) are used for modeling and simulating these scenarios.

8.3.1 Baseline scenario: Food distribution with Internal Combustion Engine Vehicles

In the baseline scenario, deliveries to the food retail branches are carried out by *ICEV trucks with a GVWR of 7.5 t, 18 t, 26 t, and 40 t*. It is the same setup as for the baseline scenario in the previous study (Martins-Turner et al., 2020, see Chapter 7). Nevertheless, it has a slightly different output because it is another simulation run and jsprit solves the VRP heuristically.

In total, the scenario consists of 1′928 jobs of 867 food retail shops, and 17 locations of the distribution centers (DCs). All locations are georeferenced. A distinction is made between nine different German retail chains. These retailers could also be differentiated into supermarkets, discounters, and self-service stores. Based on this, there are 15 carrier types determined in the observed system. The locations of each retail chain are assigned to the associated DCs. Furthermore, the freight demand per branch for an average business day is derived. The various products are aggregated into the following three groups: (i) fresh, (ii) frozen, and (iii) dry goods. As a result, in total 45 carriers are modeled independently. Estimating the daily quantity demanded by the retail branches is based on each retailer's annual sales. As a result, the freight demand for each retail

branch in Berlin is derived (Gabler et al., 2013). When determining the delivery time window for each branch, we assume that frozen and dry goods are delivered within the time window between 9:00 a.m. and 7:00 p.m., and fresh products between 4:00 a.m. and 9:00 a.m. (Martins-Turner and Nagel, 2019, see Chapter 6).

In this case, each retailer owns its carrier(s). Its DCs are also the vehicles' depots. Each distribution center is equipped with its own fleet consisting of the various truck types with their corresponding vehicle characteristics (including GVWR, vehicle capacity, transport costs, and fuel consumption; see Table 8.1). The vehicle capacity of the vehicles used to deliver fresh and dry goods is measured on the maximum number of Euro pallets that fit on the loading area of each truck type. In contrast, the measurement unit freezer box is used for the vehicle capacity for the distribution of frozen goods. We assume that three minutes for each stop (constant stop time) and additionally one minute for the concrete delivery or pickup of the single pallet to/from the branch (variable stop time) are needed.

Using a transport cost calculation (TCC), we can derive the variable (distance-dependent), fixed, and personnel (time-dependent) costs. For the TCC, we use the parameter values prepared by Martins-Turner et al. (2020), which are based on the German Bundesverkehrswegeplan (BVWP) (BMVI, 2016). This calculation is described in detail in Chapter 5, including the tables in Appendix B. Since the Bundesverkehrswegeplan (BVWP) has a national economic perspective, taxes and insurances are not included in the cost calculation (PTV, TCI, and Mann, 2016). For calculating the time-dependent transport costs, the driver wages for representative vehicle types are also given in Planco, ITP, and TUBS (2015). In contrast, taxes other than the Value Added Tax (VAT) and insurance are relevant to the carrier. For this reason, we have to consider these cost components in our TCC. For this, we use the data provided by Eurotransport (2017).

As a basis for route planning, it can be determined whether the carrier has a fixed number of trucks or independently determines the need for vehicles as part of route planning. Here, we assume that it has an infinite fleet and uses the optimal number of vehicles to distribute the goods. Therefore, the fleet composition is a result of the VRP (Schröder and Liedtke, 2014; Gabler et al., 2013, see Section 3.3). The food retailers transmit to the carriers both their freight demand to be delivered and the time window during which they should be delivered. The retail branches are supplied from their DCs. One vehicle can perform several tours per day (Martins-Turner and Nagel, 2019, see Chapter 6). To make this possible, the original Multi-Depot Vehicle Routing Problem (MDVRP) based on the job type *service* has been transformed into a VRP based on *shipments*. The job types are described in Section 3.3.2, while this adaptation is described in the study by Martins-Turner and Nagel (2019, see Section 6.3).

The present study uses the road network of the MATSim Open Berlin Scenario[1] (Ziemke, Kaddoura, and Nagel, 2019). For our simulation, we ignore passenger transport, as we are only examining the changes in freight traffic generated in the food retail sector. For generating adequate routes and travel times also in tour planning, we are using a time-dependent network (Rieser, Nagel, and Horni, 2016) that uses the link travel times from the simulation output of the MATSim Open Berlin Scenario.

8.3.2 Policy scenario: Introduction of Battery Electric Vehicles

In this scenario, we use the same input data as for the baseline scenario (see Section 8.3.1). In addition, we introduce BEVs of the same size class as the already existing ICEVs for all carriers.

[1] https://github.com/matsim-scenarios/matsim-berlin

Hence, deliveries to the food retail branches can also be carried out by *BEVs with a GVWR of 7.5 t, 18 t, 26 t and 40 t*. In this context, we point out that a larger GVWR is allowed within the European Union when using a clean propulsion system (European Parliament and Council, 2015). We assume that the battery size is designed in a way that both BEVs and ICEVs have the same payload capacity. We determine that only 70 % of the theoretical (gross) battery capacity is used as (net) capacity for the tour planning to ensure an adequate battery lifetime and to maintain a reserve for unexpected energy consumption.

Regarding the TCC of BEVs, Martins-Turner et al. (2020, see also Chapter 7) provide two different cost schemes that only differ in the chassis costs:

i) based on a market analysis assuming that the chassis prices of BEVs are 1.6 times as high as those of ICEVs ("BEV 160") and

ii) based on Fuessel (2017) assuming that the chassis prices of BEVs will correspond to those of ICEVs from the moment mass production starts ("BEV 100").

For our case study, we will use the more future-related assumption, using the cost values for equal chassis prices for BEVs and ICEVs (see case "BEV 100" in Martins-Turner et al. (2020, see Chapter 7)). The methodology of calculating the costs is the same as in the base case. It is described in more detail in Section 5.1. The resulting values are also summarized in Section 5.3, while the detailed calculation can be found in Appendix B. Table 8.1 shows the cost values for the vehicle types used in this study. Thus far, all cost parameters have been calculated without the additional GHG-emissions tax.

As already described, an additional *tax on GHG-emissions for ICEVs* is applied to support the change from ICEVs to BEVs. By such a tax, the variable costs per distance for the ICEVs increase, thereby the BEVs become more attractive. This tax should internalize the external costs of emitting GHG-emissions. Assuming a W2W production of 3.17 kilogram (kg) CO_2/l diesel (DIN EN 16258:2012, 2013), 1 € tax per ton of CO_2 leads to additional costs of 0.17 €/l diesel. If the (high) value of 300 €/t is set as an end point for a rapid change toward a greener transport system, the additional costs are 0.951 €/l diesel. The additional costs per liter of diesel due to the tax on GHG-emissions are summarized in Table 8.2.

Multiplying the additional costs per liter of diesel by the diesel consumption of the vehicle type (from Table 8.1), we can calculate the additional costs caused by the tax as well as the new variable costs per distance for each vehicle type depending on the tax rate. The updated variable costs per distance for the ICEVs are shown in Table 8.3. The implemented range constraint is applied to the BEVs, while the ICEVs are not restricted in their range for tour planning. As a consequence, each carrier gets its own fleet composition with BEVs and/or ICEVs as a result of the tour planning algorithm (Ewert et al., 2021a). Since the algorithm is cost-oriented, the fleet composition depends on the different cost structures of the vehicle types provided.

The results are presented as follows:

i) Section 8.4 will present the results of the setup developed in this section, *including the range restrictions* from Table 8.1,

ii) Section 8.5 will additionally present results *without range restriction*, since Ewert et al. (2025) showed that BEV ranges have become so large that they play less and less of a role.

Table 8.1: Characteristics for the different vehicle types. This table summarizes the results of the cost calculation and vehicle information provided in Chapter 5 and Appendix B for the current study. The cost parameters are used as inputs for the tour planning. The average energy consumption, the energy costs per 100 kilometer (km), and the range are provided as additional information. For the additional costs and the resulting changes in the variable costs per distance because of the GHG tax, please refer to Table 8.3.

vehicle type	parameter	Base: ICEV	policy[1]: BEV 100
7.5 t	fixed costs (€ /day)	63.49	74.76
	variable costs per distance[2] (€ /m)	0.00040	0.00046
	variable costs per time[3] (€ /s)	0.00490	0.00490
	energy consumption (per 100 km)	13.57 l	61 kWh
	energy costs (€ /100 km)	16.69	13.52
	range (km)	(unlimited)	100
18 t	fixed costs (€ /day)	80.47	96.26
	variable costs per distance[2] (€ /m)	0.00065	0.00055
	variable costs per time[3] (€ /s)	0.00490	0.00490
	energy consumption (per 100 km)	33.12 l	106 kWh
	energy costs (€ /100 km)	40.74	23.49
	range (km)	(unlimited)	80
26 t	fixed costs (€ /day)	82.60	111.90
	variable costs per distance [2] (€ /m)	0.00067	0.00072
	variable costs per time[3] (€ /s)	0.00490	0.00490
	energy consumption (per 100 km)	33.12 l	150 kWh
	energy costs (€ /100 km)	40.74	33.24
	range (km)	(unlimited)	133
40 t	fixed costs (€ /day)	126.58	183.93
	variable costs per distance[2] (€ /m)	0.00069	0.00078
	variable costs per time[3] (€ /s)	0.00559	0.00559
	energy consumption (per 100 km)	37.45 l	180 kWh
	energy costs (€ /100 km)	46.06	39.89
	range (km)	(unlimited)	172

[1] without the additional costs caused by the GHG-emissions tax.
[2] The variable costs per distance include the energy costs. The additional costs induced by the GHG-emissions tax are *not* included in this table. Please refer to Table 8.3 for the additional costs.
[3] The variable costs per time are the personnel costs.

Table 8.2: Additional costs per l of diesel due to a tax on GHG-emissions.

tax (€/t CO_2)	add. costs (€/l)
0	-
25	0.079
50	0.159
100	0.317
150	0.476
200	0.634
250	0.793
300	0.951

Table 8.3: Variable costs per distance for ICEVs with different GHG-emissions tax rates. The additional costs for each vehicle type (first rows) are calculated based on the diesel consumption and the additional costs per liter depending on the tax value (see Table 8.2). "Tax 300" means an additional tax of 300 € per t of CO_2 emissions. The total variable costs per distance including the additional costs are shown in the second row of each vehicle type.

veh. type	consumption (l/100 km)	Variable costs per distance (€/m)							
		No Tax	Tax 25	Tax 50	Tax 100	Tax 150	Tax 200	Tax 250	Tax 300
7.5 t	13.57	—	0.00001	0.00002	0.00004	0.00006	0.00009	0.00011	0.00013
		0.00040	0.00041	0.00042	0.00044	0.00046	0.00049	0.00051	0.00053
18 t	33.12	—	0.00003	0.00005	0.00010	0.00016	0.00021	0.00026	0.00031
		0.00065	0.00068	0.00070	0.00075	0.00081	0.00086	0.00091	0.00096
26 t	33.12	—	0.00003	0.00005	0.00010	0.00016	0.00021	0.00026	0.00031
		0.00067	0.00070	0.00072	0.00077	0.00083	0.00088	0.00093	0.00098
40 t	37.45	—	0.00003	0.00006	0.00012	0.00018	0.00024	0.00030	0.00036
		0.00069	0.00072	0.00075	0.00081	0.00087	0.00093	0.00099	0.00105

8.4 Results with range limitation

In this section, the results of the simulations with the range restriction of the BEVs are presented.

8.4.1 Tour characteristics and costs

Figure 8.1 shows the tour distances driven for each vehicle type of the scenarios including *range-restricted* BEVs. The values for the simulation without tax (Figure 8.1b) and with a tax of 300 € (Figure 8.1c) are compared to the base case with only ICEVs available (Figure 8.1a). The plots for the all tax values in this study are presented in Appendix C. The ICEVs are shown in a bluish color, while the BEVs are shown in violet tones.

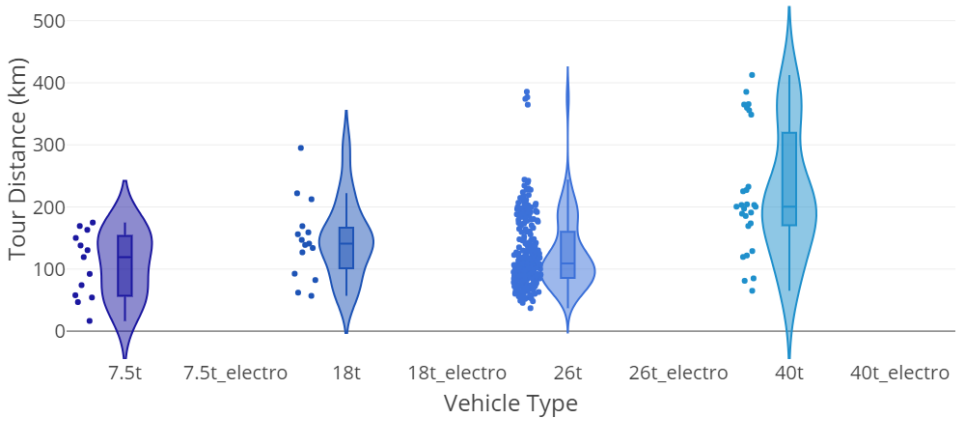
With the increasing tax on GHG-emissions, fewer ICEVs are used and more BEVs are chosen. One also sees that the BEVs are restricted in their range, and therefore they are only used for shorter distances compared to the same-sized ICEVs. When applying the highest tax value, nearly all vehicles on the shorter distances are BEVs. The ICEVs are used for the longer distances. Since the depots of some carriers in the scenario are located well outside the city limits of Berlin, the range is insufficient to supply supermarkets within Berlin using range-restricted BEVs. Figure 4.1 in Section 4.1 shows the locations of the DCs and supermarkets in the scenario. For example, the DC of the "Kaufland" supermarket chain is located in Lübbenau, approx. 100 km (one-way) by road south of the Berlin city center. So even with the range of 172 km of the 40 t BEVs, the BEVs cannot be used. But also for retail chains with the DC closer to Berlin, the BEV may have range issues. "Edeka" for example, with the DC in Mittenwalde (located approx. 15 km south of the Berlin city limits), the one-way road distance to the supermarket in the north of Berlin is approx. 50 km.[2] This carrier uses trucks with a GVWR of 18 t or 26 t for their delivery (Schröder and Liedtke, 2014). Accordingly, the range of 80 km and 133 km of the BEVs (see Table 8.1) is not sufficient for a cost-effective delivery of the supermarket in the north of Berlin, as the one-way road distance is already approx. 50 km, and the vehicles are used to deliver to several supermarkets in one tour. Please also note that the vehicles can reload goods during the day. This makes the use of non-restricted ICEVs more attractive, as it is possible to run several (sub-)tours with one vehicle, leading to savings in fixed costs. As long as the range-restricted BEVs do not have the option of recharging, e.g., during reloading goods at the DC, the range restriction prevents them from making a further (sub-) tour in terms of range. Section 8.5 gives an overview of the results without the range restriction of the BEVs.

In our study, the fleet composition is a result of the tour planning. Table 8.4 shows the results in the fleet composition (see Table 8.4a) and the vehicle kilometer (vkm) driven (see Table 8.4b) per vehicle type for each tax scenario. While 285 ICEVs are necessary to serve the daily demand in the baseline scenario, the number of vehicles used per day in the BEV scenario depends on the amount of the CO_2-tax for the ICEVs (see Table 8.4a). With an increasing tax on GHG-emissions, the number of BEVs increases and the number of ICEVs decreases. This drastic shift results from the higher fuel price and therefore higher variable costs per distance for the ICEVs as well as the cost-based objective function of the jsprit algorithm. Due to the limited range of the BEVs, the total number of vehicles used increases with the progressive shift to BEVs. Without any tax on GHG-emissions, 246 ICEVs and 43 BEVs are used. A tax of 300 €/t CO_2 will result in a fleet of 96 ICEVs and 214 BEVs. The use of the remaining ICEVs is either necessary to serve the demand

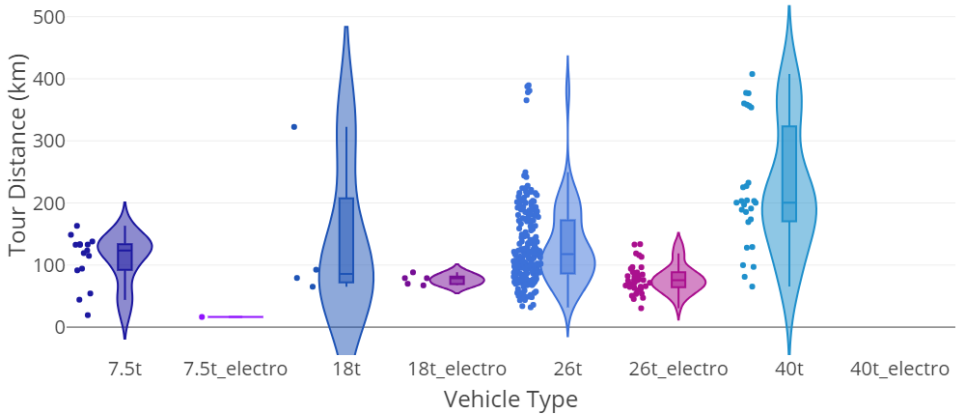
[2] The northernmost supermarket in Berlin-Frohnau is about 47 km as the crow flies and about 57 km via the usual road route away.

of the supermarkets located outside the range of the BEVs, or because it is more efficient to run a longer tour, including reloading, instead of using several BEVs.

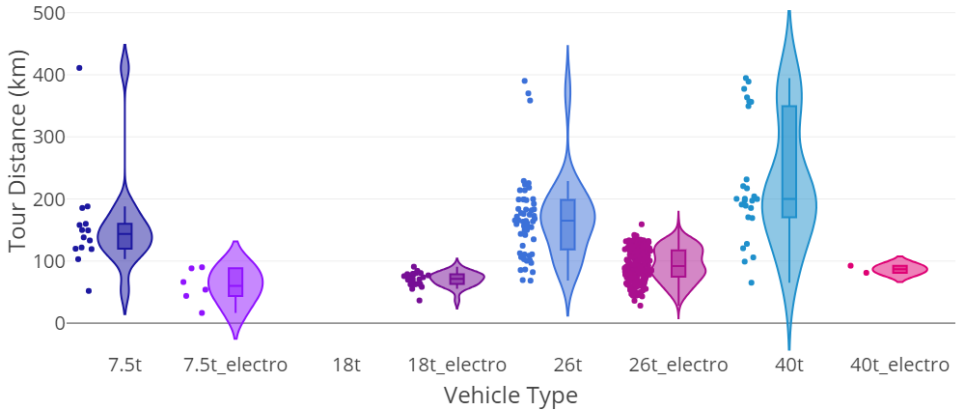
While the total number of vehicles used increases with the tax, there is a tendency to decrease in the total vkm driven (see Table 8.4b). This may be explained by the facts that i) the increased variable costs per distance of the ICEVs force the router and therefore the VRP solver to prefer a shorter mileage over a shorter travel time and ii) the BEVs are restricted in their range, and therefore, their routes are also optimized more towards shorter distances (between the different supermarkets within a tour). Due to the limited range of the BEVs, the observed shift from ICEVs to BEVs in terms of vkm driven is weaker than the corresponding shift in the total number of vehicles used.



(a) Base case: no Tax, only ICEVs



(b) No Tax



(c) Tax 300

Figure 8.1: Observed distances (vkm) driven by each vehicle sorted by their type and depending on the tax (€/t) on CO_2-emissions for the ICEVs. The BEVs are *restricted* in their range. Bluish colors represent the ICEVs and violet colors the BEVs.

Table 8.4: Results of usage per vehicle type depending on the GHG-tax for ICEVs. The range of the BEVs is *limited* by their battery capacity.

(a) Number of vehicles per day.

scenario	tax (€/t CO_2)	add. costs (€/l)	7.5 t ICEV	7.5 t BEV	18 t ICEV	18 t BEV	26 t ICEV	26 t BEV	40 t ICEV	40 t BEV	total ICEV	total BEV	Sum
base: only ICEVs	0	—	13	—	15	—	230	—	27	—	**285**	—	**285**
	0	—	15	1	4	5	200	37	27	0	**246**	**43**	**289**
	25	0.079	16	2	4	7	176	56	27	0	**223**	**65**	**288**
ICEVs	50	0.159	18	1	2	8	170	59	27	0	**217**	**68**	**285**
and range-	100	0.317	14	4	2	12	140	87	26	2	**182**	**105**	**287**
restricted	150	0.476	18	3	2	17	127	109	26	2	**173**	**131**	**304**
BEVs	200	0.634	15	5	1	20	108	123	26	2	**150**	**150**	**300**
	250	0.793	18	6	0	25	86	141	26	2	**130**	**174**	**304**
	300	0.951	14	6	0	23	56	183	26	2	**96**	**214**	**310**

(b) vehicle kilometer (vkm) driven per day.

scenario	tax (€/t CO_2)	add. costs (€/l)	7.5 t ICEV	7.5 t BEV	18 t ICEV	18 t BEV	26 t ICEV	26 t BEV	40 t ICEV	40 t BEV	total ICEV	total BEV	Sum
base: only ICEVs	0	—	1′386	—	2′194	—	28′843	—	5′995	—	**38′418**	—	**38′418**
	0	—	1′642	16	559	383	26′201	2′877	5′992	0	**34′393**	**3′277**	**37′670**
	25	0.079	1′883	96	442	519	24′482	4′447	5′995	0	**32′802**	**5′062**	**37′863**
ICEVs	50	0.159	2′092	16	210	588	23′916	4′668	5′991	0	**32′209**	**5′272**	**37′481**
and range-	100	0.317	1′635	156	292	895	20′769	7′231	5′919	174	**28′616**	**8′455**	**37′071**
restricted	150	0.476	2′514	116	270	1′231	17′828	9′302	5′918	174	**26′530**	**10′823**	**37′353**
BEVs	200	0.634	2′206	247	201	1′462	15′867	11′116	5′884	174	**24′158**	**12′998**	**37′155**
	250	0.793	2′579	264	0	1′808	13′360	12′965	5′880	174	**21′819**	**15′210**	**37′029**
	300	0.951	2′188	358	0	1′619	9′421	17′230	5′879	174	**17′488**	**19′382**	**36′870**

Figure 8.2 shows the resulting daily costs for the different cases. The values are summed over all vehicles used in the scenario. With the increasing tax on GHG-emissions, the costs for the resulting transport operations increase as well. In the base case with only ICEVs available, the costs are 87′180 € per day. For the highest tax of 300 €/t CO_2 in the scenario, the costs increase to 106′800 € per day. This is an increase of 22.5 % compared to the base case. The figure also shows the different cost types, such as the fixed costs and the variable costs per distance and per time. The fixed costs and the variable costs per distance increase with the tax on GHG-emissions because the number of vehicles used increases and the cost factor for the variable costs per distance also rises. The increase in the number of vehicles is shown in Table 8.4a, and the cost factor change is described in Table 8.3. The variable costs per time remain more or less constant between 36′700 and 37′000 € per day.

8.4.2 Emissions during operation

To calculate the emissions during operation, the vkm driven are multiplied by the specific emission factors based on the Handbook on Emission Factors for Road Transport (HBEFA) v4.1 (INFRAS, 2019). The emission factors are vehicle-type specific and depend on the vehicle's GVWR, the road type, and the speed. We are using the emission factors depending on the GVWR and the technology / fuel type (e.g., diesel or electricity), but independent of the emission concept (e.g., EURO 6), as provided by Gable, Martins-Turner, and Nagel (2022, see also Section 2.2.2.3). The overall methodology is described in Section 2.2.2 and also applied for the electrification study in Chapter 7. It includes exhaust emissions (see Table 8.5a) as well as non-exhaust emissions (see Table 8.5b), such as tire wear, brake wear, and road wear. The annual values are calculated assuming 250 workdays per year (Planco, ITP, and TUBS, 2015).

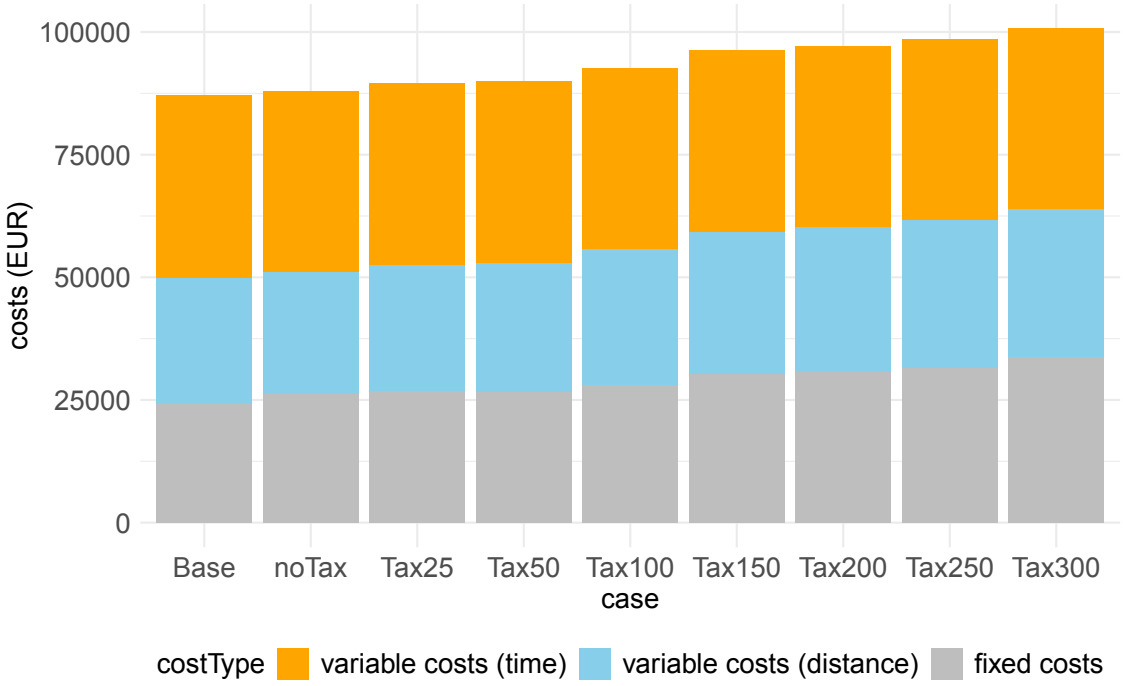


Figure 8.2: Resulting daily costs in Euro for the different cases. The range of the BEVs is *limited* by their battery capacity.

Table 8.5: Aggregated emissions of selected emission components (pollutants) from vehicle operations in t per year. The BEVs in the policy cases are restricted in their range. All values are calculated using the adjusted emission factors based on the HBEFA database. The values in parentheses are the relative changes compared to the base case with only ICEVs available.

(a) Aggregated emissions of selected *exhaust* emissions from vehicle operations in t per year.

Pollutant	Base	No Tax	Tax 25	Tax 50	Tax 100	Tax 150	Tax 200	Tax 250	Tax 300
CO_2	6′293	5′662	5′392	5′299	4′735	4′361	3′997	3′605	2′926
	—	(−10.0 %)	(−14.3 %)	(−15.8 %)	(−24.8 %)	(−30.7 %)	(−36.5 %)	(−42.7 %)	(−53.5 %)
CO	6.77	5.83	5.5	5.41	4.8	4.41	4.02	3.55	2.81
	—	(−13.9 %)	(−18.8 %)	(−20.0 %)	(−29.1 %)	(−34.8 %)	(−40.6 %)	(−47.6 %)	(−58.5 %)
NO_x	18.68	16.16	15.27	15.14	13.4	12.33	11.23	9.93	7.84
	—	(−13.5 %)	(−18.3 %)	(−19.0 %)	(−28.3 %)	(−34.0 %)	(−39.9 %)	(−46.9 %)	(−58.0 %)
PM_{10}	0.324	0.291	0.28	0.277	0.25	0.238	0.22	0.203	0.172
	—	(−10.1 %)	(−13.7 %)	(−14.5 %)	(−22.9 %)	(−26.6 %)	(−32.1 %)	(−37.2 %)	(−47.0 %)
$PM_{2.5}$	0.324	0.291	0.28	0.277	0.25	0.238	0.22	0.203	0.172
	—	(−10.1 %)	(−13.7 %)	(−14.5 %)	(−22.9 %)	(−26.6 %)	(−32.1 %)	(−37.2 %)	(−47.0 %)
BC	0.169	0.15	0.143	0.142	0.127	0.119	0.11	0.1	0.082
	—	(−11.2 %)	(−15.2 %)	(−16.2 %)	(−25.0 %)	(−29.4 %)	(−35.1 %)	(−40.9 %)	(−51.2 %)

(b) Aggregated emissions of selected *non-exhaust* (n.e.) emissions from vehicle operations in t per year.

Pollutant	Base	No Tax	Tax 25	Tax 50	Tax 100	Tax 150	Tax 200	Tax 250	Tax 300
PM_{10} n.e.	1.214	1.191	1.196	1.186	1.171	1.18	1.177	1.171	1.167
	—	(−1.9 %)	(−1.5 %)	(−2.3 %)	(−3.5 %)	(−2.8 %)	(−3.0 %)	(−3.5 %)	(−3.9 %)
$PM_{2.5}$ n.e.	0.526	0.513	0.517	0.513	0.508	0.513	0.509	0.508	0.506
	—	(−2.4 %)	(−1.6 %)	(−2.4 %)	(−3.4 %)	(−2.5 %)	(−3.3 %)	(−3.4 %)	(−3.7 %)
BC n.e.	0.0526	0.0513	0.0517	0.0513	0.0508	0.0513	0.0509	0.0508	0.0506
	—	(−2.4 %)	(−1.6 %)	(−2.4 %)	(−3.4 %)	(−2.5 %)	(−3.3 %)	(−3.4 %)	(−3.7 %)

As shown in Table 8.5a, the exhaust emissions decrease with the increasing tax on GHG-emissions and the resulting shift towards BEVs. In the high tax scenario (300 € per t CO_2), the CO_2 emissions are reduced by 53.5 % compared to the base case with only ICEVs available. The other exhaust emissions, such as carbon monoxide (CO), nitrogen oxides (NO_x), particulate matter $< 10\,\mu m$ (PM_{10}), particulate matter $< 2.5\,\mu m$ ($PM_{2.5}$), and black carbon (BC) are reduced by 58.5 %, 58.0 %, 47.0 %, 47.0 %, and 51.2 %, respectively.

In terms of non-exhaust emissions, there is only a slight decrease, e.g., for PM_{10} by 3.9 % in the high tax scenario (300 € per t CO_2) compared to the base case with only ICEVs available. The other non-exhaust emissions, namely $PM_{2.5}$ and BC, are reduced by 3.7 %, respectively. These values are in the range of the changes of vkm driven (see Table 8.4b), which decreases by approximately 4.0 % in the high tax scenario (300 € per t CO_2). This is because non-exhaust emissions are mainly caused by road and tire wear, which are not significantly influenced by the engine type (see also Section 2.2.2.2). The marginal deviation may come from the fact that the vkm by the different vehicle size classes (either by ICEVs or BEVs) are not the same in the different scenarios.

8.4.3 Well-to-Wheel emissions

We apply the W2W methodology according to JRC et al. (2014) to analyze the environmental impact of the simulated scenarios. The W2W-methodology includes the GHG-emissions from the production of diesel and electricity as well as from their use in the vehicles. Based on the observed distance traveled from the transport simulation, vehicle-type specific energy consumption, and the specific CO_2-emission factor per energy unit, we calculate the W2W GHG-emissions. The methodology is also described in Section 2.2.3 and is also applied for the electrification study (see Chapter 7) in Section 7.4.3. Please note that the results for the base case are slightly different from the results in the previous study because it is another simulation run and jsprit solves the VRP heuristically.

The W2W GHG-emissions of the different simulation cases are calculated by multiplying the observed distance traveled (see Table 8.4b, Figure 8.1) with the aggregated W2W emission factor per vkm as noted in Table 2.1 in Section 2.2.3. For calculating the annual values, again 250 business days per year are assumed (Planco, ITP, and TUBS, 2015). The resulting values per year for the different scenarios are shown in Figure 8.3.

The shift from ICEVs to BEVs driven by the increasing tax results in a significant reduction of the W2W GHG emissions. The W2W emissions of the BEVs are shown for three different energy sources:

1. the energy mix for Germany in 2018 (red),
2. the energy mix for Germany in 2030 (blue), and
3. renewable energy only (green).

As expected, the energy mix has a significant influence on the W2W emissions of the BEVs. Moreover, the W2W emissions of the BEVs are significantly lower than those of the ICEVs, even with the energy mix for Germany in 2018 (see Table 2.1). Thus, the W2W emissions decrease with the increasing tax on GHG-emissions, leading to a higher share of BEVs in the fleet and a higher share of BEVs in the total distance traveled (see Section 8.4.1), as well as with the increasing share of renewable energy in the electricity mix.

While in the base case with only ICEVs the W2W emissions are approx. 10′000 t CO_2eq per year, the W2W emissions of the *tax 300* scenario are already reduced to approx. 4′600 (−54 %)

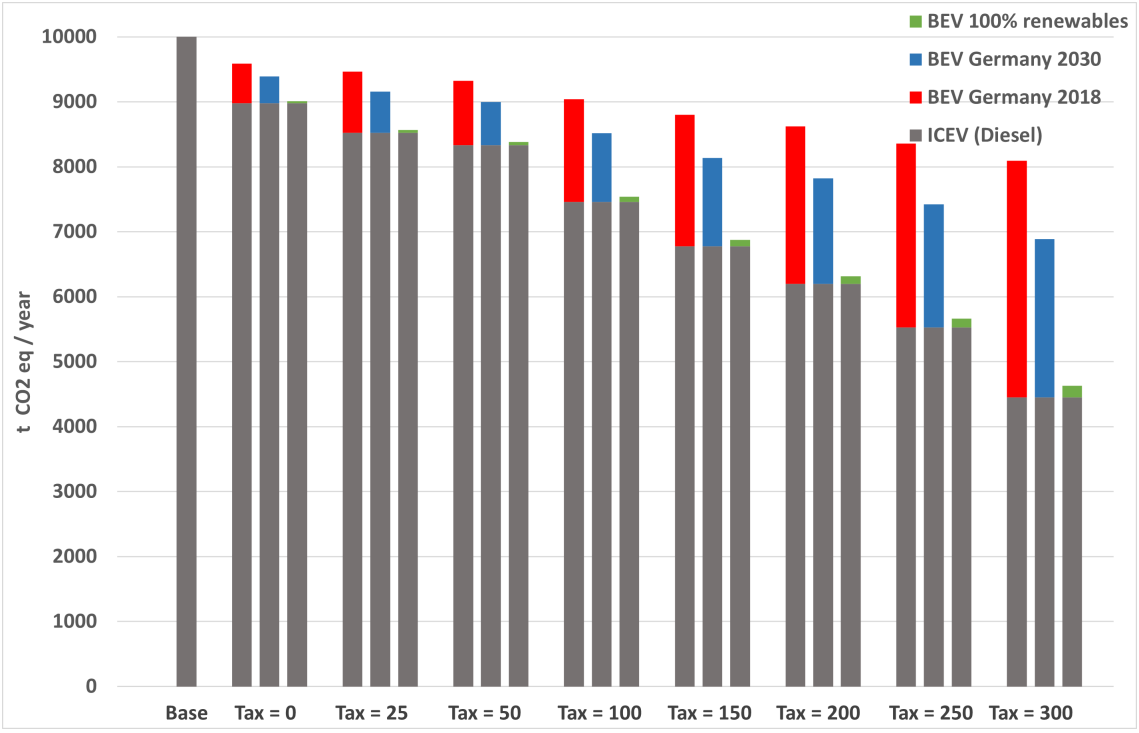


Figure 8.3: Calculated W2W-emissions in t CO_2 equivalents (CO_2eq) per year for the baseline and the BEV scenarios (tax on CO_2-emissions on ICEVs from 0 to 300 €/t) with range-restricted BEVs. The emissions of the BEVs are shown for three different energy sources: energy mix for Germany 2018 (red), for Germany 2030 (blue), and renewable-only (green). The emissions from the ICEVs are marked in gray.

to 8′000 (−20 %) t CO_2eq per year, depending on the electricity mix. As shown in Tables 8.4a and 8.4b, a significant share of ICEVs is still in use, even in the *tax 300* scenario. This results in approx. 4′450 t CO_2eq per year from the ICEVs alone in this scenario, which is approx. 44 % of the W2W emissions of the base case. This value is very much in line with the approx. 45 % remaining total vkm driven by the ICEVs in the *tax 300* scenario (see Table 8.4b).

8.5 Results without range limitation

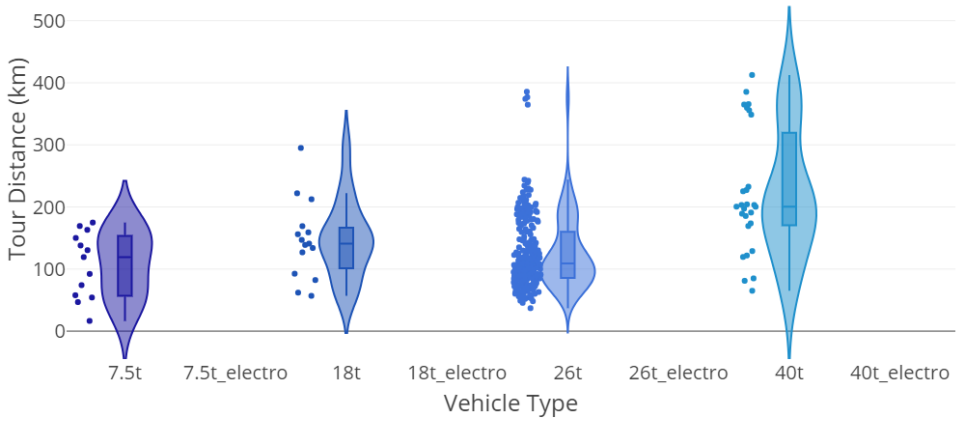
This section provides the results for the simulation *without* application of the distance constraint. Thus, the VRP solving assumes an infinite range as well for the BEVs. As discussed earlier (see Section 7.5), this means that these tours can only be driven if, e.g., the battery capacity increases or there are additional charging opportunities for a recharging during the tour. Ewert et al. (2025) showed recently that the range is no longer an issue for the food retailing scenario in Berlin. So we can assume that the range is not a limiting factor for the BEVs in this scenario anymore.

The results are analyzed in the same way as the previous case with the restriction of the range (see Section 8.4). For this reason, the results are presented in the same structure, but without further detailed explanations of the calculations.

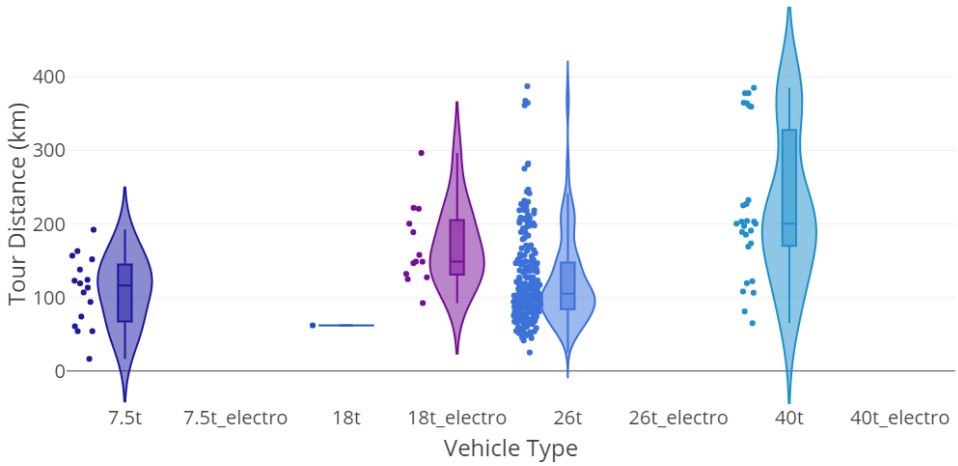
8.5.1 Tour characteristics and costs

Figure 8.4 shows the tour distances driven for each vehicle type of the scenarios including BEVs without range restriction for the cases without (Figure 8.4b) and with 300 € tax (Fig. 8.4c) compared to the base case with only ICEVs (Figure 8.4a). For all other taxes, please refer to Appendix C.

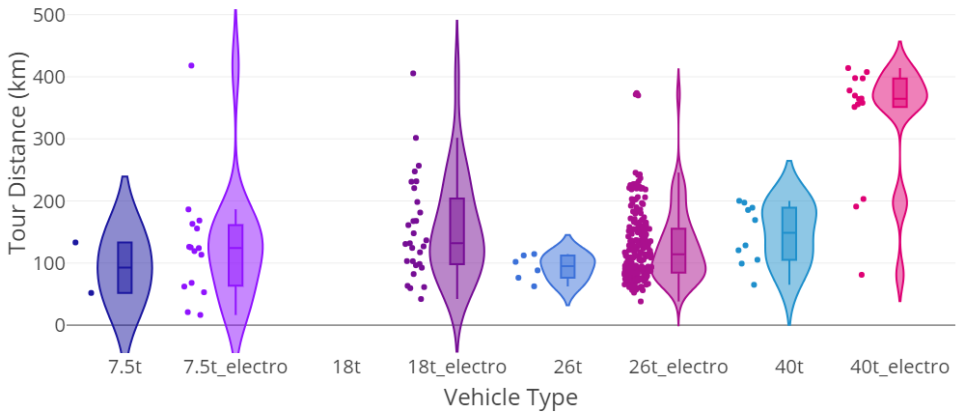
With the increasing tax on GHG-emissions, more and more tours are driven by BEVs. It is clearly visible that the BEVs are used for longer tours than in the previous case with range restriction. For the vehicles with a GVWR of 40 t, the BEVs are used more often for the longer tours, while the ICEVs are used for the shorter tours. Also visible are the gaps in the tour distance distributions, showing that vehicles with longer tours (more vkm) are used for driving several sub-tours and reloading goods in between. Another result is that even with a 300 €/t CO_2 tax, 18 ICEVs are still used. In contrast to the previous case with range restriction, now the total number of vehicles used does not increase with the tax on GHG-emissions. It is more or less constant with 277 to 287 vehicles depending on the scenarios. As a tendency, the number of vehicles used slightly decreases, which may be because the BEVs have lower variable costs per distance and higher fixed costs per day than the ICEVs (see Table 8.3), leading the VRP solving algorithm to a higher usage of the BEVs. This is also in line with the observation in Table 8.6b, showing a slight increase of the total vkm driven when the tax on GHG-emissions increases.



(a) Base case: no Tax, only ICEVs



(b) No Tax



(c) Tax 300

Figure 8.4: Observed distances (km) driven by each vehicle type depending on the tax (€/t) on CO_2-emissions for the ICEVs. On top is the base case *without* BEVs available. The BEVs are *not restricted* in their range.

Table 8.6: Results of usage per vehicle type depending on GHG-tax for ICEVs. The BEVs are *not* limited in their driving distance.

(a) Number of vehicles per day.

scenario	tax (€/t CO_2)	add. costs (€/l)	7.5 t ICEV	7.5 t BEV	18 t ICEV	18 t BEV	26 t ICEV	26 t BEV	40 t ICEV	40 t BEV	total ICEV	total BEV	Sum
base: only ICEVs	0	—	13	—	15	—	230	—	27	—	**285**	—	**285**
ICEVs and BEVs	0	—	16	0	1	13	229	0	27	0	**273**	**13**	**286**
	25	0.079	15	0	1	16	228	0	27	0	**271**	**16**	**287**
	50	0.159	16	0	1	22	158	59	27	0	**202**	**81**	**283**
	100	0.317	16	0	1	24	43	167	24	2	**84**	**193**	**277**
	150	0.476	12	6	0	23	35	180	24	3	**71**	**212**	**283**
	200	0.634	9	7	0	23	26	193	23	3	**58**	**226**	**284**
	250	0.793	2	15	0	20	24	193	15	11	**41**	**239**	**280**
	300	0.951	2	15	0	29	6	205	10	14	**18**	**263**	**281**

(b) Kilometers driven per day.

scenario	tax (€/t CO_2)	add. costs (€/l)	7.5 t ICEV	7.5 t BEV	18 t ICEV	18 t BEV	26 t ICEV	26 t BEV	40 t ICEV	40 t BEV	total ICEV	total BEV	Sum
base: only ICEVs	0	—	1′386	—	2′194	—	28′843	—	5′995	—	**38′418**	—	**38′418**
ICEVs and BEVs	0	—	1′742	0	62	2′208	28′355	0	5′994	0	**36′153**	**2′208**	**38′360**
	25	0.079	1′492	0	62	2′434	28′498	0	5′994	0	**36′045**	**2′434**	**38′480**
	50	0.159	1′833	0	61	2′929	20′074	7′614	5′993	0	**27′962**	**10′543**	**38′504**
	100	0.317	1′721	0	63	3′408	5′722	22′088	5′675	496	**13′182**	**25′992**	**39′174**
	150	0.476	1′619	613	0	3′261	3′932	23′437	5′314	877	**10′865**	**28′188**	**39′053**
	200	0.634	1′225	708	0	3′185	2′775	24′858	5′253	886	**9′254**	**29′637**	**38′891**
	250	0.793	185	1′954	0	2′829	1′981	25′844	2′517	3′619	**4′683**	**34′246**	**38′929**
	300	0.951	185	1′920	0	4′487	556	26′178	1′459	4′633	**2′200**	**37′218**	**39′418**

Figure 8.5 shows the resulting daily costs in Euro for the different cases. The values are summed up over all vehicles used in the scenario. With the increasing tax on GHG-emissions, the costs for the resulting transport operations increase as well. In the base case with only ICEVs available, the costs are 87′180 € per day. For the highest tax of 300 €/t CO_2 in the scenario, the costs increase to 98′504 € per day. This is an increase of 13 % compared to the base case. In comparison, the daily costs for the *range-restricted* scenario increase by 22 % compared to the base case when introducing the tax rate of 300 €/t CO_2 (see Section 8.4.1).

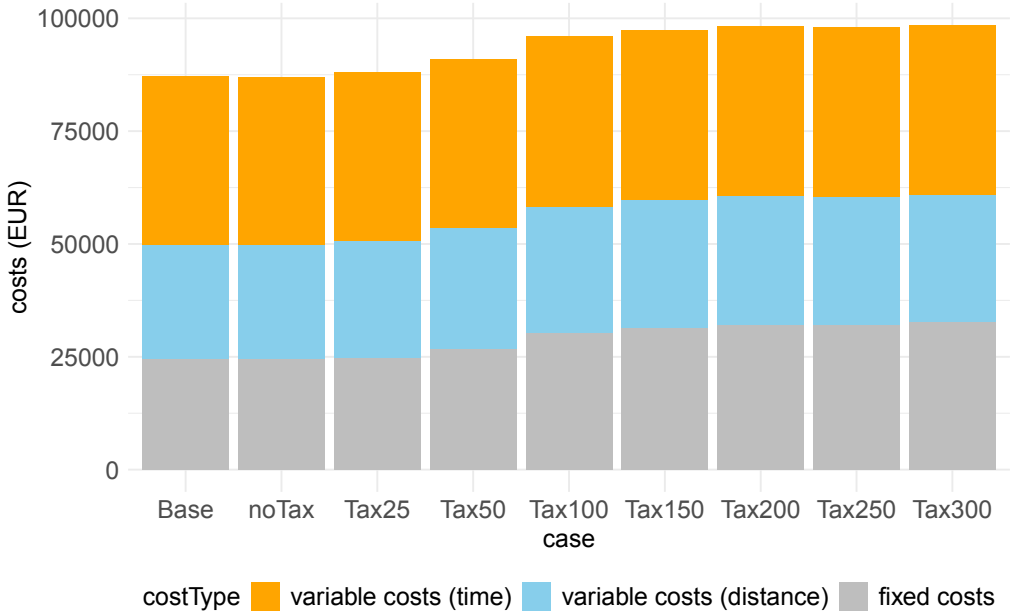


Figure 8.5: Resulting daily costs in Euro for the different cases. The BEVs are *not* limited in their driving distance.

The figure also shows the different cost types, such as the fixed costs and the variable costs per distance and per time. Since the BEVs are not limited in their driving distance, the total number of vehicles remains more or less stable with a slightly decreasing tendency (see Table 8.6a). Thus, the increase in the fixed costs comes from the higher fixed costs per BEV compared to an ICEV (see Table 8.1) and no longer from an increased fleet, as it was also in the case with the range-restricted BEVs. The sum of the variable costs per distance also increases with the tax on GHG-emissions, but also not as strongly as in the other case with range restriction. This is mainly because fewer ICEVs remain in the fleet and the total vkm driven increases when the tax increases. The variable costs per time remain more or less constant between 37′100 and 37′800 € per day.

8.5.2 Emissions during operation

The following Table 8.7 shows the emissions during operation for the cases *without* range limitation for the BEVs. The values are calculated analogously to Section 8.4.2 by multiplying the driven vkm with the specific emission factors based on HBEFA v 4.1 (INFRAS, 2019) and including the adaptation by Gable, Martins-Turner, and Nagel (2022) as described in Section 2.2.2. The emission factors are vehicle-type specific and depend on the vehicle's GVWR, the road type, and the speed.

This is done analogously to the other case with range restriction in Section 8.4.2 The overall methodology of the calculation is described in Section 2.2.2. It includes exhaust emissions (see

Table 8.7a) as well as non-exhaust emissions (see Table 8.7b), such as tire wear, brake wear, and road wear. As before, annual values are calculated assuming 250 workdays per year (Planco, ITP, and TUBS, 2015).

As a result of the stronger shift toward BEVs, the reduction in exhaust emissions is also much more noticeable. While it was, depending on the pollutant, between 47 % and 58 % in the case with range restriction, it is now approx. 92 % to 94 % for the tax 300 scenario. In the case without range restriction, already a tax of 100 €/t CO_2 leads to a reduction of the exhaust emissions by approx. 65 % to 66 % compared to the base case with only ICEVs available.

For the non-exhaust emissions, we observe a small increase (approx. 2.5 % for the tax 300 case), which is in line with the increasing vkm driven when the tax on GHG-emissions increases. In the range-restricted case, the non-exhaust emissions were reduced by up to 3.9 % for the tax 300 scenario compared to the base case with only ICEVs available. This is also in line with the decreasing vkm driven when the tax on GHG-emissions increases.

Table 8.7: Aggregated emissions of selected emission components (pollutants) from vehicle operations in t per year. The BEVs are *not* limited in their driving distance. All values are calculated using the adapted emission factors based on the HBEFA database. The values in parentheses are the relative changes compared to the base case with only ICEVs available.

(a) Aggregated emissions of selected *exhaust* emissions from vehicle operations in t per year.

Pollutant	Base	No Tax	Tax 25	Tax 50	Tax 100	Tax 150	Tax 200	Tax 250	Tax 300
CO_2	6′293	5′964	5′962	4′642	2′251	1′882	1′639	851	405
	—	(−5.2 %)	(−5.3 %)	(−26.2 %)	(−64.2 %)	(−70.1 %)	(−74.0 %)	(−86.5 %)	(−93.6 %)
CO	6.77	6.17	6.19	4.77	2.26	1.86	1.59	0.87	0.41
	—	(−8.8 %)	(−8.6 %)	(−29.5 %)	(−66.7 %)	(−72.5 %)	(−76.6 %)	(−87.1 %)	(−93.9 %)
NO_x	18.68	17.48	17.58	13.56	6.47	5.44	4.66	2.58	1.19
	—	(−6.4 %)	(−5.9 %)	(−27.4 %)	(−65.4 %)	(−70.9 %)	(−75.1 %)	(−86.2 %)	(−93.6 %)
PM_{10}	0.324	0.306	0.306	0.249	0.142	0.123	0.111	0.053	0.026
	—	(−5.4 %)	(−5.6 %)	(−23.2 %)	(−56.2 %)	(−62.0 %)	(−65.9 %)	(−83.7 %)	(−92.1 %)
$PM_{2.5}$	0.324	0.306	0.306	0.249	0.142	0.123	0.111	0.053	0.026
	—	(−5.4 %)	(−5.6 %)	(−23.2 %)	(−56.2 %)	(−62.0 %)	(−65.9 %)	(−83.7 %)	(−92.1 %)
BC	0.169	0.158	0.158	0.126	0.067	0.057	0.05	0.025	0.012
	—	(−6.4 %)	(−6.5 %)	(−25.4 %)	(−60.4 %)	(−66.2 %)	(−70.3 %)	(−85.2 %)	(−92.9 %)

(b) Aggregated emissions of selected *non-exhaust* emissions from vehicle operations in t per year.

Pollutant	Base	No Tax	Tax 25	Tax 50	Tax 100	Tax 150	Tax 200	Tax 250	Tax 300
PM_{10} n.e.	1.214	1.211	1.215	1.217	1.236	1.232	1.23	1.23	1.246
	—	(−0.2 %)	(0.1 %)	(0.2 %)	(1.9 %)	(1.5 %)	(1.3 %)	(1.3 %)	(2.6 %)
$PM_{2.5}$ n.e.	0.526	0.524	0.527	0.528	0.538	0.535	0.533	0.533	0.539
	—	(−0.3 %)	(0.3 %)	(0.4 %)	(2.3 %)	(1.7 %)	(1.3 %)	(1.3 %)	(2.4 %)
BC n.e.	0.0526	0.0524	0.0527	0.0528	0.0538	0.0535	0.0533	0.0533	0.0539
	—	(−0.3 %)	(0.3 %)	(0.4 %)	(2.3 %)	(1.7 %)	(1.3 %)	(1.3 %)	(2.4 %)

8.5.3 Well-to-Wheel emissions

The W2W GHG emissions of the different simulation cases are calculated by multiplying the observed distance traveled (see Table 8.6b, Figure 8.4) with the aggregated W2W emission factor per vkm as noted in Table 2.1 in Section 2.2.3. For calculating the annual values, again 250 business days per year are assumed (Planco, ITP, and TUBS, 2015). The resulting values per year for the different scenarios are shown in Figure 8.6.

The W2W emissions of the ICEVs (gray) decrease significantly with an increasing CO_2-tax rate, because the tour planning algorithm uses more BEVs instead of ICEVs (see Table 8.6b). Moreover, the electricity mix has a significant influence on the W2W emissions of the BEVs. With more renewable energy in the electricity mix, the W2W emissions decrease. The larger the share of BEVs in the fleet, the greater the influence of the electricity mix on the W2W emissions. Consequently, the more BEVs are on the road, the greater the potential reduction in W2W emissions when the electricity mix improves. This also applies to the BEVs that have already been purchased because they will then be charged with more sustainable electricity.

With a tax of 300 €/t CO_2, the W2W emissions are reduced by 25 % to 91 %, depending on the electricity mix, compared to the base case with only ICEVs available. The remaining ICEVs are responsible for approx. 600 t CO_2eq per year (approx. 6 %), compared to approx. 10′000 t CO_2eq per year in the base case. Even if there are only a few ICEVs remaining with only approx. 5.5 % of the vkm driven in this scenario, their share of about 64 % of the total W2W emissions in the calculation with only renewable electricity is substantial.

Comparing the results with the case of range-restricted BEVs (see Section 8.5.3) shows the gains when the range of the BEVs is not restricted. The missing range restriction for the BEVs leads to a higher share of BEVs, as well as their vkm driven, in the fleet and therefore to a larger reduction of the W2W emissions. With the range restriction, the saving in W2W emissions in the 300 €/t CO_2 scenario was only approx. 15 to 52 %, depending on the electricity mix, compared to the base case with only ICEVs available (see Section 8.5.3). In that case, 4′453 t CO_2eq per year were emitted by the remaining ICEVs. This is approx. five times more than in the case without range restriction for all vehicles, assuming a 100 % renewable electricity mix.

8.6 Conclusion and Outlook

In this study, we investigated the impact of a tax on GHG-emissions on the fleet composition of an existing case study of a food retail distribution in Berlin, Germany. We see that the tax forces the transition from ICEVs to BEVs. For the study, we added BEVs to the existing fleet of ICEVs. Solving the VRP is done as a Fleet Size and Mix Vehicle Routing Problem (FSMVRP), so that the carriers can choose between different vehicle types, and we receive the fleet composition as a result. The tax with values up to 300 €/t CO_2 increases the variable costs per distance for the ICEVs. This leads to a significant shift from the usage of ICEVs to BEVs.

In this study, we used a new method to implement a distance constraint for the VRP algorithm. We assumed that only the BEVs have a limited range because of their battery capacity. ICEVs can be used, e.g., as fallback solutions if BEVs are not sufficient.

By increasing the tax, we observed an increasing shift from the usage of ICEVs to BEVs. In addition, because of the limited range of the BEVs, there is a slight increase in the total number of vehicles used and kilometers driven compared to the baseline scenario with only ICEVs. For the

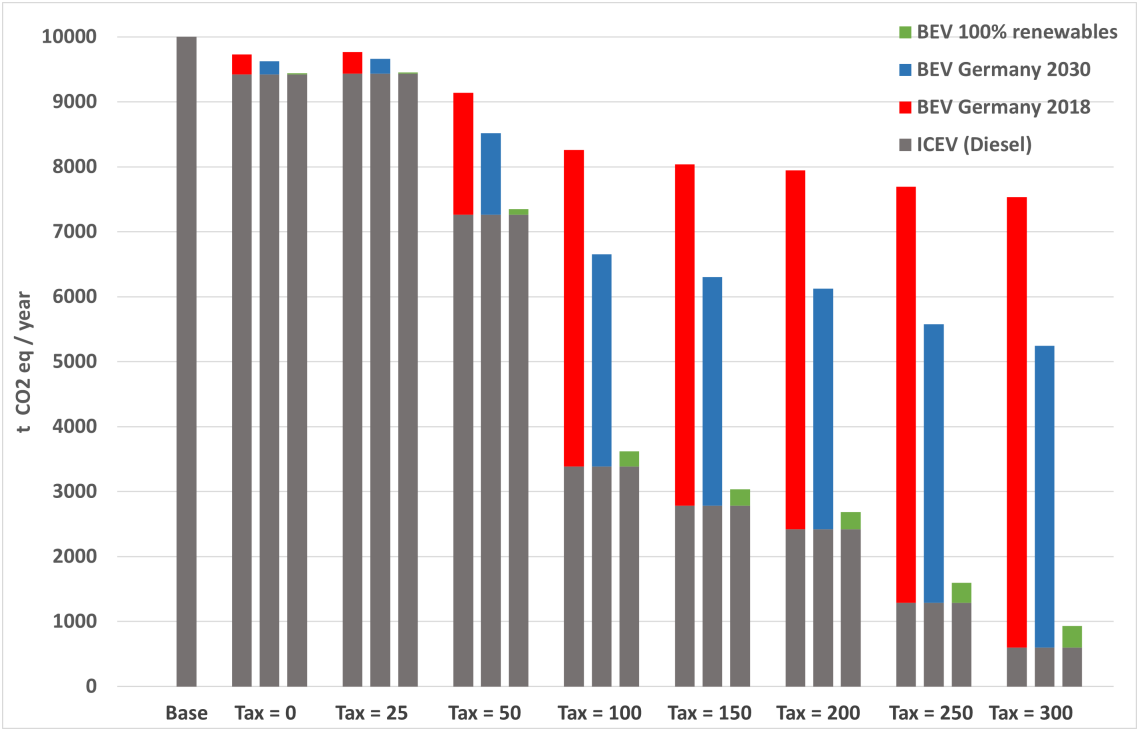


Figure 8.6: Calculated W2W-emissions in t CO_2eq per year for the baseline and the BEV scenarios (tax on CO_2-emissions on ICEVs from 0 to 300 €/t) *without* range restriction. The emissions of the BEVs are shown for three different energy sources: energy mix for Germany 2018 (red), for Germany 2030 (blue), and renewable-only (green). The emissions from the ICEVs are marked in gray.

corresponding W2W GHG-emissions, we assumed different electricity mixes. We can state that GHG-emissions decrease by more than 50 % from approx. 9′600 to 4′600 t CO_2eq/year when using renewable electricity. Assuming the emissions based on the energy production in Germany in 2018, the decrease in the same scenario would be 15 % (−1′500 t CO_2eq/year). In contrast to ICEVs, the BEVs have the potential to become more environmentally friendly, without additional investments in the vehicle fleet, just by using an energy mix with an increased proportion of renewable energy. We also analyzed the effects of the emissions while driving, using the HBEFA database. With the increasing tax and the resulting shift in the vehicle fleet, the exhaust emissions decrease. Depending on the pollutant, the reduction is between 47 % and 58 % in case of tax of a 300 €/t CO_2 compared to the base case with only ICEVs available. For the non-exhaust emissions, we observe a small decrease of up to 3.9 % (tax 300 scenario) compared to the base case with only ICEVs available, in line with the decreasing vkm driven when the tax on GHG-emissions increases.

In a second evaluation, the same case study is applied, but the BEVs are not limited in their range. This new evaluation is conducted because the ranges of the BEVs have increased since the original study. Omitting the range restriction leads to a stronger shift from the usage of ICEVs to BEVs. In this scenario with the increasing tax, the total number of vehicles used remains more or less stable, with a slightly decreasing tendency. At the same time, the total vkm driven slightly increases. These effects can be explained by the fact that BEVs have higher fixed costs and lower variable costs per distance than ICEVs. Because of the stronger shift to BEVs, the exhaust emissions while driving decrease by up to 92–94 % (tax 300 scenario; values depending on the pollutant) compared to the base case where only ICEVs are available. The non-exhaust emissions increase slightly by 2.5 % in the tax 300 scenario, which is in line with the increasing vkm driven when the

tax on GHG-emissions increases. For the W2W emissions, we observe a reduction of up to 25–91 % (tax 300 scenario; depending on the electricity mix) compared to the base case with only ICEVs available.

Summarizing the results, it can be said that regulation in favor of BEVs leads to a noticeable market reaction as soon as they become cheaper than ICEVs. Such a regulation can be done by introducing a tax on GHG-emissions, as in the present study, or e.g., by subsidizing the purchase costs of BEVs. Even the usage of BEVs with a limited range will provide significant benefits in terms of exhaust emissions from driving. The greater the share of renewable energies in the electricity mix, the greater the reduction in W2W emissions. We can also see in the scenario without range constraint that the tax value of 300 €/t CO_2 already leads to a share of 93.5 % BEVs in the fleet. This tax value is still above the current German value of 55 €/t CO_2 in the emission trade system (BEHG, § 10), but far below the value of 700 €/t CO_2 recommended by Umweltbundesamt (2020) for the year 2030.

Another approach to overcome possible range issues or driving restrictions is to change the logistics network. In Chapters 10 and 11, a 2-echelon distribution system for carriers from the Berlin food retail scenario is applied. The 2-echelon network splits up the transport into a main run from the depot to a hub, where the goods are reloaded for the last-mile delivery with other vehicles.

Part III

Reactions on Restrictions including Changes in the Logistics Network

CHAPTER 9

Modeling the Two-Echelon Vehicle Routing Problem

This chapter is an updated version of a previously presented and published paper: Martins-Turner and Nagel (2025).

9.1 Introduction and Problem Statement

Reducing greenhouse gas (GHG) emissions is one of the current major objectives to go towards a (more) sustainable future. For this, the countries participating in the 21^{st} session of the *Conference of the Parties to the United Nations Framework Convention on Climate Change* agreed to limit global warming to below 2°C above pre-industrial levels (United Nations, 2015a). Making cities and human settlements resilient and sustainable is one of the 17 Sustainable Development Goals (SDGs) of the United Nations (UN). This includes, in target 11.2, a "sustainable transport system for all, improving road safety" (United Nations, 2015b) and in target 11.7 the "universal access to safe, . . . , green and public spaces" (United Nations, 2015b).

In 2019, the European Commission (EC) agreed on the "European Green Deal". Aims include decoupling economic growth from resource use and achieving zero net GHG-emissions by 2050 (EC, 2019). To achieve this, one of the EC's targets is the reduction of emissions from transport by 90 % by 2050. Various countries have also defined their own climate protection plans, such as Germany's "Climate Action Plan 2050" (BMUB, 2016), which aims to reduce GHG-emissions from the transport sector by 40 % by 2030 compared to 1990. Within the German transport sector, road freight transport is responsible for 35 % of the carbon dioxide (CO_2) emissions (BMUB, 2018).

Electrification of the transport sector could be an appropriate solution to achieve these goals, e.g., by replacing today's Internal Combustion Engine Vehicles (ICEVs) with Battery Electric Vehicles (BEVs). This issue is increasingly discussed because of the changes in urban areas (Caggiani et al., 2020; Oliveira, Ramos, and de Sousa, 2020). One idea is to avoid driving with ICEVs in urban areas. Instead, they could be replaced by either BEVs or cargo bikes. Due to the limited range resulting from limited battery capacity, it is no longer possible to deliver goods directly from the depot to the customer (Ewert et al., 2021b; Hiermann et al., 2019).

This leads to the need for local (transshipment) hubs for a more local delivery with smaller vehicles. These hubs need to be connected to the existing main depot(s). Especially for parcels, the last mile delivery with cargo bikes is expanding. Advantages of e-cargo bikes are explored, for example, by Gruber, Kihm, and Lenz (2014).

It raises the issue of building up or updating (urban) logistics networks, which is complex. Besides all the restrictions coming from the demand side, e.g., locations, quantities, or time-windows of the jobs, there is also the question of the network design: Should there be only one tier (direct delivery)? Or is it better to have a two-echelon distribution system, using large vehicles to transport goods to transshipment hubs close to the customers, and use smaller, environmentally friendly vehicles for the last-mile distribution (Oliveira, Ramos, and de Sousa, 2022)?

Since the range of BEVs is no longer the main issue, there is a new trend: banning or charging (large) vehicles not meeting certain requirements from the inner-city. This can be done for *environmental reasons* – e.g., by introducing a Low Emission Zone (LEZ), as in Greater London, where Heavy Goods Vehicles (HGVs) that do not meet modern emission standards must pay £300 (approx. 350 €) a day for entering the London LEZ (Transport for London (TfL), 2022c). In most of London there is also an additional Ultra Low Emissions Zone (ULEZ) with stricter environmental requirements. A charge of £12.50 (approx. 14.50 €) is imposed on vehicles not meeting these requirements (Transport for London (TfL), 2022a). LEZs, which prohibit certain types of vehicles from entering certain areas of a city, can be found in other European countries as well: In Germany, for example, Berlin has implemented a LEZ with the explicit midterm goal to modernize the vehicle fleet (Senatsverwaltung für Umwelt, Verkehr und Klimaschutz Berlin (SenUVK), 2017). In France, several cities have also introduced temporal LEZs (Ministère de la transition écologique et de la cohésion des territoires, 2022).

Another reason for reducing or banning (larger) vehicles from cities is *road safety*: In Greater London, trucks over 12 t Gross Vehicle Weight Rating (GVWR) are required by the Direct Vision Standard (DVS) to achieve a certain level of direct view from the driver's cabin for entering or operating in Greater London. It is part of "the Vision Zero plan to eliminate all deaths and serious injuries on London's transport network by 2041" (Transport for London (TfL), 2022b).

In response, either significantly more small vehicles will be needed to transport goods from depots to customers, or a further two-echelon distribution network will be used. The two-echelon network allows the transport of goods with large vehicles from the (main) depot to the transshipment hub(s) located near the ban area. From there, the last-mile delivery is done by small vehicles that are allowed to enter the zone.

The Logistics Service Provider (LSP)[1] is the organizer of the transport chain and the transport of the goods from the sender to the receiver using the network (Schröder et al., 2012). Schröder et al. (2012) decided, in their multi-agent freight transport model, to have separate agents for the *LSP* and the *carrier*s. While the LSP agent organizes the transport chain, the carrier agent is designed to model a transport operator (Schröder et al., 2012). It plans and models the transport on individual parts of the transport chain.

This study is organized as follows: A brief review of related literature in the area of Two-Echelon Vehicle Routing Problems is presented in Section 9.2. Section 9.3 provides an overview of the methodology and software used for the following simulation experiments. Section 9.4 presents a first proof-of-concept study using a simple simulation experiment. In Section 9.5, an extended simulation

[1] We decided that we will use the term LSP instead of Transport Service Provider (TSP), as done by Schröder et al. (2012), since TSP is often used as an acronym for the Traveling Salesman Problem.

experiment is conducted with more jobs, an increased demand, and a vehicle-type-specific toll. The paper closes with a conclusion and outlook (Section 9.6).

9.2 Related Literature

Oliveira, Ramos, and de Sousa (2022) summarize some of the relevant Two-Echelon Vehicle Routing Problem (2E-VRP) types and their history in the context of city logistics. According to Oliveira, Ramos, and de Sousa (2022), the first formal definition of a Two-Echelon Capacitated Vehicle Routing Problem (2E-CVRP) was given by Perboli, Tadei, and Vigo (2008). Nevertheless, Crainic, Ricciardi, and Storchi (2004, 2009) are said to be the first to address the application of the two-echelon distribution systems in the context of city logistics (Oliveira, Ramos, and de Sousa, 2022). Enthoven et al. (2020) explore the application of the 2E-VRP in urban distribution, especially for e-commerce. They show that using a parcel locker to serve customers in the same area can significantly reduce driving distance. They distinguish their Two-Echelon Vehicle Routing Problem with Covering Options (2E-VRP-CO) from a location routing problem as described by Prodhon and Prins (2014), highlighting that direct visits during the delivery process are not necessary for every customer.

Hiermann et al. (2016) take a different approach to address the challenges with BEVs and their limited range by introducing the Electric Fleet Size and Mix Vehicle Routing Problem with Time Windows and Recharging Stations (E-FSMFTW). It includes the choice of recharging times (when?) and locations (where?) into the actual vehicle routes. Implementations of 2E-VRP with synchronization between vans and bicycles are done, for example, by Anderluh, Hemmelmayr, and Nolz (2017); Anderluh et al. (2019). Wang, Zhou, and Feng (2019) propose the combination of ICEVs in the first and BEVs in the second tier. Caggiani et al. (2020) solve a Two-Echelon Electric Vehicle Routing Problem with Time Windows and Partial Recharging (2E-EVRPTW-PR) as a green logistics solution for last-mile deliveries, considering synchronization between e-vans and e-cargo-bikes. Instead of using e-vans to deliver goods directly from the depot to the customer, they use the e-vans for a first tier and reload the goods for the last-mile delivery with e-cargo-bikes in traffic restricted areas. Bakach, Campbell, and Ehmke (2021) show that the use of delivery robots on the second tier can save about 70 %, up to 90 %, of the operating costs compared to conventional truck-based deliveries. A similar study on delivering parcels or small commodities in pedestrian areas or residential clusters using unmanned vehicles at the second tier is conducted by Yu, Puchinger, and Sun (2020). Boysen, Schwerdfeger, and Weidinger (2018) mixes up the idea of using small autonomous vehicles, without having hubs for the transshipment between the first and the second tier. Instead, they consider delivery robots that are transported and dropped off by large vehicles. The interconnection of different transport modes in two-echelon-models is studied, for example, by Li et al. (2021), who combine ground and unmanned aerial vehicles. In particular, they shed light on the emerging complexity of operations at hubs when considering the two modes.

The tradeoff between customer satisfaction and emissions savings in the design of the delivery process is investigated, for example, by Wang and Wen (2020). In their Low-Carbon Two-Echelon Heterogeneous-Fleet Vehicle Routing Problem (LC-2E-HVRP), they find that the introduction of a soft delivery window can lead to a reduction in carbon emissions while maintaining optimal customer satisfaction. Li et al. (2016) optimize their Two-Echelon Time-Constrained Vehicle Routing Problem (2E-TVRP) in terms of emitted carbon emissions per ton-mile by changing the hub location or minimizing empty trips.

Other studies on the 2E-VRP have also taken into account the management of inventory and the storage of goods: Qiu et al. (2021) apply the two-echelon production routing problem to hubs with cross-docking functionality. Their study highlights the importance of handling costs in determining the optimal solution. Guimarães et al. (2019) establish a connection between the two-tier supply chain and inventory management. In this context, the intermediary, located between the two tiers, is responsible for ensuring an adequate supply of incoming goods from suppliers and outgoing goods to customers. A recent development in logistics is considered by Darvish et al. (2019). They additionally investigate the possibility of flexible warehousing, thus adding the location of the hub to the optimization problem. Their study of a Flexible Two-Echelon Location Routing Problem (2E-FLRP) shows an average saving of 30 % when both the flexibility of time frame and the hub location are combined.

9.3 Methodology and Software

9.3.1 Methodology

We are using Multi-Agent Transport Simulation (MATSim) as an agent-based simulation framework for large-scale transport simulations (see Section 3.2). It is programmed in Java and the source-code and many scenarios are available as open-source/open-access scenarios (Horni, Nagel, and Axhausen, 2016).

MATSim already has a so-called *freight* contrib (see Section 3.2.2.1). Here, *carriers* have *vehicles* as *resources*, for which they plan *tours*. Tours fulfill *jobs*, which can be either *shipments*, where goods need to be transported between locations, or *services*, where only the corresponding locations need to be reached. The effects on changing the Vehicle Routing Problem (VRP) job type from *services* to *shipments* are investigated in Chapter 6.

In the present paper, LSPs are added, which have *hubs* as their resources, and can recruit carriers. That is, LSPs organize and consolidate logistics operations. LSPs and carriers can be vertically integrated, but do not have to. The overall ontology and prototypical implementation for LSPs stems from Matteis, Wisetjindawat, and Liedtke (2019); the present paper uses that framework to address a practical problem. This framework is now also part of the *freight contrib* and described in Section 3.2.2.2.

The use of LSPs allows the integrated solving of the transportation problem along the entire transportation chain from the origin to the destination. In general, this is the transport from the *sender* to the *receiver*. In order to fulfill the job(s), the LSP can select between one or more different options (*plans*). It could, for example, either make a direct delivery, or use a more or less complex hub-and-spoke network. Each of the different LSP *plans* has at least one so-called *logistics chain*[2] (Matteis, Wisetjindawat, and Liedtke, 2019). A *logistics chain* is a transport chain from the sender to the customer, including all parts, such as the carriers for the transportation or the hub(s) for reloading; in consequence, it is called `LogisticChain` in the code. Section 3.2.2.2 provides an overview of the logistics extension as part of MATSim's freight contrib.

In our studies, we will focus on the distribution of goods to the customers. Therefore, we define the (last) depot as the origin and ignore the upstream logistics chain, which transports the goods to the (last) depot. Such distribution transport chains can consist of, e.g., only one *carrier*, which solves its own VRP for the direct delivery from the depot to the customer. It can also be a logistics

[2] Matteis, Wisetjindawat, and Liedtke (2019) call it *solution*. We renamed it to make it easier to understand.

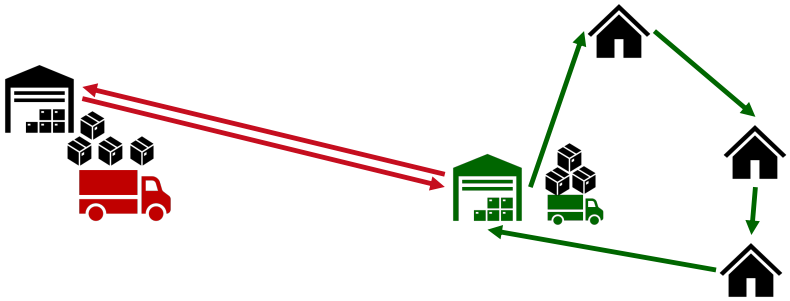


Figure 9.1: Example of a two-echelon distribution network: The large vehicle (red) transports the goods from the depot (left) to the hub (center). From there, the last-mile distribution is done by a smaller vehicle (green).

chain using a 2-echelon logistic network. In this case, it is something like a carrier that transports the goods from the depot to the *hub*, reloads them there, and transports them further with a(nother) distribution carrier.

Figure 9.1 shows an example of such a 2-echelon logistic network. The large vehicle (red) transports the goods from the depot (left) to the hub (green). From there, a smaller vehicle (green) distributes the goods over the last mile. The specific parts of the logistics chain are not planned in detail by the LSP at this stage: each carrier solves its own VRP, and decides on the specific vehicle(s) and tour(s) to transport the goods. The current implementation by Matteis, Wisetjindawat, and Liedtke (2019) works with the job type *service*. This results in more vehicles being used than necessary, as the vehicles cannot reload goods during the tour. For each tour a new vehicle with additional fixed costs is created. For the studies in Chapters 10 and 11 it has been solved by extending the framework to work with the job type *shipment* as well. The topic of the different job types is also addressed in Section 3.3.2 and Chapter 6.

9.3.2 Software

To simulate freight transport, MATSim provides the *freight* contrib. As also stated in Section 3.2.2.1, and applied in the studies in Chapters 6 and 7 and Section 2.2, the *carriers* part of MATSim's freight contrib (Section 3.2.2.1) connects MATSim (Horni, Nagel, and Axhausen, 2016, see also Section 3.2) to the open-source VRP solver jsprit (jsprit, 2024; Zilske and Joubert, 2016; Zilske et al., 2012, see also Section 3.3.2). The carriers, each defining its own VRP, are converted to jsprit. Each carrier is handled by jsprit independently of all the other carriers. Then the carrier, including the planned tours, is returned to MATSim. MATSim then creates its (driver) *agents* based on these tour plans and feeds them into the normal transport simulation.

Jsprit allows the solving of many subtypes of VRPs with, e.g., multi-depots, time restrictions, capacity constraints, infinite fleets, including the Fleet Size and Mix Vehicle Routing Problem (FSMVRP) (see also Section 3.3.1). Jsprit's algorithm is based on an iterative approach using the ruin-and-recreate principle by Schrimpf et al. (2000).

The main limitation of this approach is that each *carrier* and its solved VRP only represents one tier of the logistics network. As a result, it is not possible to address 2E-VRPs, where one or more transshipment hubs may be used on the way from the sender to the receiver. Earlier studies (e.g., Turner, 2015) have addressed this issue by splitting it into two separate sub-problems: First, the last VRP from the hubs to the customers is solved as a Multi-Depot Vehicle Routing Problem (MDVRP). From this result, one can derive how many goods are needed at each hub. This is the

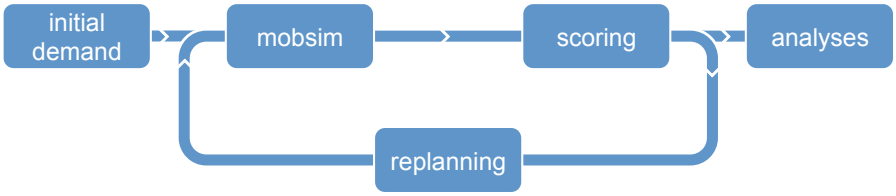


Figure 9.2: The MATSim-loop (Source: Horni, Nagel, and Axhausen (2016))

input to setting up and solving the second VRP from the originating depot(s) to the hub(s). This approach lacks the higher authority being responsible for planning the transport along the entire logistics chain: the LSP.

In the agent-based simulation framework used in the present study, the LSP is the owner of one or more *plans* (Matteis, Wisetjindawat, and Liedtke, 2019). The LSP's behavior is analogous to MATSim's standard person agents as described in more detail in Section 3.2: It selects, executes, and scores one plan per iteration. Figure 9.2 illustrates this approach. For the first studies, and because there is currently no interaction with other agents, there is only a single strategy for the replanning step: select one of the existing plans. There is *no* strategy implemented to modify/mutate these existing or create new *LSP-plans*[3].

As a consequence, the possible LSP-plans are defined in advance. For more information on the specific setup of the simulation experiments, please refer to the descriptions in Sections 9.4.1 and 9.5.1.

9.4 Simple Simulation Experiment

As a proof-of-concept study, we run a simple simulation experiment and observe the decision and result of the LSP.

9.4.1 Simple Simulation Experiment — Setup

Network For this proof-of-concept study, we use the grid network described in Section 4.3. The network (see Figure 9.3) consists of 9×9 links. Each link has a length of $\ell = 1\,\text{kilometer(km)}$ and is one-way. As one can see, each link is a continuous connection with alternating directions. The free speed on each link is constant at $v = 30\,\text{km/hour(h)} = 8.333\,\text{meter(m)/second(s)}$, resulting in a free speed travel time of $t_{\text{free}} = \ell/v = \frac{1\,\text{km}}{30\,\text{km/h}} = 120\,\text{s}$. In our study, we will have no congestion.

Location of the LSP resources As shown in Figure 9.3, the depot is located in the south (link *i(5,0)*), while the customer awaiting the shipment is located in the center (link *i(5,5)R*). The LSP is implemented with *two plans*, each with *one logistics chain*. A logistics chain is the abstract route consisting of the resources (carrier(s) and transhipment point(s)) that can be used to transport the shipment from the depot to the customer.

The logistics chain of *plan A* is the direct delivery of the shipment from the depot to the customer. The logistics chain of *plan B* is the 2-echelon delivery: from the depot to the hub and from the hub to the customer. The carriers are the resources of the LSP for transporting the shipments. Their vehicles are located at the start of the transport job. For the direct delivery (plan A), this is at the

[3]Plan modification is introduced and applied in the meantime by Richter, Martins-Turner, and Nagel (2024).

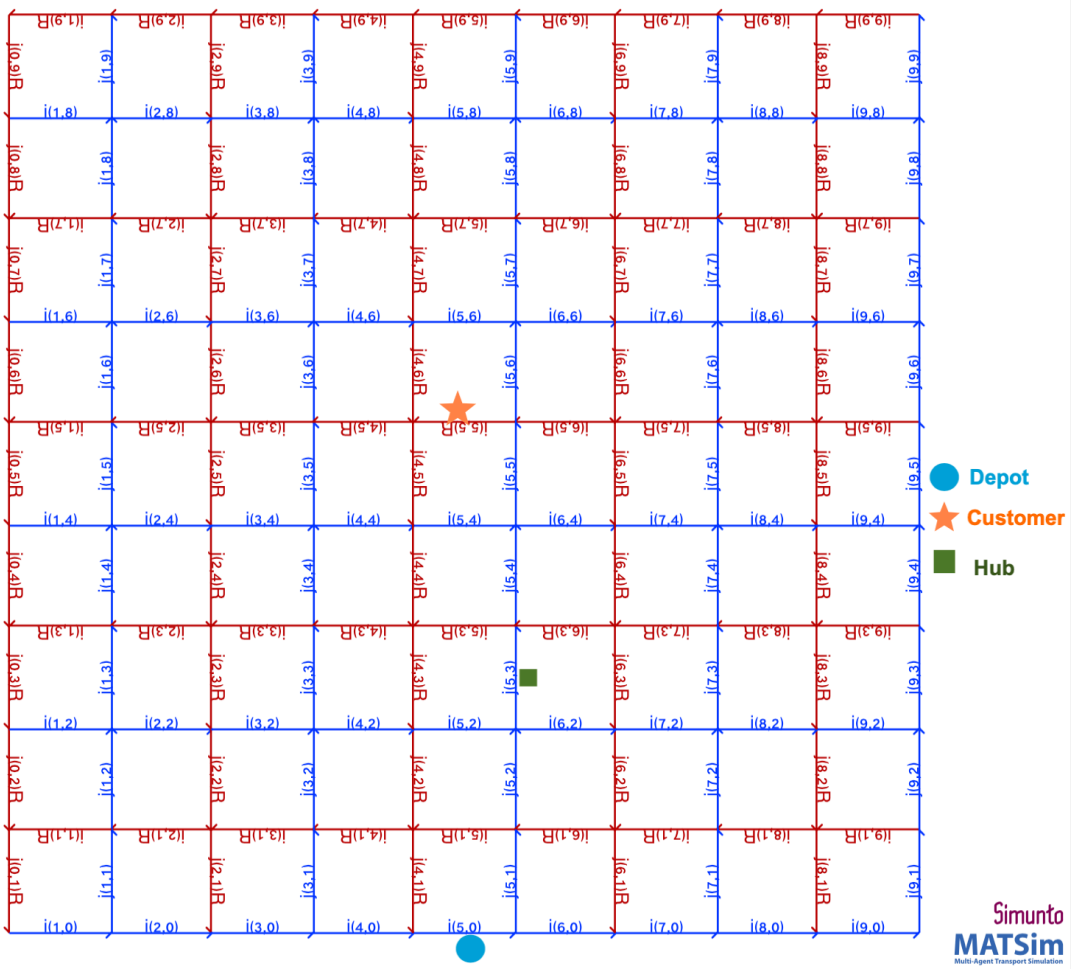


Figure 9.3: Simple scenario: The grid network, including the location of the depot (origin), the customer (destination), and the transshipment hub. All roads are one-way. The color indicates the direction: blue: positive direction, red: negative (return) direction.

depot, while for plan B one carrier starts at the depot for the main run, and one carrier at the hub for the last-mile delivery. The hub is located at link *j(5,3)*.

Table 9.1: Cost parameters for the different simulation setups. Each carrier has only one vehicle type available, so the carrier's costs are equal to the costs of that type. *Case 1*: Same costs for all carriers, no costs for the hub; *Case 2*: Costs of carriers starting from the hub are significantly lower than the costs of carriers starting at the depot, no costs for using the hub; *Case 3*: Same as Case 2, but with additional costs for using the hub.

(a) Cost parameters and transport capacity for the different carriers

logistics chain element	Cost type	Value
carrier type I	fixed (€ /day)	150
	per distance (€/m)	0.01
	per time (€/s)	0.01
	capacity (units)	50
carrier type II	fixed (€ /day)	25
	per distance (€/m)	0.001
	per time (€/s)	0.005
	capacity (units)	5
hub	fixed (€ /day)	0 or 100

(b) Carrier type usage in the different simulation setups (cases)

LSP-Plan	(Logistics Chain Element)	Case 1	2	3
A	(direct)	I	I	I
B	depot → hub	I	I	I
	hub → customer	I	II	II
	hub (€ /day)	0	0	100

Simulation Experiments To show that the LSP will make the right choice and select the better plan as expected, we run the scenario several times, each time with a slightly different setup. In all setups, there is only *one* LSP with *two* different plans. Each plan has only *one* logistics chain: Plan A with a direct delivery logistics chain, and plan B with a logistics chain using a hub in between. The simulation is run for two iterations, so the LSP tries and scores its two different plans, and then selects the better one.

We have found that in many cases the direct delivery has the lower costs. A relatively lower cost for the two-echelon alternative may occur if, for example, there is a low-cost solution for urban delivery, such as an electric cargo bike, or if the entry of long distance freight vehicles into the urban core is penalized, e.g., by a toll (Bakach, Campbell, and Ehmke, 2021; Yu, Puchinger, and Sun, 2020).

The following cases are considered — see also Table 9.1:

1. Same transport costs for all carriers. This should lead to the selection of plan A, since the cost is lower (= the score is higher).

2. Highly reduced transport costs for the carrier from the hub to the customer. Because of the significantly lower variable costs for the second stage, plan B has a lower total cost (= higher score) and should therefore be selected.

3. Same as before, but now with additional costs for using the hub. Again, plan A should have a better (higher) score and should therefore be selected by the LSP.

The different cost values are summarized in Table 9.1a. Table 9.1b shows the assignment of the carrier types and costs for using the hub to the individual cases. Everything else, e.g., the network and demand, remains the same.

9.4.2 Simple Simulation Experiment — Results

Table 9.2 shows the results for all cases. As one can see, the score of plan A (direct delivery) remains constant, as it is the same setup in all cases. Plan B (with hub) has a different score for each case. As described in Table 9.1 (see Section 9.4), the elements of plan B's logistics chain are modified: for case 2 the costs for the distribution carrier (hub → customer) are reduced. In case 3, this advantage is overcompensated by the costs for the hub. The scores change accordingly, e.g., the score of plan B in case 3 is lower than in case 2 by the 100 € hub cost.

Table 9.2: Resulting scores and the plans selected (by the LSP) for the three different simulated cases. Depending on the setup (costs for the different plan elements of plan B), a different plan is selected. *Plan A*: direct delivery; *Plan B*: using a transshipment hub.

	Case 1		Case 2		Case 3	
Plan	A	B	A	B	A	B
score	−285	−480.4	−285	−278.3	−285	−378.3
selected?	x			x	x	

Note that the score has a negative sign. The lower the absolute value of a negative score, the lower the cost and the *better* the plan. The selected plan is marked with (x). One can see that the LSP selects the *better* plan in all cases.

Figure 9.4 shows the different routes driven by the vehicles in the simulation. Figure 9.4a is the visualization of plan (A), while Figure 9.4b shows the two segments of the 2-echelon delivery: depot→hub and hub→customer.

The corresponding shipment schedules are shown in Table 9.3. For the direct delivery (plan A), there is only one carrier. It transports the shipment directly to the customer (see Table 9.3a). For plan B, one can see that the shipment is loaded by the first carrier (mainCarrier), transported, and unloaded after 361 seconds. It is then handled at the hub and transported by the second carrier (distributionCarrier), where it is unloaded at time 730 (see Table 9.3b).

Table 9.3: Schedule for the shipment to get transported from the depot to the customer.

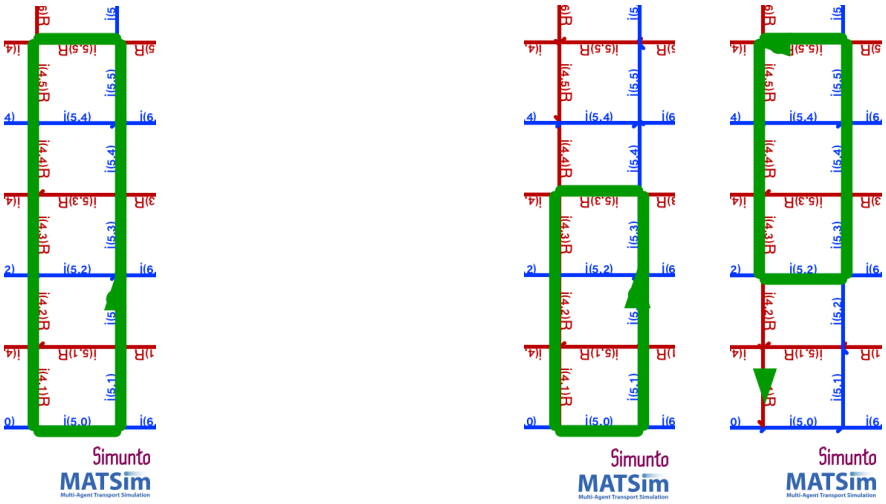
(a) Plan A: Direct delivery depot→customer

Logistics Chain Element	Activity	Time [s] Start	End
	LOAD	0.0	0.0
mainCarrier	TRANSPORT	0.0	720.0
	UNLOAD	720.0	720.0

(b) Plan B: Transporting depot→hub, handling at hub, and delivery depot→customer

Logistics Chain Element	Activity	Time [s] Start	End
	LOAD	0.0	0.0
mainCarrier	TRANSPORT	0.0	361.0
	UNLOAD	361.0	361.0
hub	HANDLE	361.0	371.0
	LOAD	370.0	370.0
distributionCarrier	TRANSPORT	370.0	730.0
	UNLOAD	730.0	730.0

The results are rather limited because of the limited scope and illustrative nature of this study. Nevertheless, we can conclude that the plan selection and thus the behavior of the LSP are in line with the expectations.



(a) Plan A: Direct delivery depot→customer

(b) Plan B: Transporting the good depot→hub (left) and hub→customer (right).

Figure 9.4: Simulation output: Vehicle routes driven depending on the selected plan.

9.5 Extended Simulation Experiment

Since we have been able to show that the framework works as expected, the simulation experiment is extended in the direction of the latter planned real-world case studies. On the one hand, more jobs will be created to show non-trivial solutions with more vehicles. On the other hand, a toll for large trucks will be introduced.

9.5.1 Extended Simulation Experiment — Setup

Network and Location of the LSP Resources The main parts of the setup from the Simple Simulation Experiment (see Section 9.4.1) are also used for the extended simulation experiment: the road network and the locations of the depot and hub. The number of jobs and the total amount of goods to be delivered from the depot have been changed. A total of ten jobs are randomly created as follows: The customers are randomly placed within the area marked in Figure 9.5 — called *inner-city* for this study. The demand size requested by each customer (= per job) is also randomly generated in the interval [1:5].

Simulation Experiments The costs and transport capacities for the resources of the logistics chains (see Table 9.1a in Section 9.4.1) remain unchanged, too. Again, the LSP has the two plans, A and B. The most practice-related setting from the first part of the study is used: Case 3 (Table 9.1b): Strongly reduced transport costs for the carrier serving the hub→customer delivery, and additional extra costs for using the hub.

In order to reduce the number of large vehicles in the inner-city (see Section 9.1), an additional cordon toll for the inner-city (see Figure 9.5) will be introduced. The toll fee is set to 25 €. This is far below the values in London for an older HGV entering the London LEZ, which is £300 (approx. 350 €) (Transport for London (TfL), 2022c), and above the daily charge of £12.50 (approx. 14.50 €) for entering the London ULEZ (Transport for London (TfL), 2022c) with a smaller vehicle not

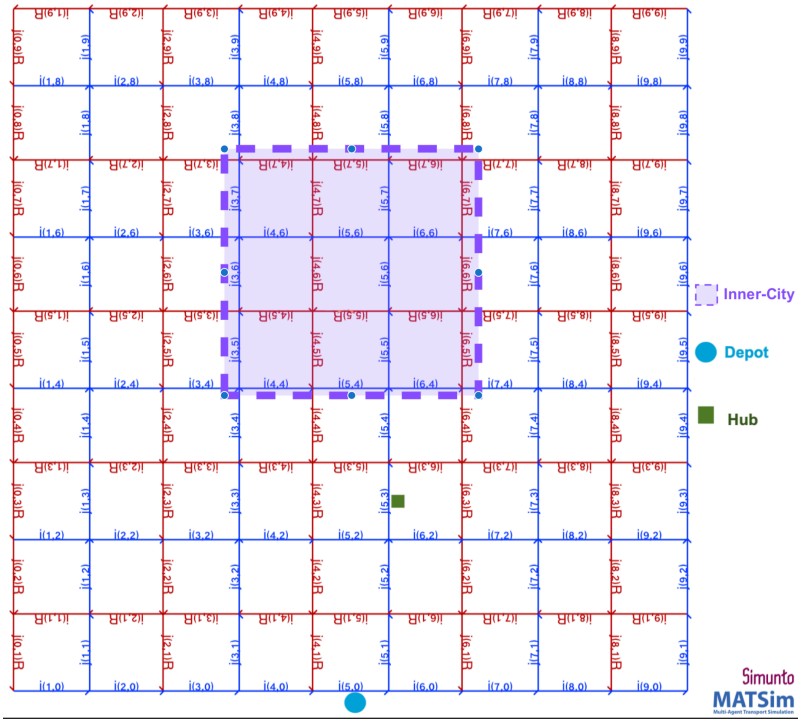


Figure 9.5: Extended scenario: The grid network, including the location of the depot (origin), the transshipment hub, and the inner-city zone. Within the inner-city zone, the ten customers (destinations) are placed randomly. The border of the zone is at the same time as the border of the additional cordon toll for large vehicles.

Table 9.4: Parameters for the different simulation setups. The setting is analogous to case 3 in Table 9.1b. The cost settings (I, II) belong to Table 9.1a. Deviating, ten different customers located in the inner-city are served. Case 4: Same as case 3, but with ten customers; Case 5: Same as case 4, but with a cordon toll for large vehicles crossing the border to the inner-city zone.

LSP-Plan	Logistics Chain Element	Case 4	Case 5
A	(direct)	I	I
B	depot→hub	I	I
	hub→customer	II	II
	hub (€ /day)	100	100
(both)	cordon toll on large vehicles (€)	0	25

meeting the more restrictive ULEZ standards[4]. The new, extended cases and their cost rates are summarized in Table 9.4.

9.5.2 Extended Simulation Experiment — Results

The ten randomly distributed customers have a total demand of 20 units. Figures 9.6 and 9.7 show the routes for the two different plans. One can see that, in contrast to the simple scenario, now in both plans several customers are served by one vehicle (tour). Figure 9.6 shows the resulting

[4]Note: Large vehicles (lorries, vans or specialist heavy vehicles (all over 3.5 tonnes) and buses, minibuses and coaches (all over 5 tonnes)) do not need to pay the ULEZ charge (Transport for London (TfL), 2022c)

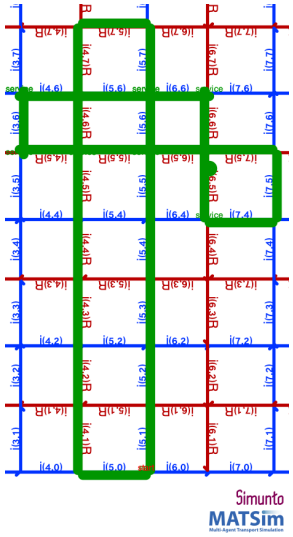
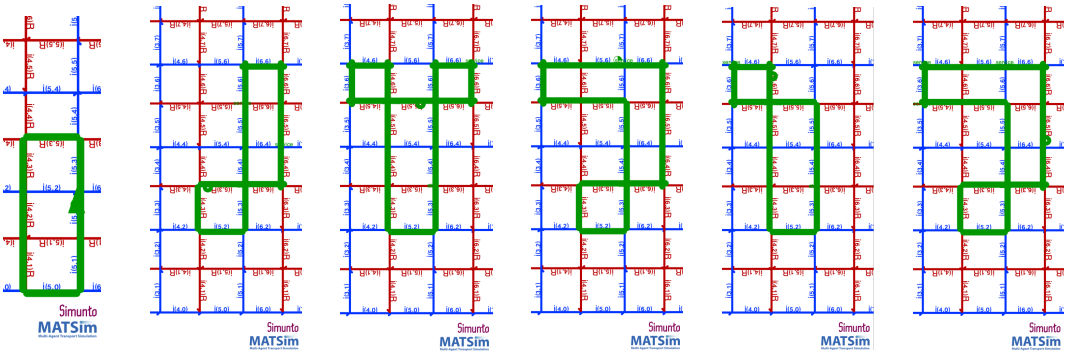


Figure 9.6: Simulation output for the extended scenario. Plan A is the selected plan for case 4: Direct delivery of all goods from the depot, using a large vehicle.



(a) depot→hub **(b)** hub→customer: In total, five tours are driven to fulfill all last-mile delivery jobs.

Figure 9.7: Simulation output for the extended scenario. Plan B is the selected plan for case 5: Using the hub.

tours for plan A, which is the selected one in case 4. The large vehicle is used for all deliveries in a single tour directly from the depot. Figure 9.7 shows the tours for plan B, which is selected in case 5. The large vehicle is used to transport all goods from the depot to the hub (Figure 9.7a). For the last-mile delivery, five tours with the small vehicle are planned (Figure 9.7b). Because of the one-way network, there is a lot of extra mileage to reach the links of interest.

The resulting scores and selected plans are summarized in Table 9.5. It also includes the number of tours for the selected plan And the total mileage driven by all vehicles. Because of the significantly lower vehicle costs, this becomes the better alternative after implementing the toll for the large vehicles in the inner-city. The reaction of the LSP shows that both the plan execution and, depending on it, the plan selection also work for a non-trivial 2E-VRP. This includes the reaction of the LSP to a vehicle-type-specific toll.

Table 9.5: Resulting scores and the by the LSP selected plan for the two additional simulated cases. Depending on the setup (costs for the different plan elements of plan B), a different plan is selected. Plan A: direct delivery; plan B: using transshipment hub.

	Case 4		Case 5	
Plan	A	B	A	B
score	-469.6	-588.9	-494.6	-488.9
selected?	x			x
# of tours	1	-	-	1 + 5
vehicle mileage driven [km]	28	-	-	80

9.6 Conclusion and Outlook

In this study, we applied the concept of Logistics Service Providers (LSPs) to an agent-based framework. An LSP is responsible for transporting goods through its logistics network from the origin to the destination. In contrast to previous studies, not only a VRP from the depot to the customer is solved. Instead, it is possible to define a transport chain with transshipment hubs. An LSP can choose between different plans for how it would like to transport the shipments. The decision is based on the score of each plan. In our case, each plan represents an abstract path (logistics chain) for the transport. Abstract means that it is defined only in terms of the facilities (depot, hubs) used, and the connections (transport by a carrier) between these facilities, as well as from the last facility to the customer. Therefore, different elements in the transport chain have their own behavior, e.g., the distribution carrier solves its own VRP.

We show that the plan scoring and selection works as expected. For this purpose, we use an artificial grid network scenario and evaluate three different cases. In all cases, we have one LSP with two different plans. In plan A, the goods are directly transported from the depot to the customer with a large (and more expensive) vehicle. In contrast, plan B has a transshipment hub in between. The three cases differ in the cost structure of the different logistics chain elements. Depending on this setup, either plan A or plan B will be selected by the LSP.

After this proof-of-concept, we extended the simple simulation experiment by introducing i) more shipments and ii) a cordon toll. A total of ten shipments with random destinations and random quantities are used. As a result, the last-mile distribution (hub→customer) can only be done with several tours that are planned by the distribution carrier. Again, the LSP chooses the plans as expected: plan A (direct transport) is the better option until an additional toll on large vehicles is introduced. Because of the toll, plan B (using the hub, last-mile delivery with smaller and cheaper vehicles) is the better option.

Outlook Again, this is a proof-of-concept study. The next steps are i) to further increase the computational complexity, e.g., by having different vehicle types per carrier and/or significantly more jobs and customers. It is also planned to run standard instances of the 2E-VRP with our framework for validation. Then we will ii) apply this approach to already existing case studies, e.g., for the supply of supermarkets in a large city such as Berlin, the largest city and capital of Germany[5]. Another possible use case could be the delivery of parcels.

[5]One application dealing with the Berlin Food Retailing scenario (see Section 4.1) has been published in the meantime by Richter, Martins-Turner, and Nagel (2024). In that study we additionally introduced and applied different innovative replanning strategies, modifying the plans over the iterations.

As long as we assume that the "direct" delivery will be the cheaper variant (e.g., needs fewer vehicles, no costs for additional hubs, saving on handling costs at the hub), this needs to be done in conjunction with the introduction of a Low Emission Zone (LEZ), a ban on large vehicles for certain areas, or the introduction of a vehicle type specific toll. Studies investigating this are presented in Chapters 10 and 11. An even further extension would be to simulate the whole chain including collection run — main run — distribution run, with a Fleet Size and Mix Vehicle Routing Problem (FSMVRP) at each stage.

Another shortage of the current study is that the current framework, as set up by Matteis, Wisetjindawat, and Liedtke (2019), solves the VRP based on *services* instead of *shipments* (see Section 3.3.2 and Chapter 6). This leads to – especially for the distribution from the hub – too many vehicles in the simulation, running only for a relatively short time, and causing a lot of fixed costs. This is also fixed in the studies presented in the following Chapters 10 and 11.

CHAPTER 10

Applying the Two-Echelon Distribution Concept to an Urban Food Retail Case Study

10.1 Introduction and Problem Statement

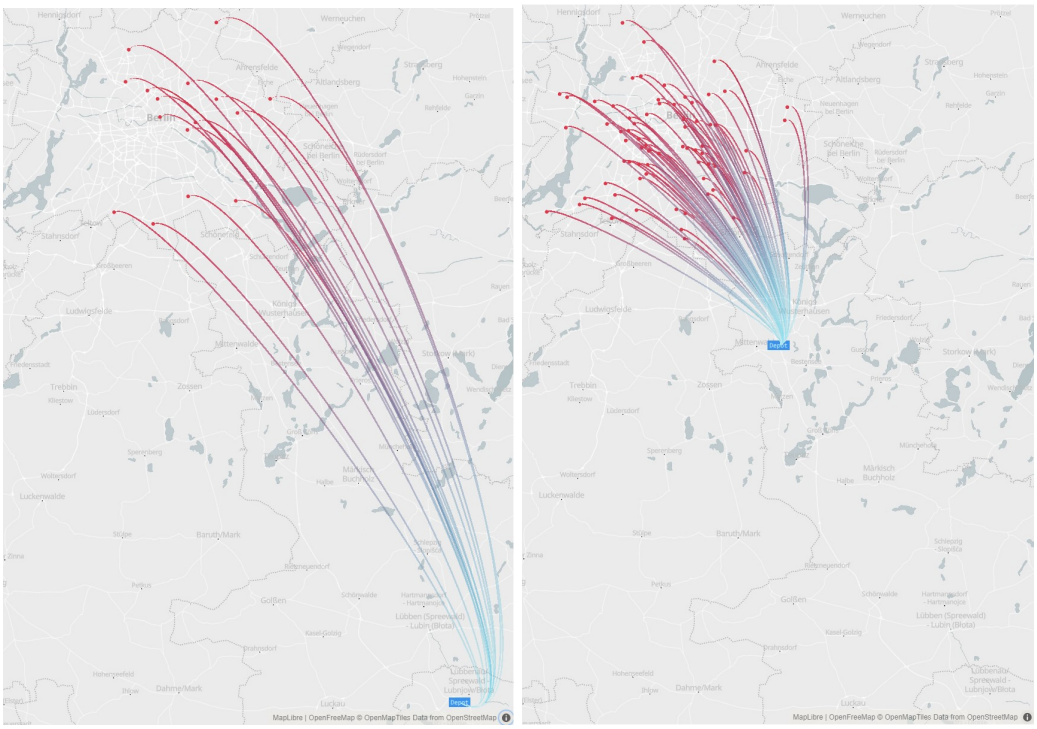
Urban freight transport faces significant challenges, including traffic congestion, environmental concerns, and the need for efficient last-mile delivery solutions. To address these challenges, the two-echelon distribution concept has emerged as a promising approach. With the implementation of the Logistics Service Provider (LSP) as its own agent in Multi-Agent Transport Simulation (MATSim) (see Section 3.2.2.2), it is now possible to simulate the distribution along a two-echelon structure in an agent-based traffic simulation framework. In the previous Chapter 9, this simulation approach was successfully applied to a simplified grid scenario. In this and the following chapter, it will be transferred and applied to a more realistic urban food retail scenario in Berlin (see Section 4.1).

In Chapter 6, the idea of using Urban Consolidation Centers (UCCs) for food retailing in Berlin was already presented. But in that approach, there was no LSP agent implemented, coordinating the two-echelon distribution. There, it was assumed that all shops located inside the Low Emission Zone (LEZ) in the city-center are delivered via the UCC (hub), while all shops outside the zone are delivered directly from the depot. Since the availability of the LSP agent, we can overcome this fixed assumption and transfer it to a decision made by the LSP.

In this chapter, the existing *carrier*-based food retailing scenario is transferred into an LSP-based scenario. Section 10.2 describes this transfer step-by-step, starting with the simulation results from the year 2019 (see Part II). The result is an up-to-date base case for the policy investigation presented in Chapter 11.

10.2 Methodology

In this and the following study (see Chapter 11), the approach of the LSP is applied for the Berlin food retailing scenario.



(a) Kaufland **(b)** Edeka

Figure 10.1: Overview of the transport jobs for both selected carriers. (Visualized with Simwrapper (Charlton, 2026), background map from OpenStreetMap (2026)).

Carriers / LSP For these studies, two different carriers from the food retailing scenario presented in Section 4.1 were selected:

- Kaufland, with the depot near Lübbenau, approx. 75 kilometers (km) south-east of the Berlin city limit and 95 km from the Berlin city center, with 17 jobs (shipments) at 16 different locations and a total demand of 347 pallets.
- Edeka, with the depot in Berlin significantly closer to the city (approx. 15 km south of the Berlin city limit; 35 km from the Berlin city center), with 72 jobs at 68 different locations and a total demand of 895 pallets.

The jobs and demand represent the demand for an average workday. These two carriers were selected in order to examine whether their different requirements would lead to structurally different solutions. At the same time, both are located along the same access road and can set up their transshipment hub at the same location in the simulation to ensure comparability. The hub location is set close to the inner-city, but still outside the existing LEZ. Figure 10.1 gives an overview of the different transport jobs from the depots to the customers of both carriers.

For each of the existing carriers, a new LSP is created in the simulation, with the same locations and the same demand as the respective carrier. As described in Section 3.2.2.2, the LSP is modelled as its own agent. It organizes the transport of the shipments into so-called logistics chains.

Logistics chains A logistics chain describes the different elements that can be used to transport a shipment from the depot to the customer. These elements are either carriers for transporting the shipments, or hubs as transshipment points between different carriers. The two simplest logistics chains, which have already been presented in the previous study by Martins-Turner and Nagel (2025) (see Chapter 9), are:

1. *direct carrier* for the direct delivery from the depot to the customers,
2. two carriers with a hub in between for the delivery using the *two-echelon chain*: main run from the depot to the hub, reload at the hub, and last-mile distribution from the hub to the customers.

In the previous study by Martins-Turner and Nagel (2025) (see Chapter 9), the LSP agent has exactly two different and independent plans to choose from, with these two options. In that case, the LSP only needs to run so many MATSim iterations until all plans have been evaluated. No plan modification is necessary in the replanning phase because the environment (traffic congestion) is deterministic, and plans never change. The only MATSim strategy used is the *BestPlanSelector*, so the LSP selects the best of these two possible plans. All shipments are delivered using the same logistics chain as defined in the selected plan.

Richter, Martins-Turner, and Nagel (2024) introduce a third option, combining these two logistics chains in one LSP-plan. This means that this plan now uses both chains. Each shipment is assigned to one of the two chains, so that some shipments are delivered directly from the depot to the customers, while other shipments are delivered via the hub. This plan is more complex because the LSP now needs to decide which shipment is delivered via which chain. As a starting point before the first iteration, all jobs of the LSP are randomly[1] assigned to the available chains of the plan.

Plan modification As the best distribution/assignment is not clear from the beginning, the co-evolutionary strategy approach of MATSim is used to modify the plans iteratively (replanning). The *RandomShiftingStrategy* of the LSP first copies the plan, and then, in the copy, moves one randomly selected shipment from one chain to the other within this plan. Additionally, a non-innovative strategy is added here with a lower probability: the *BestPlanSelector* strategy selects the best-scored of the existing plans from the plan set. As standard in MATSim, only a certain number of plans will be kept per agent (see Section 3.2.1). In this case, this number is set to five. Once there are more than five plans, the plan with the worst score is removed from the plan set. Please note that regardless of whether the plan is modified or not, the carriers run their tour planning in each MATSim iteration.

This study focuses on the transformation of the existing carrier-based delivery system (see, e.g., studies in Chapters 6 to 8) to an LSP-based delivery system. It will be the basis for the following study (see Chapter 11), in which different policy measures are examined. In total, the following two steps are carried out:

- re-run of carrier-based-simulation and comparison with the results from 2019 (see Section 10.3),
- transfer to an LSP-based simulation (see Section 10.4) .

10.3 Updating the carrier-based simulation

This setup represents the situation in which the carriers deliver the shipments directly from their depot to the customers *without* using an LSP agent. Here, only the carriers package (see Section 3.2.2.1) of MATSim is used.

[1] There are also other assignment strategies available, e.g., all shipments on a specific chain, or a round-robin distribution. None of them uses a Two-Echelon Vehicle Routing Problem (2E-VRP) solver.

10.3.1 Simulation setup

To have the comparison as consistent as possible within the thesis, the simulation output from the previous studies in Part II is taken. The latest base-case run from Chapter 8 with only Internal Combustion Engine Vehicles (ICEVs) available is used. It will be referred to in the following as the *simulation run from 2019*. To avoid effects based on code changes over time, when evaluating the LSP-based approach in Section 10.4, the same *carrier*-based run is run again with the current MATSim version 2026.0-PR4285. In the following, this will be referred to as the *simulation run from 2025*. Both the 2019 and 2025 simulations are run with 10′000 jsprit iterations and only a single MATSim iteration. Furthermore, additional investigations are carried out in this chapter. Specifically, the influence of the number of jsprit iterations and the influence of the number of jobs on the results are investigated. These serve to conduct the later LSP-based simulation with well-founded settings.

In the 2019 study, congestion was included using a so-called time-dependent network. As described in Section 3.2.1 this is done by generating so-called network change events (NCEs) from the output of the MATSim Open-Berlin scenario. These events contain information about the observed travel-time during a specific time-period for each link. Currently, in the LSP simulation, the time-dependent network is not implemented. Therefore, two setups of the 2025 simulation runs were performed:

1. with the time-dependent network to compare the results with the run from 2019, and
2. without the time-dependent network as the basis for the comparison with the LSP simulations in Section 10.4.

10.3.2 Results

10.3.2.1 Compare runs from 2025 with runs from 2019

Table 10.1 compares these different simulation runs. It shows that the overall results are in the same magnitude. As expected, the results are not the same, because jsprit uses a heuristic approach to solve the Vehicle Routing Problem (VRP) and changes to the code have been made over the last years. A similar effect has been observed already between the studies in Chapter 7 and Chapter 8. Comparing the runs of 2019 and the one of 2025, including the time-dependent network, the resulting cost differs by $6'159\,€ - 6'147\,€ = 12\,€$ for the Edeka carrier. This is a relative change of $12\,€/6'159\,€ = 0.19$ %. The solution for Kaufland, differs by 295 € or 6 %. Interestingly, the new runs in 2025 came to a solution with fewer vehicles needed. At the same time, the travel time has been significantly increased for both carriers. Comparing the two runs per carrier from 2025 shows the effect of the congestion from the time-dependent network. Without congestion, the travel time is significantly lower, while the costs are also lower. The number of vehicles used remains equal, while the vehicle kilometers (vkm) remain almost the same.

10.3.2.2 Influence of number of jsprit iterations

In the LSP-based simulation, we will use MATSim's co-evolutionary strategy approach to iteratively improve the solution of the LSP (see e.g. Section 3.2.2.2 and Chapter 11 or Richter, Martins-Turner, and Nagel (2024)).

In each MATSim iteration, the LSP will schedule (= plan) its carrier(s). Scheduling/planning a carrier means running jsprit to solve the carrier's VRP. As long as no MATSim iteration was run,

Table 10.1: Key figures of the baseline scenario with the carrier-based approach. It compares the two different simulation runs from 2019 and 2025. For 2025 two setups were run: with and without time-dependent network (TDN). All runs were done using 10′000 jsprit iterations.

carrier	year of simulation	costs (€)	# veh.	distance (vkm)	travel time (hour (h))
Kaufland	2019	4′904	13	2′601	38.04
	2025-withTDN	4′609	10	2′598	42.36
	2025-noTDN	4′513	10	2′577	38.30
Edeka	2019	6′159	17	3′222	57.65
	2025-withTDN	6′147	16	3′122	65.43
	2025-noTDN	5′984	16	3′103	56.93

it is computationally easy to run jsprit with 10′000 iterations. Running 200 MATSim iterations with two carriers result in up to $2 \cdot 200 \cdot 10'000 = 4'000'000$ jsprit iterations to be run in total. When only running 1′000 jsprit iterations per carrier and MATSim iteration, it would be possible to run $4'000'000 \div 2 \div 10'000 = 2'000$ MATSim iterations. This very rough calculation ignores, e.g., the time of the replanning itself and everything else that is needed to run a new MATSim iteration, as well as that setting up the initial solution of the VRP also takes some time. Nevertheless, since the VRP solving is the most computationally time-consuming task, it will give an impression of the trade-off between running more MATSim iterations, or trying to find an even better (cheaper) VRP solution. Due to the additional MATSim iterations in the following LSP simulations, the number of jsprit iterations should be limited.

To show how the solution converges and which number of jsprit iterations is sufficient, several simulation runs with different numbers of jsprit iterations were started with the new software version from 2025. Table 10.2 presents the development of some key figures for the two carriers in the 2025 run: Kaufland (Table 10.2a) and Edeka (Table 10.2b). The VRP of Kaufland consists of 17 jobs and thus is significantly smaller than the Edeka VRP with 72 jobs (see Section 10.2). The smaller problem for *Kaufland* does not improve any further after 50 jsprit iterations (see Table 10.2a)[2]. For *Edeka* there are only a few gains in terms of cost when running more than 1′000 iterations.

[2]In the case with the time-dependent network, there is another small change in the solution when running 500 instead of 250 iterations. However, this only changes the total costs by (rounded) one euro and is therefore not considered significant. The tables can be found in Table D.1 in Appendix D.

Table 10.2: Development of some key figures fo the simulations, depending on the number of jsprit iterations. New runs from 2025 *without* time-dependent network. The run after which the results are (more or less) stable is **highlighted**.

(a) Kaufland (VRP with 17 jobs)

# jsprit iterations	# veh.	distance (vkm)	travel time (h)	fixedCosts (€)	varCostsTime (€)	varCostsDist (€)	totalCosts (€)
1	9	2′751	40.51	1′139	1′514	1′898	4′551
10	10	2′576	38.39	1′266	1′471	1′777	4′514
50	**10**	**2′577**	**38.30**	**1′266**	**1′469**	**1′778**	**4′513**
100	10	2′577	38.30	1′266	1′469	1′778	4′513
250	10	2′577	38.30	1′266	1′469	1′778	4′513
500	10	2′577	38.30	1′266	1′469	1′778	4′513
1′000	10	2′577	38.30	1′266	1′469	1′778	4′513
2′500	10	2′577	38.30	1′266	1′469	1′778	4′513
5′000	10	2′577	38.30	1′266	1′469	1′778	4′513
10′000	10	2′577	38.30	1′266	1′469	1′778	4′513

(b) Edeka (VRP with 72 jobs)

# jsprit iterations	# veh.	distance (vkm)	travel time (h)	fixedCosts (€)	varCostsTime (€)	varCostsDist (€)	totalCosts (€)
1	19	3′267	59.00	1′567	2′621	2′186	6′373
10	18	3′235	58.48	1′487	2′611	2′167	6′265
50	18	3′228	58.14	1′487	2′605	2′163	6′255
100	17	3′185	58.18	1′404	2′606	2′134	6′144
250	17	3′185	58.18	1′404	2′606	2′134	6′144
500	17	3′182	58.10	1′404	2′605	2′132	6′141
1′000	**16**	**3′161**	**57.72**	**1′322**	**2′598**	**2′118**	**6′038**
2′500	16	3′147	57.27	1′322	2′590	2′109	6′021
5′000	16	3′147	57.29	1′322	2′590	2′108	6′020
10′000	16	3′104	56.93	1′322	2′584	2′079	5′985

10.3.2.3 Influence of the job sizes

When running the LSP-based simulation, the jobs are split so that each job fits into a smaller vehicle. Without this splitting, the VRP could not be solved for all jobs because, in the policy case, vehicles may be too small when a ban on certain vehicle types is introduced (see Chapter 11). The splitting ensures that any job whose demand exceeds the maximum vehicle capacity is divided into multiple jobs as follows:

1. Calculate the number of full vehicles required to meet the job's demand.
2. Create that many jobs, each with a demand equal to the maximum vehicle capacity.
3. If a remaining demand exists (i.e., demand not covered by the full vehicles), create one additional job with that remaining demand.
4. Ensure that all split jobs share the same location and time windows as the original job.
5. Assign the duration of the split jobs proportionally to their size and ensure that the total duration of all split jobs equals the duration of the original job.

Table 10.3 shows the number of jobs generated by splitting the original jobs, assuming a maximum Gross Vehicle Weight Rating (GVWR) of 18 ton (t) or 7.5 t. In the original configuration, Edeka has 72 jobs to deliver 895 pallets to 68 locations, while Kaufland has 17 jobs to deliver 347 pallets to 16 locations. Splitting the jobs to fit vehicles with a maximum GVWR of 18 t yields 92 jobs

for Edeka and 28 jobs for Kaufland. For vehicles with a maximum GVWR of 7.5 t, the number of jobs increases to 119 for Edeka and 43 for Kaufland. This increase is substantial, especially for Kaufland, where the number of jobs more than doubles. Figure 10.2 visualizes job sizes depending on the capacity restriction imposed by the maximum GVWR. It shows that the split limits jobs to the vehicles' capacity: 16 pallets for the 18 t truck and 10 pallets for the 7.5 t truck. Additionally, many small jobs are created for the remaining demand.

Table 10.3: Number of jobs per carrier depending on the capacity restriction due to the maximum GVWR.

	original	max. 18 t	max. 7.5 t
Kaufland	17	28 (+65 %)	43 (+153 %)
Edeka	72	92 (+28 %)	119 (+65 %)

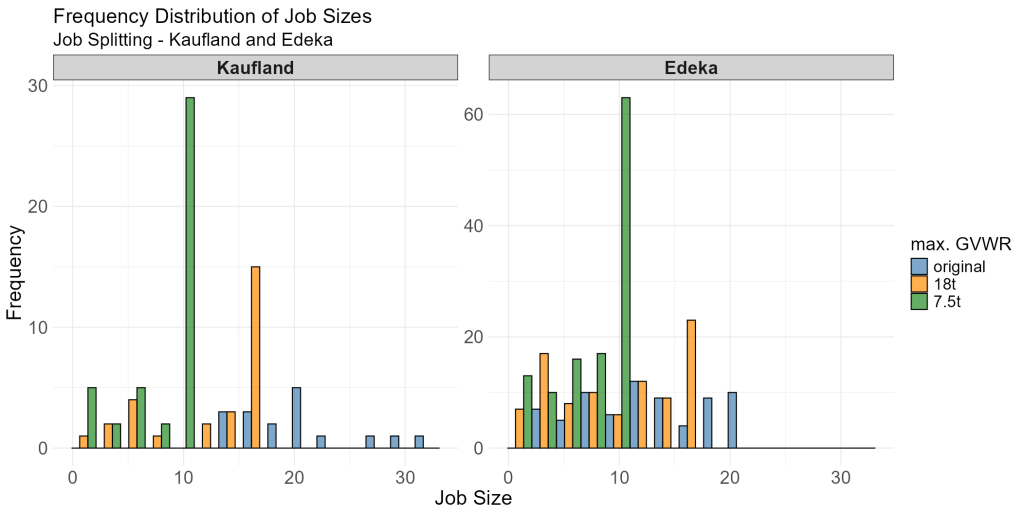


Figure 10.2: Distribution of job sizes (given in "number of pallets") per carrier depending on the capacity restriction due to the maximum GVWR.

As shown in Section 10.3.2.2 above, the number of jobs has an influence on the number of jsprit iterations needed for solving the VRP. Therefore, we repeat the investigation of different numbers of jsprit iterations, now using split jobs. The split is done so that the jobs fit into vehicles with a maximum GVWR of 18 t. The key figures of that run are presented in Table 10.4.

Comparing them with the results in Table 10.2 shows that other solutions are found when using split jobs, which is expected as the solution space is different. For Kaufland, now 11 vehicles (instead of 10) are needed to serve the jobs. For Edeka, the number of vehicles ranges from 18–25 (instead of 16–19), depending on the number of jsprit iterations. Comparing the solutions with the highest number of jsprit iterations, we see that for Kaufland, the total cost reduces from 4′513 € to 4′242 €. Thus, the solution with split jobs is better than the solution without split jobs. In contrast to that, the total cost for Edeka increases from 5′985 € to 6′334 €. So it finds a worse solution with split jobs than without split jobs. This is surprising, as one would expect that the solution with split jobs should be better than the solution without split jobs, as the solution space is larger and at least the same solution should be findable. Already the initial solution (1^{st} iteration) is significantly different with 25 instead of 19 vehicles, and also higher total costs (6′988 € instead of

Table 10.4: Development of some key figures for the simulations depending on the number of jsprit iterations. New runs from 2025 *without* time-dependent network. The jobs are split, so that each job fits into the vehicle with a GVWR of 18 t.

(a) Kaufland VRP with 28 jobs

# jsprit iterations	# veh.	distance (vkm)	travel time (h)	fixedCosts (€)	varCostsTime (€)	varCostsDist (€)	totalCosts (€)
1	11	2′213	33.08	1′392	1′365	1′527	4′284
10	11	2′204	33.14	1′392	1′366	1′520	4′279
50	11	2′204	33.14	1′392	1′366	1′520	4′279
100	11	2′204	33.14	1′392	1′366	1′520	4′279
250	11	2′195	33.02	1′392	1′364	1′515	4′271
500	11	2′190	32.82	1′392	1′360	1′511	4′263
1000	11	2′188	32.87	1′392	1′361	1′510	4′263
2500	11	2′171	32.4	1′392	1′351	1′498	4′242
5000	11	2′171	32.4	1′392	1′351	1′498	4′242
10000	11	2′171	32.4	1′392	1′351	1′498	4′242

(b) Edeka VRP with 92 jobs

# jsprit iterations	# veh.	distance (vkm)	travel time (h)	fixedCosts (€)	varCostsTime (€)	varCostsDist (€)	totalCosts (€)
1	25	3′402	61.26	2′059	2′661	2′268	6′988
10	23	3′468	63.04	1′898	2′692	2′321	6′911
50	21	3′320	60.32	1′732	2′644	2′220	6′597
100	21	3′320	60.32	1′732	2′644	2′220	6′597
250	21	3′320	60.32	1′732	2′644	2′220	6′597
500	21	3′320	60.49	1′730	2′647	2′215	6′593
1000	20	3′364	62.35	1′650	2′680	2′249	6′578
2500	19	3′278	59.74	1′567	2′634	2′194	6′395
5000	19	3′278	59.74	1′567	2′634	2′194	6′395
10000	18	3′301	59.87	1′487	2′636	2′211	6′334

6′373 €). Together with the challenge that heuristic approaches may get stuck in local optima, this may explain the worse solution with split jobs.

Another observation is that the number of jsprit iterations needed to find a stable solution increases with the increased number of jobs of the VRP. While in the unsplit case Kaufland needed only 50 jsprit iterations to find a stable solution, now the solution with 2′500 iterations has the same result as the run with 10′000 iterations. For Edeka, with 2′500 instead of 1′000 iterations are needed to find a more-or-less stable solution.

10.4 Updated scenario: LSP-based simulation

In this section, the new LSP-based approach is used. The results are compared with the non-LSP-based approach, which is used as a baseline.

10.4.1 Simulation setup

The data of the carriers (Kaufland and Edeka) are now converted to an LSP each. During this conversion, the jobs are split so that each job fits into the 18 t truck (see above). As mentioned

above (see Sections 9.3.1 and 10.2), there are different *logistics chains* that can be defined in the LSP-plan. These chains describe the abstract path for transport of the shipment from its origin to its destination (see also Section 3.2.2.2).

Logistics chains and LSP-plans In this study, the following logistics chains are used, representing the two different delivery concepts that are compared in this study:

1. direct delivery: only one carrier. Used for the direct delivery from the depot to the customer.
2. two-echelon delivery: two carriers and one hub. Used for the chained delivery with one carrier for the main run from the depot to the hub, reloading of the goods at the hub, and the second carrier for the distribution run from the hub to the customer.

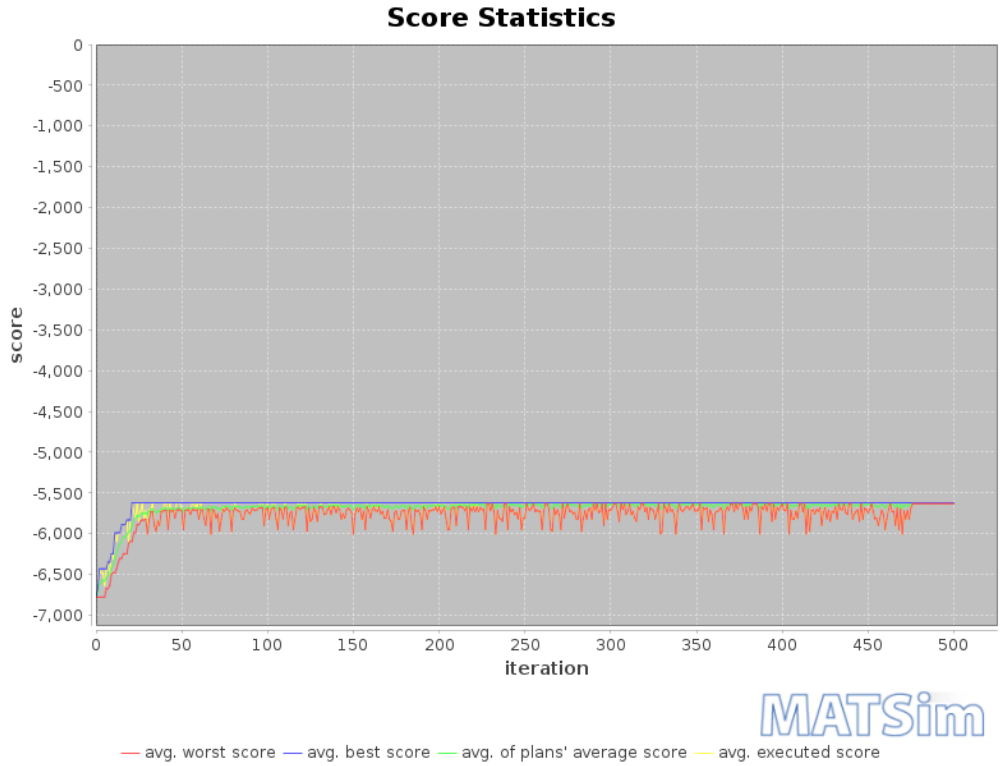
In the first step, the LSP gets only one (initial) plan, with only one of these logistics chains, i.e., only direct delivery or only two-echelon delivery. No innovative replanning strategy is set up, so the LSP will keep this logistics chain in its plan. As a consequence, everything is simulated separately with all jobs on the corresponding logistics chain. From an overall perspective, these are the corner-cases where either only direct delivery or only two-echelon delivery is used. Since the direct delivery logistics chain only has one single carrier for the delivery, the result should be similar to the ones in Section 10.3. As long as the LSP has exactly *one* plan, with either the direct *or* the two-echelon delivery logistics chain, it is sufficient to run only one MATSim iteration, because the plan-selection option is not needed, since there is only one (unchanged) plan to choose from and no innovation replanning strategy (see Sections 10.2 and 10.3). This is in contrast to, e.g., the study in Chapter 9, where an LSP has both plans in its choice set and was able to try out both and select the better one.

Moreover, it is also possible to have an approach combining these two chains in one LSP-plan. This allows the LSP to transport some shipments directly from the depot and other shipments via the hub to the customer. In this approach, the run of MATSim iterations is necessary because during the replanning phase, the LSP can modify its plan and move a shipment from one logistics chain to the other. Then, a new scheduling of the plan is done, including a new VRP solving for the carriers using jsprit.

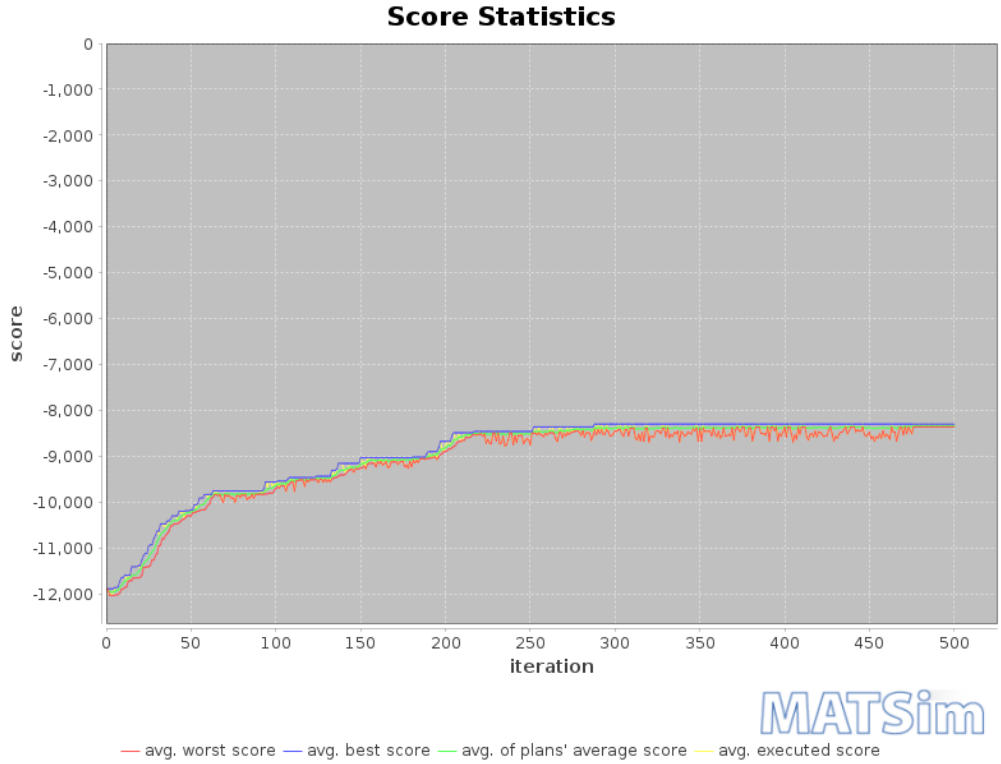
MATSim iterations Based on the results from Section 10.3.2, 1′000 jsprit iterations will be used for the tour planning of both Kaufland and Edeka. This seems to be a good trade-off between saving run-time (even if jobs are split up) and the quality of the solution. In this scenario only ICEVs are available, so the vehicle types are the same as in the carrier-based simulation in Section 10.3. To explore which number of MATSim iterations is sufficient to reach a stable level in the LSP scores, an initial simulation with 500 MATSim iterations is performed. After 95 % of the iterations, the innovative replanning strategy is switched off and only plan selection is performed (see Section 3.2.1). The innovation switch-off does not prevent each carrier of an LSP from rerunning the tour planning using jsprit. As a result of the heuristic VRP solving, this may end up with a different solution, even if there is no change in the job assignment to the different logistics chains and thus their carrier.

Figure 10.3 shows the score development of the LSPs over the number of MATSim iterations. For the Kaufland LSP, the scores of the *best* plan stabilize after 21 MATSim iterations (see Figure 10.3a); for the Edeka LSP, after 287 MATSim iterations (see Figure 10.3b).[3] In Section D.2 some additional plots of runs with fewer MATSim iterations are presented. From these runs, no randomness effect is

[3] As mentioned later in Section 10.4.2.1, it looks like that there are better solutions available, which will not be found with the current setup.



(a) Kaufland



(b) Edeka

Figure 10.3: Score development of the selected plan of the LSP over the MATSim iterations. The innovative strategies are switched off after 95 % of the 500 iterations.

visible when running the same scenario with the same or a different number of MATSim iterations again. What is visible is a fluctuation of the *worst score* (red graph) of the LSP, which is the score of the worst plan in the choice set of the LSP. Once the innovation is switched off, this also stays constant, because no modified plans are added to the choice set of the LSP anymore. Also, the assumption that the heuristic VRP solving may lead to different solutions, does not appear to be the case, because the score remains constant after the innovation switch-off, even if the carriers are still rerunning their tour planning using jsprit.

Summary of simulation study setup Based on all the investigations above, the following setup is used for the studies.

In total there are the following possible setups for the LSPs. Each LSP is set up with exactly *one* initial plan, consisting of either one or both of the above-mentioned logistics chains, leading to three different scenarios:

1. direct delivery only: one plan with the direct delivery logistics chain only,
2. two-echelon delivery only: one plan with the two-echelon delivery logistics chain only,
3. both chains: one plan with both logistics chains, allowing the LSP to switch the shipments between the two chains during the replanning[4].

The available vehicle types of the direct carrier and the distribution carrier are the same as used in the original study by Schröder and Liedtke (2014); Gabler et al. (2013, see also Section 4.1):

- Kaufland: ICEVs with a GVWR of 18 t and 40 t
- Edeka: ICEVs with a GVWR of 18 t and 26 t

For the main run carrier in the two-echelon chain, the larger of the two vehicle types is chosen. In contrast, direct delivery carrier and distribution carrier, if applicable, select between the two vehicle types or employ a combination of both. The vehicle specifications are the same as in the carrier-based simulation in Section 10.3 and can be found in Table 5.1 in Chapter 5.

As described in Section 3.2.2.2, the score (representing the costs) of an LSP-plan is the sum of all costs of its carriers, its hub, and, if applicable, the toll. The daily costs for the hub are set to 100 €, which is approx. 3′000 € per month. Toll is not applied in the current study. The tour planning for all carriers delivering goods to the destination, is done using jsprit with 1′000 iterations. For the main run carrier, which is responsible for transporting the shipments from the depot to the hub in the two-echelon chain, no tour planning is done.

The results of the LSP simulation are compared to the baseline of the carrier-based simulation using the program code from 2025 as prepared in Section 10.3. The tour planning is done with 1′000 jsprit iterations as well. All simulations are run *without* the time-dependent network and thus without congestion effects from other traffic.

10.4.2 Results

The results of the different scenarios are presented in the following. The structure and the calculations are done similarly to those in Chapters 7 and 8. They are separated into the following elements:

- key figures and operating costs,
- emissions during operations, and
- the well-to-wheel emissions.

[4] This is done by using the `RandomShipmentShiftingModule`: The innovative strategy in this module creates a copy of the current plan and shifts one randomly selected shipment from one logistics chain to another logistics chain within the same plan. This allows the LSP to explore different assignments of shipments to the different logistics chains (see also "Replanning" in Section 3.2.2.2)

10.4.2.1 Key Figures and Operating Costs

The key values for the different scenarios are presented in Table 10.5. This includes the total number of vehicles used, the vkm and time traveled, as well as the costs of all carriers. The total costs are split into the following components:

- *fixed costs* for the vehicles used in the scenario,
- *variable costs per distance* based on the vkm driven by the vehicles, and
- *variable costs per time* for the driver.
- *costs for the hub*, if available.

The carrier-based simulation from 2025 with only one direct carrier, delivering all shipments directly to the customers (see Section 10.3), serves as base case. To be comparable, the job-splitting for all runs is the same: Each job fits into a vehicle with a maximum GVWR of 18 t.

It shows for Kaufland and Edeka that the central values of the direct delivery simulation only ("LSP: direct") slightly differ from the base case. This is expected due to the heuristic approach of the VRP-solving algorithm. Because of the different setup (with and without LSP), it cannot be expected that the results are equal, since the initialization of the pseudo-random number generator takes place at different points.

The other corner case, with all deliveries on the two-echelon chain ("LSP: two-echelon"), results in much higher values. A key driver is the large number of additional vehicles required compared with direct delivery. The case where the LSP has both options available ("LSP: both chains") is located somewhere in between. It indicates that the combination of the initial assignment of the jobs on the different chains, in combination with the simple replanning strategy, does not come close to the best solution of the (direct delivery) corner case: Theoretically, it should find a solution that is at least as good as the best of the corner cases. So, it appears that the algorithm gets stuck in a local optimum. The 500 MATSim iterations that were run are far more than needed for a stable result, since Figure 10.3 in Section 10.4.1 showed that there is no improvement after 21 iterations for Kaufland and 287 for Edeka in this simulation run. Thus, adding only more MATSim iterations for replanning will most probably not resolve the issue.

Table 10.5: Development of some key figures for the simulations, depending on the simulation case. The base scenario is calculated with the carrier-based approach, delivering all shipments directly to the customers. The other scenarios are calculated with the LSP-based approach: i) one direct chain, ii) one two-echelon chain, and iii) both chains allowing the LSP to choose for each shipment: direct and two-echelon delivery.

(a) Kaufland

scenario	veh. (#)	distance (vkm)	travelTime (h)	fixedCosts (€)	varCosts time (€)	varCosts dist. (€)	costs hub (€)	totalCosts (€)
carrier-based	11	2′188	32.87	1′392	1′361	1′510	—	4′263
LSP: direct	11	2′240	32.19	1′392	1′347	1′546	—	4′285
LSP: two-echelon	22	2′946	43.71	2′739	1′909	2′030	100	6′777
LSP: both chains	17	2′518	37.58	2′106	1′677	1′735	100	5′619

(b) Edeka

scenario	veh. (#)	distance (vkm)	travelTime (h)	fixedCosts (€)	varCosts time (€)	varCosts dist. (€)	costs hub (€)	totalCosts (€)
carrier-based	20	3′364	62.35	1′650	2′680	2′249	—	6′578
LSP: direct	23	3′305	61.12	1′896	2′658	2′209	—	6′762
LSP: two-echelon	66	4′017	72.51	5′451	3′649	2′691	100	11′893
LSP: both chains	36	3′361	60.71	2′971	2′981	2′247	100	8′299

10.4.2.2 Emissions during operations

The emissions during operation are calculated using the Handbook on Emission Factors for Road Transport (HBEFA) database as described in Section 2.2.2.3. They are based on the vkm driven, the vehicle-type-specific energy consumption, the road type, and the traffic state per link and vehicle.

As before, the daily values are multiplied by 250 workdays per year (Planco, ITP, and TUBS, 2015) to get the annual emissions. Table 10.6 shows the aggregated emissions of selected exhaust (Table 10.6a) and non-exhaust (Table 10.6b) pollutants from vehicle operations in t per year. The observations for the emissions while driving follow the overall tendency of the vkm as shown in Table 10.5. The cases of direct delivery using the LSP approach are similar to the base case with the carrier-based approach. This is expected because it is a similar solution, based on another initialization of the heuristic VRP-solving algorithm due to a different simulation setup. In the case of delivering all jobs using the 2-echelon logistics chain, the emissions increase by approx. 1/3 (Kaufland) and approx. 18% (Edeka). When allowing the LSP to choose for each job on which of both logistics chains it gets delivered, an increase by approx. 14.% for Kaufland and a marginal decrease for Edeka is observed. So despite the fact that the solution for Edeka needs more vehicles, the overall mileage and also the emissions remain more or less the same.

Table 10.6: Aggregated emissions of selected emission components from vehicle operations in kg per year. All values are calculated using the adjusted emission factors based on the HBEFA database. The values in parentheses are the relative changes compared to the base case.

(a) Aggregated emissions of selected *exhaust* emissions from vehicle operations in kilogram (kg) per year.

Pollutant	Kaufland				Edeka			
	Base	LSP direct	LSP 2E	LSP both	Base	LSP direct	LSP 2E	LSP both
CO_2	3′677′653	376′487	494′612	422′523	564′335	554′696	672′380	563′351
	—	(2.4%)	(34.5%)	(14.9%)	—	(−1.7%)	(19.1%)	(−0.2%)
CO	233	235	311	267	378	371	444	372
	—	(0.9%)	(33.6%)	(14.6%)	—	(−1.9%)	(17.5%)	(−1.5%)
NO_x	572	568	760	653	965	946	1′132	946
	—	(−0.7%)	(32.8%)	(14.1%)	—	(−2%)	(17.4%)	(−2%)
PM_{10}	10.9	11.0	14.6	12.5	17.3	16.9	20.5	17.1
	—	(1.4%)	(34.1%)	(14.7%)	—	(−1.8%)	(18.7%)	(−0.7%)
$PM_{2.5}$	10.9	11.0	14.6	12.5	17.3	16.9	20.5	17.1
	—	(1.4%)	(34.1%)	(14.7%)	—	(−1.8%)	(18.7%)	(−0.7%)
BC	4.9	5.0	6.6	5.6	7.9	7.8	9.4	7.8
	—	(0.9%)	(33.8%)	(14.6%)	—	(−1.9%)	(18.2%)	(−1.1%)

(b) Aggregated emissions of selected *non-exhaust* (n.e.) emissions from vehicle operations in kg per year.

Pollutant	Kaufland				Edeka			
	Base	LSP direct	LSP 2E	LSP both	Base	LSP direct	LSP 2E	LSP both
PM_{10} n.e.	70.9	72.7	95.2	81.1	107	106	127	107
	—	(2.5%)	(34.3%)	(14.5%)	—	(−1.4%)	(18.7%)	(−0.2%)
$PM_{2.5}$ n.e.	26.2	26.5	35.1	30.1	41.8	41.0	49.5	41.4
	—	(1.4%)	(34.1%)	(14.9%)	—	(−1.9%)	(18.6%)	(−0.8%)
BC n.e.	2.6	2.7	3.5	3.0	4.2	4.1	5.0	4.1
	—	(1.4%)	(34.1%)	(14.9%)	—	(−1.9%)	(18.6%)	(−0.8%)

10.4.2.3 Well-to-Wheel emissions

The Well-to-Wheel (W2W) emissions are calculated as described in Section 2.2.3 by multiplying the vkm driven with the vehicle type specific energy consumption and the W2W emission factors (see Table 2.1).

Figure 10.4 shows the calculated W2W emissions in t CO_2 equivalents (CO_2eq) per year for the baseline and the different policy scenarios. The values increase according to the changes in the vehicle-type-specific mileage (please see Tables D.3b and D.4b for the vehicle type specific values). The absolute values and relative changes of the W2W emissions can be found in Section D.4. For Kaufland, the W2W emissions increase by 2.4 % (direct), 34.2 % (2-echelon) and 14.8 % (both chains). The increase for Edeka is 0.2 % (direct), 21.7 % (2-echelon) and 1.9 % (both chains). In the base case, only the largest available vehicle is used. In all LSP cases, only a few (or none) vkm are driven by the smaller vehicles, so the influence of the different vehicle types and their lower fuel consumption is only marginal in these cases. Moreover, only ICEVs are available, so no effect of the usage of Battery Electric Vehicles (BEVs) is observed.

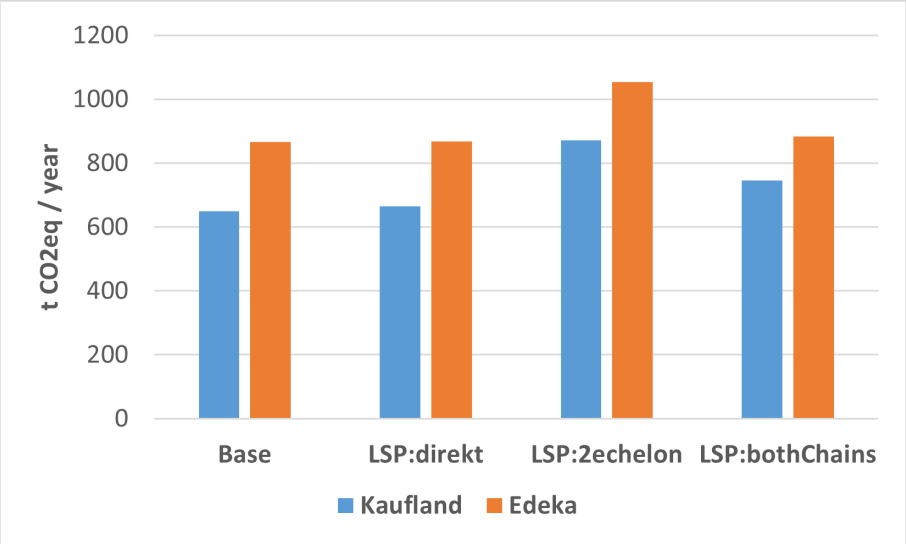


Figure 10.4: Calculated W2W emissions in t CO_2eq per year for the baseline and the different policy scenarios.

10.5 Conclusion, Discussion and Outlook

In this chapter, the conversion of a carrier-based MATSim simulation to an LSP-based simulation is presented for two selected carriers of the Berlin Food Retail scenario. The focus is on the systematic development of a baseline scenario for the implementation of policy measures, presented in Chapter 11. The LSP-based simulation is set up using the same conditions as in the carrier-based simulation, e.g., the same vehicle types, the same cost parameters, and the same demand.

In a first step, the carrier-based simulation is presented, which serves as the base case for this development. Besides presenting the results from earlier studies, the carrier-based simulation is re-run with the current version of MATSim. In a second step, the LSP-based simulation is set up. It allows the implementation of different logistics chains that are not possible in the carrier-based simulation. Two different types of logistics chains are implemented:

- direct delivery from the depot to the customer, and
- two-echelon delivery via a hub, including a main run and a delivery run.

The LSP may use one of these chains for all shipments, or both chains and decide for each shipment, which chain to use. First of all, only one plan per LSP is set up, containing only the *direct* chain. As a consequence, all shipments are put onto the direct chain, with the direct carrier delivering all shipments directly to the customers. This allows a direct comparison of the results of the carrier-based approach and the LSP-based approach. The second corner case is that the LSP has only the *two-echelon* chain in its plan set. As the third and final case, the LSP-based simulation is set up with one plan containing *both chains*, allowing the LSP to choose for each shipment which chain to use. Here, the co-evolutionary strategy approach is used to improve the plan iteratively during the MATSim iterations. The results of the different scenarios are presented and discussed.

The different runs are also used to evaluate how many MATSim and jsprit iterations are needed. Moreover, the effect of splitting the existing demand into smaller shipments on the solution and the number of jsprit iterations is analyzed.

Results The simulation results demonstrate that the *direct-only LSP configuration* essentially replicates the carrier-based baseline simulation: vehicle counts, traveled kilometers, total operating costs, and emissions differ by only about 1 % or less. This confirms that, when the LSP is restricted to the single direct logistics chain, the LSP-based framework can serve as a drop-in replacement for the traditional carrier model setup.

In contrast, the *two-echelon configuration* dramatically increases the fleet size (Kaufland +100 %, Edeka +230 %) and raises total costs by 59 % (Kaufland) and 81 % (Edeka). Correspondingly, emissions while driving climb by about one-third for Kaufland and about 18 % for Edeka. The Well-to-Wheel emissions increase by about 34 % (Kaufland) and 22 % (Edeka).

The setup with *both the direct and two-echelon chains* available in a single LSP plan, results in intermediate changes. The total costs increase by about 32 % for Kaufland and by about 26 % (Edeka), while emissions (while driving, as well as W2W) grow by approx. 15 % for Kaufland and remain essentially unchanged for Edeka. This indicates that allowing the LSP to assign shipments to one or the other chain does *not* result in lower or equal costs, as the best (corner) case, as one would have expected.

Discussion and Outlook The last point, that the case with both chains available does not find a better or at least equal solution as the best corner case with only one chain highlights that the setup of i) the initial assignment of jobs to a chain and/or ii) the replanning algorithm needs improvement.

Another point to discuss is the very high computation time because of many MATSim iterations with many jsprit iterations each. Together with the situation that the implemented replanning algorithm only makes small changes, it would be a major improvement to start with the existing VRP-solution from the previous iteration instead of running it from scratch. Currently, this is not implemented. Moreover, each carrier of the LSP solves its VRP in each MATSim iteration, regardless of whether the (LSP) plan was changed or only an existing (LSP) plan was selected. It would be good to have an option to decide whether the VRP should be solved again or not. The potential issue that re-solving an unchanged VRP leads to a different solution because of the heuristic approach of jsprit is not observed here.

Another finding in this study is that splitting the demand in smaller pieces leading to a solution with fewer costs is only achieved for one of the two carriers. For the other one, the solution is worse,

even if at least the same solution must be achievable. Here, the initial solution in combination with the defined heuristic approaches seems to end in some kind of local optimum. A remarkable disadvantage of the split is that the individual shipments are smaller and thus more jobs are needed to deliver the same demand. More jobs increase the complexity of the VRP, leading to more computation time. The reason for the job-splitting is that the LSP needs to be able to move jobs between the different logistics chains. If at least one part of one chain has only small vehicles available, all jobs must be small enough to get transported. This is important for cases, e.g., in the following study (see Chapter 11), where some destinations can only be reached by a specific chain.

The usage of the two-echelon chain currently produces results with many vehicles and thus increases the fixed costs. This comes from the fact that the vehicles on the main run, transporting the goods from the depot to the hub, are only used for one trip and thus no VRP is solved for them. This inefficiency of not re-using vehicles has also been addressed in Chapter 6. For the practical application in the current use case, it is important to decide whether shuttling with few vehicles makes sense for logistics operation or if there is only a small time-window in which the goods need to be transported from the depot to the hub.

To improve the current situation and address several of the limitations mentioned, it would be great to have a quite good initial solution. Besides the level of the VRP solving, this is only valid for the LSP decision regarding the assignment of the shipments to the logistics chains. Therefore, it would be great to have a 2E-VRP solver included, which can solve the 2E-VRP directly and use its solution as an initial LSP plan. Then we can take the solution of this solver as a starting point for the LSP and use the co-evolutionary strategy approach to improve this solution iteratively given all the other conditions in the MATSim simulation that this solver was not able to use. A possible implementation of the 2E-VRP-solver may start from a relaxed version of the work by Yu, Puchinger, and Sun (2020), who introduces a two-echelon urban delivery problem with autonomous vehicles on the second echelon. Another starting point could be the work by Caggiani et al. (2020), proposing a formulation for Two-Echelon Capacitated Electric Vehicle Routing Problem with Time Windows and Partial Recharging. Both are implemented as Mixed-Integer Linear Programming (MILP) problems. Anderluh, Hemmelmayr, and Nolz (2017) include the temporal and spatial synchronization into the 2E-VRP solving using a metaheuristic solving approach. For the replanning phase, e.g., Richter, Martins-Turner, and Nagel (2024) showed the influence of different re-planning strategies, leading to room for further improvements.

Besides those improvement possibilities, the LSP-based simulation of the Berlin food retailing scenario is now set up and ready to be used for the implementation of different policy measures, which are presented in Chapter 11. The results presented in the present chapter will serve as a base case for these studies.

CHAPTER 11

Reactions to Zero-Emission and Safety Zone Restrictions in Urban Food Retail Logistics

This chapter is an edited version of an article submitted to the EWGT 2026 conference, which is currently under review: Martins-Turner and Nagel (2026).

11.1 Introduction and Problem Statement

Urban freight transport faces significant challenges, including traffic congestion, environmental concerns, and the need for efficient last-mile delivery solutions. One approach to deal with it is the use of micro-depots, which are small-scale distribution centers located within urban areas. These micro-depots serve as hubs for receiving goods from larger distribution centers and facilitate the last-mile delivery process.

Policy measures are increasingly being discussed and implemented to restrict certain types of vehicles from entering inner-city areas. This can be done for *environmental reasons* – e.g., by introducing a Low Emission Zone (LEZ) (or Zero Emissions Zone (ZEZ)), as e.g., in London, United Kingdom (Transport for London (TfL), 2022c), Germany (e.g., in Berlin, Senatsverwaltung für Umwelt, Verkehr und Klimaschutz Berlin (SenUVK), 2017), or several cities in France with temporal LEZs (Ministère de la transition écologique et de la cohésion des territoires, 2022). Vehicles not meeting the requirements are either banned or charged with a toll. Besides the environmental approach, another concept is to restrict the access of vehicle types for safety reasons: In Greater London, trucks over 12 ton (t) Gross Vehicle Weight Rating (GVWR) have, as part of "the vision zero plan to eliminate all deaths and serious injuries on London's transport network by 2041" (Transport for London (TfL), 2022b), special requirements for entering the city zone(s).

In the current study, we will explore the effects of banning certain vehicle types from an inner-city zone on the logistics chains. Again, the case of the Berlin food retailing industry Section 4.1 is used. In contrast to the studies presented in Chapters 7 and 8 the companies now can *change its logistic network*. Possible reactions include the switch to vehicles that are still permitted, as well as the use of a two-echelon delivery via a hub located near the inner-city limit, or a mix of both. Relevant

concepts of the Two-Echelon Vehicle Routing Problem (2E-VRP) are summarized by Oliveira, Ramos, and de Sousa (2022). According to them, Perboli, Tadei, and Vigo (2008) authored the first formal definition, while Crainic, Ricciardi, and Storchi (2004, 2009) addressed the application in the context of city logistics. Other studies and implementations have been done, e.g., by Anderluh, Hemmelmayr, and Nolz (2017); Anderluh et al. (2019); Wang, Zhou, and Feng (2019); Caggiani et al. (2020). Please also refer to Section 9.1 for more background information.

11.2 Methodology

11.2.1 Simulation setup

This study uses the agent-based transport simulation framework Multi-Agent Transport Simulation (MATSim) (Horni, Nagel, and Axhausen, 2016). In particular, the freight extension of MATSim (see Section 3.2.2.2) is used, which allows modeling the logistics processes in more detail, including the use of micro-depots and the associated delivery routes.

The ban of the vehicles from the city center is implemented in the simulation by defining a prohibitively high toll (€1000) for all vehicle types to be banned. In this study, two different types of zones are introduced:

i) a ZEZ, banning all Internal Combustion Engine Vehicles (ICEVs), and
ii) a safety zone, banning all vehicles with a GVWR $> 7.5\,\mathrm{t}$.

The zone shape is set according to the existing LEZ of Berlin (see Senatsverwaltung für Umwelt, Verkehr und Klimaschutz Berlin (SenUVK), 2017), with a size of approx. 88 square kilometers (km^2). To allow delivery within the zones, feasible vehicle types are provided at the hub. For more information on both concepts, please also refer to Section 9.1.

As a case study, the Berlin food retailing industry scenario is used. This scenario was originally built by Schröder and Liedtke (2014). It has been updated and used over the past years for various studies regarding the decarbonization of urban freight transport (see, e.g., Martins-Turner and Nagel, 2019; Martins-Turner et al., 2020; Ewert et al., 2021a, 2025). For the current studies, the same two different carriers as used in Chapter 10 from the food retailing scenario (see Section 4.1) are selected to examine whether their different requirements would lead to structurally different solutions:

- Kaufland with the depot near Lübbenau, approx. 75 kilometer (km) away from the Berlin city limit and 95 km away from the Berlin city center, with 17 jobs at 16 different locations and a total demand of 347 pallets.
- Edeka with the depot in Mittenwalde, significantly closer to Berlin (approx. 15 km south of the city limit; 35 km away from the city center), with 72 jobs at 68 different locations and a total demand of 895 pallets.

The demand represents an average workday.

In contrast to earlier studies regarding decarbonization (see, e.g., Martins-Turner et al., 2020; Ewert et al., 2021a), the companies can now *change the logistics network* (see Martins-Turner and Nagel, 2025). With this new approach it is possible to model and simulate the goods transport along a logistics chain, including the 2E-VRP. MATSim's freight extension has been extended to allow such simulations (Matteis, Wisetjindawat, and Liedtke, 2019; Martins-Turner and Nagel, 2025, see also Section 3.2.2.2 and Chapters 9 and 10). The advantage of the agent-based approach

is that we have the trajectories (time and space) of each single vehicle, as well as information about loading and unloading the goods in or out of these vehicles.

The main agent in this simulation is the Logistics Service Provider (LSP). In this case study, one LSP is created for each of the companies defined above; thus, two LSPs are created in total. Each LSP has a list of jobs for the goods to be transported as demand. To transport these goods and build the logistics chains, the LSP has hubs and carriers (with a fleet of vehicles) available. Each LSP can choose between two different *logistics chains* to deliver the shipments to the customers:

- direct delivery from the depot to the customer, or
- two-echelon delivery via a hub located near Berlin's inner-city zone.

Both chains are available in the same LSP-plan, so the LSP can choose the best option for each shipment individually. All shipments are initially assigned to the two-echelon chain. Due to MATSim's iterative approach, the LSP can change (replan) its plan over the iterations to react to the restrictions introduced by the ZEZ or the safety zone, and at the same time improve its plan to reduce costs. Replanning means that the LSP can change the assignment of a shipment to a logistics chain. Due to the changes in the plans, the carriers (which belong, as resources, to the chains, not to the plans) have changes in the jobs they have to transport, and thus the tours of the vehicles will change. To take this into account, the tour planning of the carriers – run with 1′000 jsprit (jsprit, 2024) iterations – is re-run in each of the 500 MATSim iterations[1].

The results of the measures introduced in the current study are compared to the results of the base case. All simulations, base and policy cases, are run with the same software code (MATSim version 2026.0-PR4285 [2]). Only the input parameters for the different simulation runs were changed. The costs for the hub are set to 100 € per day, as done in Section 10.4. The ban of certain vehicle types is done by using the *roadpricing* contrib (see Section 3.2.4). The toll value is set to a very high value of 1′000 € for the specified vehicle type. All other vehicle types are not affected by the toll.

In the original food retailing scenario (see Section 4.1), different retailers have different vehicle sizes available:

- Edeka: 18 t and 26 t GVWR,
- Kaufland: 18 t and 40 t GVWR.

Due to the ban of certain vehicle types in the ZEZ and the safety zone, the carriers have to use other vehicle types for deliveries within these zones. In case of the ZEZ, the carriers have to use Battery Electric Vehicles (BEVs); while in the safety zone, they have to use small vehicles with a GVWR of 7.5 t. These are added for the direct deliveries and are used for the delivery carriers in the two-echelon chain. Table 11.1 gives an overview of the vehicle types available for the different carriers in the different cases. For the main run, the current implementation only allows one vehicle type. Therefore, the largest of the original available ICEV is taken.

The results of the policy cases are compared with the base cases. These are the cases without any restrictions. The vehicle specifications (see Section 5.1), including the cost parameters and the maximum capacity, are the same as in the studies in Chapters 7, 8, and 10.

In Section 10.3.2.3 it is observed that the simulation result depends on the demand structure. If existing shipments are split into smaller shipments, another solution is found. To avoid this influence on the results, the following cases are used as base cases for the current studies:

[1] To be consistent with the previous studies in Chapter 10, all simulations are run with 500 MATSim iterations.
[2] This corresponds to commit cc7c698 on github.com/matsim-org/matsim-libs/.

Table 11.1: Available vehicle types for the different carriers in the different simulation cases. The direct carrier is used only for the direct logistics chain, while the main run and delivery run carriers are used for the two-echelon chain. In the ZEZ case, ICEVs are not considered for the delivery carrier, since its main task is to serve all delivery locations within the ZEZ. Similarly, in the safety zone case, only the small vehicle type is considered for the delivery carrier. For the main run carrier, no vehicle type selection is possible. Therefore, the largest ICEV vehicle for the company is considered, since it is cheaper than the same-sized BEV.

	case	carrier	7.5 t		18 t		26 t		40 t	
			ICEV	BEV	ICEV	BEV	ICEV	BEV	ICEV	BEV
Kaufland	base	direct			✓				✓	
		main run							✓	
		delivery run			✓				✓	
	ZEZ	direct			✓	✓			✓	✓
		main run							✓	
		delivery run				✓				✓
	safety zone	direct	✓	✓	✓	✓			✓	✓
		main run							✓	
		delivery run	✓	✓						
Edeka	base	direct			✓		✓			
		main run					✓			
		delivery run			✓		✓			
	ZEZ	direct			✓	✓	✓	✓		
		main run					✓			
		delivery run				✓		✓		
	safety zone	direct	✓	✓	✓	✓	✓	✓		
		main run					✓			
		delivery run	✓	✓						

1. ZEZ: all shipments are split into smaller shipments, with a maximum size of 16 pallets (capacity of vehicles with 18 t GVWR). This leads to 28 shipments for Kaufland and 92 shipments for Edeka.[3]
2. Safety zone: all shipments are split into smaller shipments, with a maximum size of 10 pallets (capacity of vehicles with 7.5 t GVWR). This leads to 43 shipments for Kaufland and 119 shipments for Edeka.

11.2.2 Emission calculation

In this study, two different approaches are used to calculate the emissions of the vehicles in the simulation:

1. exhaust plus non-exhaust emissions from vehicles while driving
2. Well-to-Wheel (W2W) analysis based on the vehicle kilometer (vkm) and specific emission factors.

This approach is the same as done in, e.g. Chapters 7 and 8.

The first approach calculates the *emissions while driving, using MATSim's* emissions *contrib* (see Section 3.2.3). It is based on the emission factors from the Handbook on Emission Factors for Road Transport (HBEFA) (INFRAS, 2019, see Section 2.2.2.3). HBEFA is a well-known tool

[3] This case corresponds to the case described in Section 10.4.

for estimating traffic-related emissions across Europe. It provides detailed emission factors and energy-consumption data for a wide variety of vehicle categories, fuel types (called 'technologies' by HBEFA), road types, and traffic situations, with an emphasis on emissions occurring while driving. Regarding vehicle categories, HBEFA distinguishes, for example, passenger cars, Light Commercial Vehicles (LCVs), Heavy Goods Vehicles (HGVs), buses, and motorcycles. For each category it offers emission factors for various engine technologies (e.g., diesel, gasoline, electric, hybrid), vehicle sizes (e.g., weight classes for trucks), and emission standards (e.g., Euro3, Euro4, Euro5, Euro6). Road types are divided into urban, rural, and highway networks, each characterized by specific traffic conditions and speed profiles. Traffic situations are classified by average speed ranges, from free-flowing traffic to heavily congested conditions. Applying these emission factors enables straightforward quantification of key pollutants, covering both exhaust and non-exhaust emissions.

The differentiation into exhaust and non-exhaust emission is done because even a fully decarbonized transport sector is not emissions-free. Main sources of non-exhaust emissions are the abrasion of brakes, tires, and road surfaces, as well as the (re)suspension of road dust (Grigoratos and Martini, 2014; INFRAS, 2019). For certain pollutants, such as particulate matter $< 10\,\mu m$ (PM_{10}), particulate matter $< 2.5\,\mu m$ ($PM_{2.5}$), and black carbon (BC), a significant share of emissions originates from these *non-exhaust* (n.e.) sources (see e.g., Kaddoura, Ewert, and Martins-Turner, 2022). In this study, we focus on the following pollutants:

- exhaust emissions: carbon dioxide (CO_2), carbon monoxide (CO), nitrogen oxides (NO_x), PM_{10}, $PM_{2.5}$, and BC
- non-exhaust emissions: PM_{10} n.e., $PM_{2.5}$ n.e., and BC n.e..

The second approach is the calculation of the $W2W$ emissions (see Section 2.2.3). This approach includes the emissions from fuel or electricity production as well as the emissions from the vehicle operation (JRC et al., 2014). For the ICEV, a diesel consumption between 13.57 liter (l)/100 km for trucks with a GVWR of 7.5 t and 37.45 l/100 km for the trucks with a GVWR of 40 t is assumed (Planco, ITP, and TUBS, 2015). Following (DIN EN 16258:2012, 2013), a factor of 3′170 gram (g) CO_2 equivalents (CO_2eq)/l of diesel is used to calculate the W2W emissions for the ICEV. For the BEV, an energy consumption between 61 and 180 kilowatt hours (kWh)/100 km is assumed (Martins-Turner et al., 2020). Moreover, three different factors are used to represent different electricity mixes in Germany:

- 518 g CO_2eq/kWh in 2018 (Icha and Kuhs, 2019),
- 347 g CO_2eq/kWh in 2030 (Wietschel, Kühnbach, and Rüdiger, 2019), and
- 25 g CO_2eq/kWh for renewable energies (Wietschel, Kühnbach, and Rüdiger, 2019).

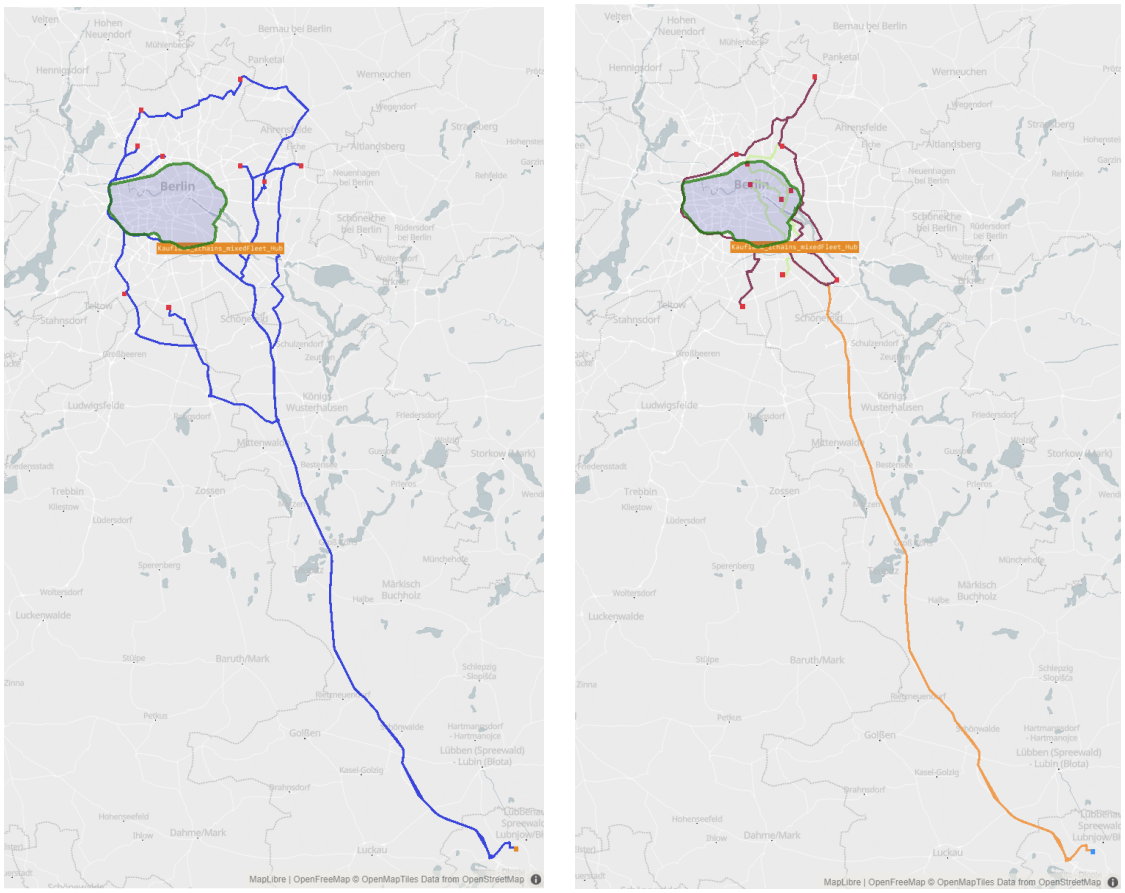
With all these numbers, the W2W emission factors per distance driven are calculated. Table 2.1 in Section 2.2.3 summarizes the W2W emission factors per 100 vkm for the different vehicle types used. To calculate the total W2W emissions of a vehicle, the vkm driven by this vehicle is multiplied by the corresponding factor from Table 2.1. For the calculation of the annual emissions, we assume 250 workdays per year (Planco, ITP, and TUBS, 2015).

11.3 Results

The results of the simulation are presented as follows: Section 11.3.1 presents the tour characteristics and costs, Section 11.3.2 shows the emissions during operations, and Section 11.3.3 presents the well-to-wheel emissions.

11.3.1 Tour characteristics and costs

Figures 11.1 and 11.2 exemplify the resulting tours for two combinations: Figure 11.1 shows the resulting tours for Kaufland under the ZEZ restriction, and Figure 11.2 shows the tours for Edeka under the safety zone restriction. Figures 11.1a and 11.2a show the tours driven directly from the depot to the destination (direct chain), while Figures 11.1b and 11.2b show the tours driven via the hub (two-echelon chain). Both companies (Edeka, Kaufland) respond to the introduced restrictions by using the two-echelon chain for transshipment and distributing the goods to the restricted zone with BEVs or smaller vehicles. Customers outside the zone are served either with the direct chain or with the two-echelon chain.

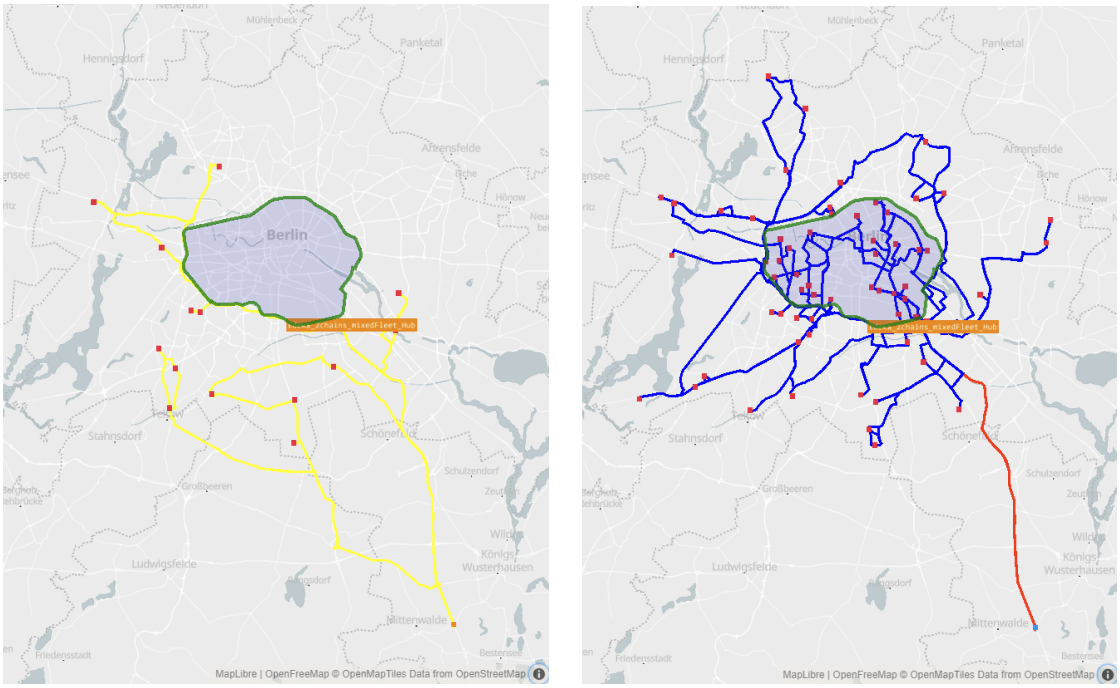


(a) Tours of the direct delivery chain. All vehicles are 40 t ICEVs.

(b) Tours of the 2e delivery chain. Main run tours (40 t ICEVs) are shown in orange, delivery run tours (all BEVs): dark red 18 t, light green 40 t.

Figure 11.1: Resulting tours for the Kaufland case with ZEZ. ICEVs are banned from the highlighted restricted area. The vehicle tours have different colors, depending on the vehicle type used for the tour. The hub is located at the orange description south-east of the restricted area. (Visualized with Simwrapper (Charlton, 2026), background map from OpenStreetMap (2026)).

Table 11.2 presents a comprehensive overview of the key values for the different simulations. Table 11.3 shows the distribution of vehicles by type across the different scenarios, while Table 11.4 shows the corresponding vkm driven by all vehicles of a specific type. As explained above and summarized in Table 11.1, the availability of the vehicle type depends on the company — Kaufland or Edeka — as well as on the simulation case.



(a) Tours of the direct delivery chain. All vehicles are 26 t ICEVs.

(b) Tours of the 2e delivery chain. Main run tours (26 t ICEVs) are shown in red, delivery run tours (all 7.5 t ICEVs) in blue

Figure 11.2: Resulting tours for the Edeka case with safety zone. Vehicles over 7.5 t GVWR are banned from the highlighted restricted area. The vehicle tours have different colors, depending on the vehicle type used for the tour. The hub is located at the orange description south-east of the restricted area. (Visualized with Simwrapper (Charlton, 2026), background map from OpenStreetMap (2026)).

The results show a mixed response under the ZEZ restriction, but a clear reaction under the safety zone restriction. For Kaufland, the *ZEZ case* shows slightly improved results: costs reduce from 5′619 € to 5′557 € (−1.1 %), and mileage decreases from 2′518 to 2′497 km (−0.8 %). It looks like the heuristic approach found a slightly more efficient solution than for the base case, using one fewer vehicle (16 instead of 17). Since same sized vehicles have the same loading capacity — regardless of whether they are ICEVs or BEVs — this cannot cause the other number of vehicles. In reaction to the ZEZ, in total 5 out of the 16 vehicles are now BEVs, serving all demand within and some outside the ZEZ. For Edeka, with the depot closer to the city and other demand distribution (more locations, smaller size), the effects of the ZEZ case are much stronger: costs increase by +27.7 %, the vehicle fleet grows from 36 to 50 vehicles (+38.9 %), mileage increases by +12.6 %, and travel time by +12.1 %. Here comes the effect of the 2-echelon chain into play: a significant share of the demand is shifted to the 2-echelon chain, resulting in two vehicles being needed for what was one vehicle before (direct delivery). Most of the additional vehicles are also caused by the main run carrier, which in the current setup, is not able to run several transport tours from the depot to the hub[4]. Both companies are enabled in the policy case to use BEVs, in contrast to the base case with only ICEVs available, for the direct delivery from the depot to all customers, whether they are located in the ZEZ or not. Also in this case, we can observe that the demand within the ZEZ is served only by BEVs.

The *safety zone* causes a different reaction from the companies, forcing them to use smaller

[4]The effect of using one vehicle for several subtours during the day is investigated in Chapter 6.

Table 11.2: Comparison of key values for the different cases. All changes are compared to the corresponding base case, which is the case without any restrictions.

(a) Case: ZEZ. All cases are calculated with shipments, with a maximum size of 16 pallets (capacity of vehicles with 18 t GVWR).

Company	Case	Costs (€)	# vehicles	mileage (km)	travel time (h)
Kaufland	base	5′619	17	2′518	37.6
	ZEZ	5′557	16	2′497	37.8
		(−1.1 %)	(−5.9 %)	(−0.8 %)	(+0.5 %)
Edeka	base	8′299	36	3′361	60.7
	ZEZ	10′594	50	3′784	68.0
		(+27.7 %)	(+38.9 %)	(+12.6 %)	(+12.1 %)

(b) Case: Safety zone. All cases are calculated with shipments, with a maximum size of 10 pallets (capacity of vehicles with 7.5 t GVWR).

Company	Case	Costs (€)	# vehicles	mileage (km)	travel time (h)
Kaufland	base	6′354	21	2′551	39.1
	safety zone	6′369	24	3′294	59.6
		(+0.2 %)	(+14.3 %)	(+29.1 %)	(+52.4 %)
Edeka	base	10′485	54	3′674	70.3
	safety zone	11′300	60	4′832	97.6
		(+7.8 %)	(+11.1 %)	(+31.5 %)	(+38.8 %)

Table 11.3: Absolute number of vehicles used by vehicle type for each case. Entries with — indicate that the vehicle type is not available in the corresponding case, while entries with 0 indicate that the vehicle type is available, but not used.

(a) Case: ZEZ.

Company	Case	7.5 t		18 t		26 t		40 t		Total		
		ICEV	BEV	ICEV	BEV	ICEV	BEV	ICEV	BEV	ICEV	BEV	Sum
Kaufland	Base	—	—	1	—	—	—	16	—	17	—	17
Kaufland	ZEZ	—	—	0	2	—	—	11	3	11	5	16
Edeka	Base	—	—	1	—	35	—	—	—	36	—	36
Edeka	ZEZ	—	—	0	3	34	13	—	—	34	16	50

(b) Case: Safety zone.

Company	Case	7.5 t		18 t		26 t		40 t		Total		
		ICEV	BEV	ICEV	BEV	ICEV	BEV	ICEV	BEV	ICEV	BEV	Sum
Kaufland	Base	—	—	0	—	—	—	21	—	21	—	21
Kaufland	Safety Zone	12	0	0	0	—	—	12	0	24	0	24
Edeka	BaseSafety	—	—	0	—	54	—	—	—	54	—	54
Edeka	Safety Zone	19	0	0	0	41	0	—	—	60	0	60

vehicles to deliver to the restricted area. Even if BEVs are available in the policy cases as well, no BEVs are used, neither by Kaufland nor Edeka. For Kaufland, costs rise only slightly (+0.2 %), while the number of vehicles increases from 21 to 24 (+14.3 %). Half of the fleet now consists of the 7.5 t ICEVs, while the other half are 40 t ICEVs. Due to the small vehicle now being available and the option to deliver the demand in several subtours to the same location, we observe an increase in mileage of 29.1 % and travel time of 52.4 %. For Edeka, the safety zone increases costs by 7.8 %.

Table 11.4: vkm driven by vehicle type for each case. Entries with — indicate that the vehicle type is not available in the corresponding case, while entries with 0 indicate that the vehicle type is available, but not used.

(a) Case: ZEZ.

Company	Case	7.5 t		18 t		26 t		40 t		Total		
		ICEV	BEV	ICEV	BEV	ICEV	BEV	ICEV	BEV	ICEV	BEV	Sum
Kaufland	Base	—	—	46	—	—	—	2472	—	2518	—	2518
	ZEZ	—	—	0	140	—	—	2268	89	2268	229	2497
Edeka	Base	—	—	252	—	3109	—	—	—	3361	—	3361
	ZEZ	—	—	0	712	2098	974	—	—	2098	1686	3784

(b) Case: Safety zone.

Company	Case	7.5 t		18 t		26 t		40 t		Total		
		ICEV	BEV	ICEV	BEV	ICEV	BEV	ICEV	BEV	ICEV	BEV	Sum
Kaufland	Base	—	—	0	—	—	—	2551	—	2551	—	2551
	Safety	1225	0	0	0	—	—	2069	0	3294	0	3294
Edeka	Base	—	—	0	—	3674	—	—	—	3674	—	3674
	Safety	2356	0	0	0	2476	0	—	—	4832	0	4832

The number of vehicles used increases from 54 to 60 (+11.1 %), while mileage increases by 31.5 %, and travel time by 38.8 %.

Overall, the results show that the dominant difference lies not only in the policy itself but also among the different companies, which have differing requirements due to their locations and demand structures. Moreover, mileage and travel times change considerably more than monetary costs, indicating the necessity of studies such as this one. Otherwise, one may overestimate cost implications or underestimate traffic and emission consequences, or, as in the case of the safety zone, one would not have been able to provide such detailed results at all.

11.3.2 Emissions during operations

The changes in the logistics chains and thus the tours of the vehicles also lead to changes in the emissions. The emissions during operations are calculated using the HBEFA database as described in Sections 2.2.2.3 and 11.2. They are based on the vkm driven by the vehicles (see Table 11.2), the vehicle type specific energy consumption, the road type, and the traffic state.

The daily values are multiplied by 250 workdays per year (Planco, ITP, and TUBS, 2015) to get the annual emissions. Table 11.5 shows the aggregated annual emissions of selected exhaust (Table 11.5a) and non-exhaust (Table 11.5b) pollutants from vehicle operations.

It demonstrates that the implemented zones lead to different effects on pollutant emissions: Under the ZEZ case, the *exhaust* emissions under investigation (CO_2, CO, NO_x, PM_{10}, $PM_{2.5}$, and BC) decrease for both Kaufland and Edeka compared to the baseline, with the reduction being stronger for Edeka (about −38 % to −48 % depending on the pollutant) than for Kaufland (about −10 % to −17 %). In the safety zone case, the exhaust emissions increase for both companies compared to the baseline, with similar relative changes (about +31 % to +36 %) as for Kaufland (about +29 % to +43 %).

For *non-exhaust* emissions, for the ZEZ the reduction is significantly smaller than for the exhaust emissions, with Kaufland showing a reduction of about −0.5 %, while for Edeka they increase

Table 11.5: Aggregated emissions of selected emission components from vehicle operations in kilogram (kg) per year. All values are calculated using the adjusted emission factors basing on the HBEFA database. The values in parentheses are the relative changes compared to the corresponding base case of each policy scenario.

(a) Aggregated emissions of selected *exhaust* emissions from vehicle operations in kg per year.

	ZEZ				Safety			
	Kaufland		Edeka		Kaufland		Edeka	
Pollutant	Base	Policy	Base	Policy	Base	Policy	Base	Policy
CO_2	422′523	381′176	563′351	351′783	427′984	550′391	615′829	806′814
	—	(−9.8 %)	—	(−37.6 %)	—	(+28.6 %)	—	(+31.0 %)
CO	267	231	372	211	273	372	415	558
	—	(−13.6 %)	—	(−43.3 %)	—	(+36.2 %)	—	(+34.3 %)
NO_x	653	541	946	490	675	960	1′077	1′468
	—	(−17.1 %)	—	(−48.1 %)	—	(+42.3 %)	—	(+36.3 %)
PM_{10}	12.5	10.9	17.1	10.0	12.7	17.0	19.0	25.3
	—	(−12.4 %)	—	(−41.5 %)	—	(+33.6 %)	—	(+33.2 %)
$PM_{2.5}$	12.5	10.9	17.1	10.0	12.7	17.0	19.0	25.3
	—	(−12.4 %)	—	(−41.5 %)	—	(+33.6 %)	—	(+33.2 %)
BC	5.6	4.9	7.8	4.5	5.8	7.8	8.8	11.8
	—	(−13.6 %)	—	(−43.3 %)	—	(+36.0 %)	—	(+34.2 %)

(b) Aggregated emissions of selected *non-exhaust* (n.e.) emissions from vehicle operations in kg per year.

	ZEZ				Safety			
	Kaufland		Edeka		Kaufland		Edeka	
Pollutant	Base	Policy	Base	Policy	Base	Policy	Base	Policy
PM_{10} n.e.	81.1	80.7	107.0	120.2	82.3	104.8	117.2	151.8
	—	(−0.6 %)	—	(+12.3 %)	—	(+27.2 %)	—	(+29.6 %)
$PM_{2.5}$ n.e.	30.1	29.9	41.4	46.6	30.7	41.1	45.9	61.4
	—	(−0.5 %)	—	(+12.5 %)	—	(+34.2 %)	—	(+33.7 %)
BC n.e.	3.0	3.0	4.1	4.7	3.1	4.1	4.6	6.1
	—	(−0.5 %)	—	(+12.5 %)	—	(+34.2 %)	—	(+33.7 %)

by about −12.5 % compared to the base case. In the ZEZ cases, forcing a switch to BEVs, we see that even if the exhaust emissions are reduced due to the policies, this does not mean that the non-exhaust emissions are reduced as well. The different implications for non-exhaust, as for exhaust emissions when switching from ICEV to BEV, have already been observed in other studies (e.g., Kaddoura, Ewert, and Martins-Turner, 2022) and are explained in Section 2.2.2.2. In the safety zone case, the non-exhaust emissions increase for both companies compared to the baseline, with Kaufland showing an increase of about +27 % to +34 % and Edeka showing an increase of about +30 % to +34 % depending on the pollutant. This corresponds more or less to the increase in the exhaust emissions and is based on the changes in the vkm driven by the different sized vehicles. As stated in Section 11.3.1, in the safety zone cases, all vehicles selected by the algorithm remain ICEVs, even though BEVs were available (see Table 11.1), because the BEVs are more expensive than the ICEVs and thus not used in the optimization.

Overall, the results do not only re-confirm that environmental policies (such as the ZEZ) may pull into different, potentially mutually inconsistent directions, but also show that agent-based simulations can provide quantitative estimates of the corresponding trade-offs.

11.3.3 Well-to-Wheel emissions

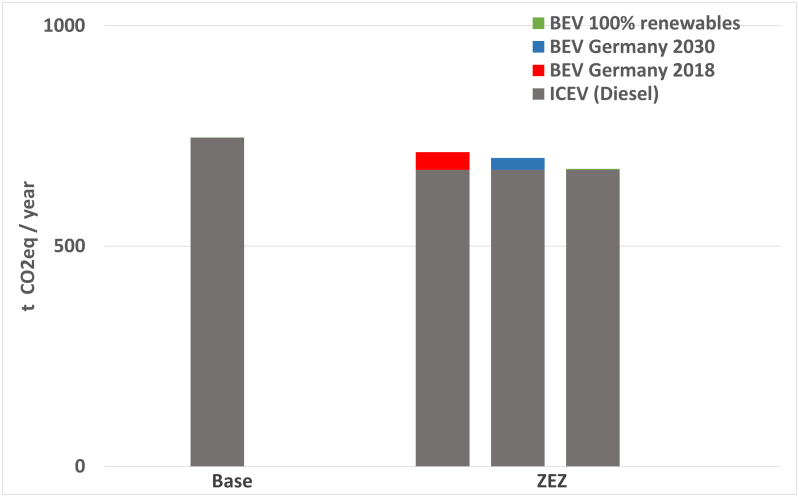
The W2W emissions are calculated as described in Section 11.2.2 by multiplying the vkm driven with the vehicle type specific W2W emission factors (see Table 2.1). The W2W emissions of the BEV are calculated for three different electricity production scenarios.

Figure 11.3 shows the calculated annual W2W emissions in t CO_2eq for the ZEZ case. For both companies, Kaufland and Edeka, the W2W emissions decrease compared to the baseline. This is mainly driven by the BEVs being available and used and thus fewer (remaining) W2W emissions from ICEVs. Moreover, it shows (again[5]) that the electricity mix[6] has a significant influence. With the electricity mix of 2018, a reduction of 5.1 % is observed for Edeka, while for Kaufland the reduction is 4.6 %. With renewable energy, the benefits of the BEVs become visible. Now, the results for both carriers differ: while for Edeka a reduction of 36 % is observed for the renewable electricity mix, the emissions of Kaufland only go down by 9.5 %. This is expected, because the depot of Kaufland is located farther away from the city center and thus the share of the vkm driven by BEVs is smaller than for Edeka, whose depot is located closer to the city center.

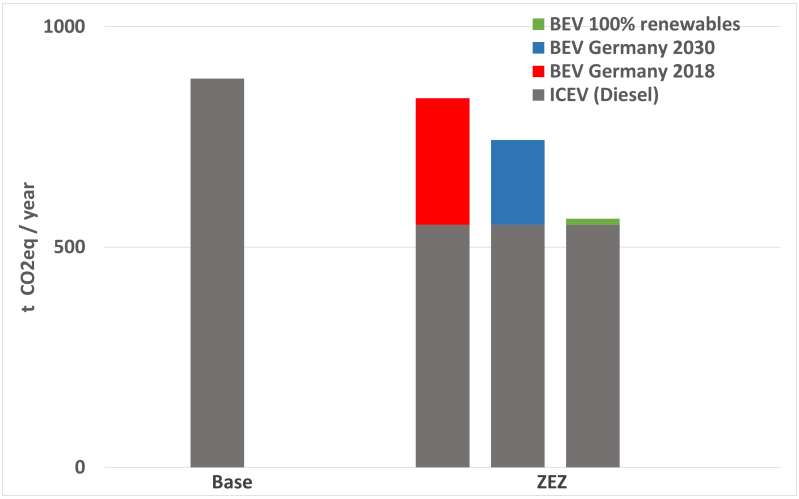
For the *safety zone* case, where only ICEVs are used (see Section 11.3.1), the overall W2W emissions slightly decrease. So, there is no influence of the energy mix. Caused by the changes to smaller, and thus less fuel consuming, vehicles, the W2W emissions are slightly decreasing: for Kaufland the emissions reduce from 757 to 746 t CO_2eq per year (−1.5 %), while for Edeka they go down from 964 to 903 t CO_2eq per year (−6.3%). This is somewhat surprising, because the (exhaust) emissions while driving (see Section 11.3.2) based on the HBEFA emission factors increase by around 30 %. It can only be explained by the fact, that teh two calculation approaches use different fuel consumption values. While the W2W calculation in this thesis only depends on an average fuel consumption per vehicle type, the calculation of the other emissions, using HBEFA includes more relevant details, such as road type, speed, and traffic states. An increase in the assumed fuel consumption for the smaller vehicles, combined with an increase for the larger vehicles, both by 20 % in the simple W2W approach, leads to an increase of the W2W emissions by 6.8 % (Kaufland) and by 7.2 % (Edeka). This underlines the high sensitivity to the assumptions made for the chosen approach.

[5] See also the study in Chapter 8.

[6] The W2W factors for electricity assumed in this study are (see Section 2.2.3): 518 g CO_2eq/kWh in 2018, 347 g CO_2eq/kWh in 2030, and 25 g CO_2eq/kWh for renewable energy.



(a) Kaufland



(b) Edeka

Figure 11.3: Calculated annual Well-to-Wheel (W2W)-emissions in t CO_2eq when introducing a ZEZ. The emissions of the BEVs are shown for three different energy sources: energy mix for Germany 2018 (red), for Germany 2030 (blue), renewable-only (green). The emissions from the ICEVs are marked in gray.

11.4 Conclusion and Outlook

In this study, we applied different vehicle-type dependent driving restrictions in a case study for the supply of supermarkets in Berlin, Germany. The restrictions are either a ZEZ or a safety zone (ban large trucks) for the city center. The LSP can react by adapting its logistics chain and using a hub for the last mile delivery with vehicles complying with the zone restriction. We observe that the results not only depend on the policy, but also on the demand and location structure of the affected companies.

In terms of costs, the solution for one company (Kaufland) remains more or less equal to the base case, regardless of the policy, while for the other company (Edeka), the costs increase by 8 to 28 % depending on the restriction.

The ZEZ has no significant influence on the key values (costs, # of vehicles, mileage, and travel time) for one company (Kaufland). Nevertheless, a reduction of exhaust emissions between 9.8 and

17.1 % depending on the pollutant is observed due to the usage of some BEVs. For the second company, with the depot located closer to the customer (Edeka), the number of vehicles used significantly increases (+14 vehicles; +39 %). The mileage and travel time of all vehicles increase by approx. 12 %. Due to the electrification of parts of the fleet, the exhaust emissions while driving reduce by −37.6 to −48.1 % depending on the pollutant. For the *non-exhaust* emissions, an increase of approx. 12.5 % is observed. This is because BEVs are not emission-free and still a source of non-exhaust emissions. The W2W analysis shows an significant influence of the electricity mix on the emissions from the BEVs, leading to a decrease of the overall W2W by approx. 5% (electricity mix from 2018), up to 9.5 % (Kaufland) or 36 % (Edeka), when using renewable electricity.

For the safety zone policy, we observe, that smaller vehicles are used, leading to an increase in the number of vehicles (11 to 14 %), while the mileage increases by around 30 % depending on the company. For one company, the costs remain almost the same, while for the other, the costs increase by approx. 8 % when implementing the policy. Since no BEVs are used, the increased mileage of ICEVs causes an increase in exhaust and non-exhaust emissions (27 to 42 %), depending on the pollutant and company. For the W2W emissions, we observe that the assumptions made have a significant influence on the results.

The technical approach works as intended, since the customers inside the restricted area are only served by allowed vehicles, either directly or by using the 2-echelon logistics chain and thus reacting to the policies by changing the transport chain for the different delivery jobs. However, several improvements are still possible. For the general outlook regarding the simulation of LSP, please also refer to the corresponding Section 10.5. The framework is rather slow because every MATSim iteration starts many jsprit runs. In the co-evolutionary strategy, only one shipment moves per iteration, but the Vehicle Routing Problem (VRP) is solved from scratch for each carrier. Re-using the previous VRP solution, or skipping the VRP-solving when the plan has not changed, would dramatically reduce runtime. This functionality is not yet implemented. Splitting demand into smaller pieces allows the usage of smaller vehicles and thus the associated fixed costs. The downside is that it creates many shipments (jobs). More shipments (jobs) increase the VRP complexity and thus the computation time. The split is required in scenarios where only very small delivery vehicles are allowed (e.g., safety-zone case). Another improvement to the current framework would be to add the tour planning for the main carriers (transport: depot to hub), including the Fleet Size and Mix Vehicle Routing Problem (FSMVRP)-solving and the reuse of the same vehicle for several sub-tours on a day.

The current LSP setup can only adjust shipment-to-logistics-chain assignments in small steps. This makes the search prone to local optima and slows convergence. In particular, some customers are served by different logistics chains, causing several trucks to travel to the same locations. This is inefficient because, in the observed case, the vehicles are large enough to allow single visits for these customers. Integrating a dedicated 2E-VRP solver could produce a high-quality initial LSP plan. The co-evolutionary strategy could then refine this plan, incorporating additional information from the multi-agent transport simulation. Such a combined approach appears promising for future work.

CHAPTER 12

Conclusion and Outlook

12.1 Conclusion

This dissertation investigates decarbonization strategies for urban freight transport through a simulation-based approach, examining the technical feasibility, economic implications, and operational consequences of transitioning commercial vehicle fleets to zero-emission technologies. Drawing on agent-based modeling techniques implemented in the Multi-Agent Transport Simulation (MATSim) framework, the research progresses from fundamental questions regarding vehicle routing optimization to comprehensive policy scenario analyses. The studies presented in this thesis (see Chapter 6 – Chapter 11) address a series of research questions that collectively provide a holistic assessment of how urban freight systems can transition toward environmental sustainability. By integrating vehicle electrification strategies, policy instruments such as carbon dioxide (CO_2)-taxation, and advanced logistics network designs into a unified analytical framework, this work contributes insights into the mechanisms, trade-offs, and opportunities associated with decarbonizing urban commercial transport. The main use case in this thesis is the urban food retail sector in the city of Berlin, Germany. The integration of a Logistics Service Provider (LSP) agent represents an important step towards complete transport simulation modeling, improving the simulation of commercial (freight) transport. While the current implementation provides a solid foundation for analyzing urban freight logistics, there is potential for further algorithmic refinements—such as enhanced Two-Echelon Vehicle Routing Problem (2E-VRP) solution methods, improved replanning strategies for the evolutionary algorithm, or computational speed-ups through re-using results from previous iterations—which are discussed as perspectives for future work in the Outlook (Section 12.2).

Answering the Research Questions The research questions (see Section 1.2) of this thesis are addressed in two parts of this thesis, as summarized in Table 12.1. Part II focuses on the electrification of urban freight transport *without changing the logistics network* (Chapter 6 – Chapter 8, answering RQ 1 – RQ 8), while Part III addresses the reactions *including changes in the logistics network* (Chapter 9 – Chapter 11, answering RQ 9 – RQ 13).

Table 12.1: Research questions and their corresponding chapters.

Part	Research Question(s)	Chapter
Part II: Electrification without changing the Logistic Network	RQ 1	Chapter 6: How Driving Multiple Tours Affects the Results of Last-Mile Delivery Vehicle Routing Problems
	RQs 2 to 4	Chapter 7: Replacement of the fleet's vehicles by electric vehicles
	RQs 5 to 8	Chapter 8: Effects of a GHG emission tax on the fleet composition
Part III: Reactions on Restrictions including Changes in the Logistics Network	RQ 9	Chapter 9: Modeling the Two-Echelon Vehicle Routing Problem
	RQs 10 and 11	Chapter 10: Applying the Two-Echelon Distribution Concept to an Urban Food Retail Case Study
	RQs 12 and 13	Chapter 11: Reactions to Zero-Emission and Safety Zone Restrictions in Urban Food Retail Logistics

The investigation demonstrates that the capability of a driver to conduct multiple tours per day significantly influences Vehicle Routing Problem (VRP) solutions. This finding underscores the necessity of incorporating multi-tour operations into realistic last-mile delivery scenarios to ensure accurate and practically applicable results (RQ 1).

Through the systematic electrification of the commercial fleet, this thesis establishes the extent to which direct conversion from Internal Combustion Engine Vehicles (ICEVs) to Battery Electric Vehicles (BEVs) is feasible in the urban freight transport setting. The analysis reveals that range limitations of BEVs may be a critical constraint and thus, ICEVs are still needed for the longer distances. With improving technology (e.g., batteries or charging infrastructure) this technical limitation vanishes (RQs 2 to 4).

Furthermore, the integration of differentiated CO_2 tax levels into the vehicle routing and fleet composition decisions demonstrates the influence of policy instruments on the ICEV-to-BEV ratio during the transition phase. This effect is clearly visible and increases with tax rates from 25 € up to 300 € per ton (t) CO_2. At the time of the study, 300 € per t CO_2 represented a high level. Current recommendations suggest 990 € per t CO_2 for 2025 (German Environment Agency, 2026). The resulting fleet transition reduces exhaust emissions through decreased ICEV usage, while non-exhaust emissions remain present. The reduction in Well-to-Wheel (W2W) emissions is smaller, due to the impacts of battery and electricity production, where the electricity mix plays a significant role. The results indicate that appropriate fiscal measures can effectively support and accelerate the decarbonization process while maintaining economic viability for transport operators (RQs 5 to 8).

The modeling of the 2E-VRP is successfully established and integrated into an agent-based simulation framework. This development enables the representation of hub-and-spoke delivery systems within the MATSim simulation environment, facilitating the investigation of multi-stage logistics networks (RQ 9).

The implementation of an LSP agent demonstrates the feasibility of choosing between one-echelon (direct delivery) and two-echelon (hub-based) delivery systems. The results show differentiated effects on operational costs, vehicle kilometers traveled, and emissions depending on the logistics network topology used. The LSP-based approach provides flexible network design options that can be adapted to regulatory constraints and economic optimization objectives (RQs 10 and 11).

The introduction of driving restrictions, such as a Zero Emissions Zone (ZEZ) or safety zone, for large vehicles in inner-city areas triggers measurable changes in the logistics network and its

operational usage. The analysis demonstrates that city hubs play a central role in successfully implementing such restrictions through cargo transshipment and consolidation. The results show that while such measures increase operational complexity, intelligent logistics network design—particularly through two-echelon systems with strategically located hubs—can mitigate adverse economic impacts and support urban decarbonization objectives (RQs 12 and 13).

Overarching Contributions This dissertation contributes to the following key findings:

1. **Feasibility of Direct Electrification:** The research establishes the extent to which immediate conversion of urban commercial vehicle fleets to BEVs is technically and economically viable under current and near-future conditions, while identifying the primary limiting factors.
2. **Role of Policy Instruments:** The thesis provides empirical evidence demonstrating the extent to which CO_2 taxation and similar fiscal measures can effectively support fleet decarbonization strategies and incentivize operator behavior toward sustainability objectives.
3. **Network Design Options:** The investigation demonstrates that advanced policy measures such as entry restrictions for conventionally-powered vehicles can be effectively implemented through intelligent logistics concepts—particularly city hubs and two-echelon delivery systems.
4. **Integrated Assessment Framework:** By systematically varying fleet composition, CO_2 tax levels, and logistics network topology, this dissertation provides a comprehensive assessment of the economic, operational, and environmental consequences of urban freight decarbonization strategies.

12.2 Outlook

In future research projects, the use of an extended VRP solver may be useful to not only address range restrictions as done by Ewert et al. (2021b). Moreover, it should be able to include more BEV-specific challenges, such as recharging. This could be addressed by including a solver for electric-VRPs, as presented, e.g., in the work of Hiermann et al. (2016); Wang, Zhou, and Feng (2019); Mahmoud et al. (2022). Moreover, including a more detailed energy consumption calculation model for BEVs, such as implemented in MATSim's `ev` contrib, would significantly increase the accuracy of the results.

Furthermore, due to technical and economic progress, today's BEVs have a significantly greater range than many of the vehicles included in the studies of this thesis. So, some issues are solved for the urban setting. An updated study for the studies in Chapters 7 and 8 has been published in the meantime, showing that (a) the range of current BEVs is sufficient and (b) they are cost-beneficial compared to ICEVs (see Ewert et al., 2025).

As decarbonizing urban freight transport appears increasingly feasible in the near future, long-distance freight transport comes into focus and should be addressed in further research projects. Some investigations are running (see e.g. Fadranski, Tietz, and Göhlich, 2025; Menter et al., 2023; Tietz et al., 2025). Long-distance freight transport presents even greater challenges than urban transport, not only due to larger daily mileage. Additionally, vehicles may not return to the same or another depot for overnight stops. This leads to additional challenges in building a sufficient charging infrastructure. For the European Union (EU), a binding expansion plan has been enacted: Alternative Fuels Infrastructure Regulation (AFIR) (see European Parliament and Council of the European Union, 2026). The rollout is being driven by, e.g., industry joint-venture projects such as Milence (see Milence, 2026). In parallel, a publicly funded national coordination body—the

Nationale Leitstelle Ladeinfrastruktur—is responsible for coordinating and supporting the expansion of the charging infrastructure (Nationale Leitstelle Ladeinfrastruktur, 2026).

Future research could also address the introduction of autonomous trucks and their potential implications.

Intermodal freight transport represents another promising research direction, combining trucks for first- and last-mile delivery with railroad systems for long-distance transport. For this, further studies might extend the used freight contrib with its `logistics` package as set up in Part III. Other groups like the Schweizerische Bundesbahnen (SBB) have started with simulating combined road and rail transport for freight, including terminals for loading containers from Heavy Goods Vehicles (HGVs) to cargo trains and vice versa (see Kaddoura et al., 2024a). Additional components required for such simulations include mode-choice models for freight transport and dedicated railroad transport simulation. The latter is addressed, e.g., with the new `railsim` contrib of MATSim (Kaddoura et al., 2024b).

Regarding the assessment of environmental aspects, this dissertation goes up to the level of a W2W analysis, including production of the energy sources needed for the vehicle movement. Using the Life Cycle Assessment (LCA) approach, the full environmental impact of the transport can be assessed, including the production of the vehicles and their components, as well as the production of the energy sources used for propulsion. Syré (2026) developed a framework that integrates LCA and Total Cost of Ownership (TCO) into a single, structured methodology for evaluating decarbonization strategies in transportation.

Appendix

APPENDIX A

Data structure representation of an LSP.

Figure A.1 shows the data representation of an LSP. In this Figure, a modified and shortened extract of the XML data structure is presented. The LSP, its resources and structure is described in Section 3.2.2.2.

```
<lsp id="myLSP">
    <resources>
        <carrier id="mainCarrier"/>
        <hub id="myHub" location="somewhere" fixedCost="100.0">
            <scheduler capacityNeedFixed="10.0" capacityNeedLinear="1.0"/>
        </hub>
        <carrier id="distributionCarrier"/>
        <carrier id="directCarrier"/>
    </resources>
    <shipments>
        <shipment id="1" from="A" to="B" size="16" startPickup="32400.0" endPickup=
        "68400.0" startDelivery="32400.0" endDelivery="68400.0" pickupServiceTime=
        "2880.0" deliveryServiceTime="2880.0"/>
        <shipment id="2" from="C" to="D" size="4" startPickup="32400.0" endPickup=
        "68400.0" startDelivery="32400.0" endDelivery="68400.0" pickupServiceTime=
        "720.0" deliveryServiceTime="720.0"/>
    </shipments>
    <LspPlans>
        <LspPlan score="-250.0" selected="true">
            <logisticChains>
                <logisticChain id="directChain">
                    <logisticChainElement id="directCarrierElement" resourceId=
                    "directCarrier"/>
                </logisticChain>
                <logisticChain id="hubChain">
                    <logisticChainElement id="mainCarrierElement" resourceId=
                    "mainCarrier"/>
                    <logisticChainElement id="HubElement" resourceId="myHub"/>
                    <logisticChainElement id="distributionCarrierElement" resourceId=
                    "distributionCarrier"/>
                </logisticChain>
            </logisticChains>
            <shipmentPlans>
                <shipmentPlan shipmentId="A" chainId="hubChain">
                    <element .... />
                    <element .... />
                </shipmentPlan>
                <shipmentPlan shipmentId="B" chainId="hubChain">
                    <element .... />
                    <element .... />
                </shipmentPlan>
            </shipmentPlans>
        </LspPlan>
        <LspPlan score="-300.0" selected="true">
            <logisticChains>
                <logisticChain id="directChain">
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                    "directCarrier"/>
                </logisticChain>
                <logisticChain id="hubChain">
                    <logisticChainElement id="mainCarrierElement" resourceId=
                    "mainCarrier"/>
                    <logisticChainElement id="HubElement" resourceId="myHub"/>
                    <logisticChainElement id="distributionCarrierElement" resourceId=
                    "distributionCarrier"/>
                </logisticChain>
            </logisticChains>
            <shipmentPlans>
                <shipmentPlan shipmentId="A" chainId="directChain">
                    <element .... />
                    <element .... />
                </shipmentPlan>
                <shipmentPlan shipmentId="B" chainId="directChain">
                    <element .... />
                    <element .... />
                </shipmentPlan>
            </shipmentPlans>
        </LspPlan>
    </LspPlans>
</lsp>
```

Figure A.1: Simplified data representation of an LSP.

APPENDIX B

Vehicle Cost Calculation

The following Tables B.1 to B.3 contain the detailed calculation of cost parameters for the vehicle types used in the case studies. For more information about the methodology and the data sources, please refer to Chapter 5.

Table B.1: Cost calculation of ICEVs.

Vehicle type		Truck 7.5t	Truck 18t	Truck 26t		Truck 40t	
Model		Atego 818L/TGL 12.220 BL	TGX 18.440 XLX	Mercedes Actros 2544 LL	MAN TGM 18.340 BL	Trailer 7.75m	Sum
Chassis	Eu	48′475.00	86′200.00	96′900.00	68′500.00	24′500.00	93′000.00
Battery costs (if electric)	Eu						
List price without tires	Eu	48′475.00	86′200.00	96′900.00	68′500.00	24′500.00	93′000.00
Tires	Eu	1′512.00	2′892.00	3′856.00	2′892.00	1′828.00	4′720.00
Service life	a	11	11	11	11	11	
Mileage	km/a	25′893	45′151	63′537	80′024	45′179	
Tire mileage	km	61′994	135′000	98′000	133′000	190′000	
Operating time	h/a	2′039	2′282	2′282	3′000	2′620	
Days of use	d/a	250	250	250	250	250	
Insurance (comprehensive + liability)	Eu/a	4′882.00	6′729.00	6′729.00	6′891.00	405.00	7′296.00
Vehicle tax	Eu/a	410.00	665.00	665.00	665.00	671.00	1′336.00
Half purchase price with tires	Eu	24′237.50	43′100.00	48′450.00	34′250.00	12′250.00	46′500.00
Half purchase price without tires	Eu	23′481.50	41′654.00	46′522.00	32′804.00	11′336.00	44′140.00
Half of interest (1.7%)	Eu/a	412.04	732.70	823.65	582.25	208.25	790.50
Half of depreciation	Eu/a	2′134.68	3′786.73	4′229.27	2′982.18	1′030.55	4′012.73
Storage	Eu/a	928.00	1′096.00	1′096.00	1′096.00	1′096.00	2′192.00
Vehicle administration costs	Eu/a	7′107.00	7′107.00	7′107.00	8′069.00	7′950.00	16′019.00
Total maintenance costs	Eu/a	15′873.72	20′116.43	20′649.92	20′285.43	11′360.80	31′646.23
Total maintenance costs	**Eu/d**	**63.49**	**80.47**	**82.60**	81.14	45.44	**126.58**
Mileage-dependent depreciation	Eu/100km	8.24	8.39	6.66	3.73	2.28	6.01
Tire usage	Eu/100km	2.44	2.14	3.93	2.17	0.96	3.14
Repairs, etc.	Eu/100km	12.37	14.02	15.53	12.44	1.34	13.78
Total basic operating costs (excl. wages, energy)	**Eu/100km**	**23.05**	**24.55**	**26.12**	18.34	4.58	**22.92**
Wage costs	**Eu/veh-h**	**17.64**	**17.64**	**17.64**	**20.14**		**20.14**
Energy Consumption	l or kWh / 100km	13.57	33.12	33.12	37.45		37.45
Specific costs	Eu/l or Eu/kWh	1.23	1.23	1.23	1.23		1.23
Energy costs	Eu/100km	16.69	40.74	40.74	46.06	0.00	46.06
Resulting Cost parameters							
fixed costs	**Eu/d**	**63.49**	**80.47**	**82.60**	81.14	45.44	**126.58**
variable costs (distance)	**Eu/m**	**0.00040**	**0.00065**	**0.00067**	0.00064	0.00005	**0.00069**
variable costs (time)	**Eu/s**	**0.00490**	**0.00490**	**0.00490**	0.00559	0.00000	**0.00559**

Table B.2: Cost calculation of BEVs assuming that the chassis have the same cost as ICEVs: BEV 100

Vehicle type		Truck 7.5t	Truck 18t	Truck 26t BEV 100	Truck 40t BEV 100		
Model		Orten E75 TL - 87kWh	Orten E 180 AX - 122 kWh	FE electric - 286 kWh	EForce - 443 kWh	Trailer 7.75m	Sum
Chassis	Eu	48′475.00	86′200.00	96′900.00	68′500.00	24′500.00	93′000.00
Battery costs (if electric)	Eu	52′200.00	73′200.00	171′429.00	265′714.00		265′714.00
List price without tires	Eu	100′675.00	159′400.00	268′329.00	334′214.00	24′500.00	358′714.00
Tires	Eu	1′512.00	2′892.00	3′856.00	2′892.00	1′828.00	4′720.00
Service life	a	11	11	11	11	11	
Mileage	km/a	25′893	45′151	63′537	80′024	45′179	
Tire mileage	km	61′994	135′000	98′000	133′000	190′000	
Operating time	h/a	2′039	2′282	2′282	3′000	2′620	
Days of use	d/a	250	250	250	250	250	
Insurance (comprehensive + liability)	Eu/a	4′882.00	6′729.00	6′729.00	6′891.00	405.00	7′296.00
Vehicle tax	Eu/a	410.00	665.00	665.00	665.00	671.00	1′336.00
Half purchase price with tires	Eu	50′337.50	79′700.00	134′164.50	167′107.00	12′250.00	179′357.00
Half purchase price without tires	Eu	49′581.50	78′254.00	132′236.50	165′661.00	11′336.00	176′997.00
Half of interest (1.7%)	Eu/a	855.74	1′354.90	2′280.80	2′840.82	208.25	3′049.07
Half of depreciation	Eu/a	4′507.41	7′114.00	12′021.50	15′060.09	1′030.55	16′090.64
Storage	Eu/a	928.00	1′096.00	1′096.00	1′096.00	1′096.00	2′192.00
Vehicle administration costs	Eu/a	7′107.00	7′107.00	7′107.00	8′069.00	7′950.00	16′019.00
Total maintenance costs	Eu/a	18′690.15	24′065.90	29′899.30	34′621.91	11′360.80	45′982.71
Total maintenance costs	**Eu/d**	**74.76**	**96.26**	**119.60**	138.49	45.44	**183.93**
Mileage-dependent depreciation	Eu/100km	17.41	15.76	18.92	18.82	2.28	21.10
Tire usage	Eu/100km	2.44	2.14	3.93	2.17	0.96	3.14
Repairs, etc.	Eu/100km	12.37	14.02	15.53	12.44	1.34	13.78
Total basic operating costs (excluding wages, energy)	**Eu/100km**	**32.22**	**31.92**	**38.39**	33.43	4.58	**38.02**
Wage costs	**Eu/veh-h**	**17.64**	**17.64**	**17.64**	**20.14**		**20.14**
Energy Consumption	l/100km or kWh/100km	61.00	106.00	150.00	180.00		180.00
Specific costs	Eu/l or Eu/kWh	0.22	0.22	0.22	0.22		0.22
Energy costs	**Eu/100km**	**13.52**	**23.49**	**33.24**	39.89	0.00	**39.89**
Resulting Cost parameters							
fixed costs	**Eu/d**	**74.76**	**96.26**	**119.60**	138.49	45.44	**183.93**
variable costs (distance)	**Eu/m**	**0.00046**	**0.00055**	**0.00072**	0.00073	0.00005	**0.00078**
variable costs (time)	**Eu/s**	**0.00490**	**0.00490**	**0.00490**	0.00559	0.00000	**0.00559**

Table B.3: Cost calculation of BEVs assuming that the chassis are 60 % more expensive as for the ICEVs: BEV 160

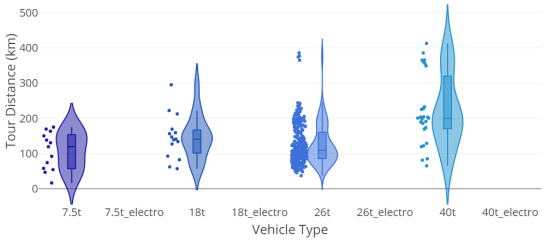
Vehicle type / Model		Truck 7.5t Orten E75 TL - 87kWh	Truck 18t Orten E 180 AX - 122 kWh	Truck 26t FE electric - 286 kWh	Truck 40t BEV 160 EForce - 443 kWh	Truck 40t BEV 160 Trailer 7.75m	Truck 40t BEV 160 Sum
Chassis	Eu	77′560.00	137′920.00	155′040.00	109′600.00	24′500.00	134′100.00
Battery costs (if electric)	Eu	52′200.00	73′200.00	171′429.00	265′714.00		265′714.00
List price without tires	Eu	129′760.00	211′120.00	326′469.00	375′314.00	24′500.00	399′814.00
Tires	Eu	1′512.00	2′892.00	3′856.00	2′892.00	1′828.00	4′720.00
Service life	a	11	11	11	11	11	
Mileage	km/a	25′893	45′151	63′537	80′024	45′179	
Tire mileage	km	61′994	135′000	98′000	133′000	190′000	
Operating time	h/a	2′039	2′282	2′282	3′000	2′620	
Days of use	d/a	250	250	250	250	250	
Insurance (comprehensive + liability)	Eu/a	4′882.00	6′729.00	6′729.00	6′891.00	405.00	7′296.00
Vehicle tax	Eu/a	410.00	665.00	665.00	665.00	671.00	1′336.00
Half purchase price with tires	Eu	64′880.00	105′560.00	163′234.50	187′657.00	12′250.00	199′907.00
Half purchase price without tires	Eu	64′124.00	104′114.00	161′306.50	186′211.00	11′336.00	197′547.00
Half of interest (1.7%)	Eu/a	1′102.96	1′794.52	2′774.99	3′190.17	208.25	3′398.42
Half of depreciation	Eu/a	5′829.45	9′464.91	14′664.23	16′928.27	1′030.55	17′958.82
Storage	Eu/a	928.00	1′096.00	1′096.00	1′096.00	1′096.00	2′192.00
Vehicle administration costs	Eu/a	7′107.00	7′107.00	7′107.00	8′069.00	7′950.00	16′019.00
Total maintenance costs	Eu/a	20′259.41	26′856.43	33′036.21	36′839.44	11′360.80	48′200.24
Total maintenance costs	**Eu/d**	**81.04**	**107.43**	**132.14**	147.36	45.44	**192.80**
Mileage-dependent depreciation	Eu/100km	22.51	20.96	22.08	21.15	2.28	23.44
Tire usage	Eu/100km	2.44	2.14	3.93	2.17	0.96	3.14
Repairs, etc.	Eu/100km	12.37	14.02	15.53	12.44	1.34	13.78
Total basic operating costs (excluding wages, energy)	**Eu/100km**	**37.32**	**37.13**	**41.54**	35.77	4.58	40.35
Wage costs	**Eu/veh-h**	**17.64**	**17.64**	**17.64**	**20.14**		**20.14**
Energy Consumption	l/100km or kWh/100km	61.00	106.00	150.00	180.00		180.00
Specific costs	Eu/l or Eu/kWh	0.22	0.22	0.22	0.22		0.22
Energy costs	**Eu/100km**	**13.52**	**23.49**	**33.24**	39.89	0.00	**39.89**
Resulting Cost parameters							
fixed costs	**Eu/d**	**81.04**	**107.43**	**132.14**	147.36	45.44	**192.80**
variable costs (distance)	**Eu/m**	**0.00051**	**0.00061**	**0.00076**	0.00076	0.00005	**0.00080**
variable costs (time)	**Eu/s**	**0.00490**	**0.00490**	**0.00490**	0.00559	0.00000	**0.00559**

APPENDIX C

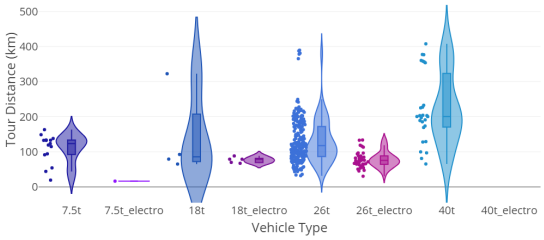
Influence of CO2 tax on the tour planning

Figure C.1 shows the tour distances driven for each vehicle type of the scenarios including *range-restricted* BEVs (Figures C.1b to C.1i) compared to the base case with only ICEVs available (Figure C.1a). The ICEVs are shown in a bluish color, while the BEVs are shown in violet tones. These results belong to Section 8.4.1.

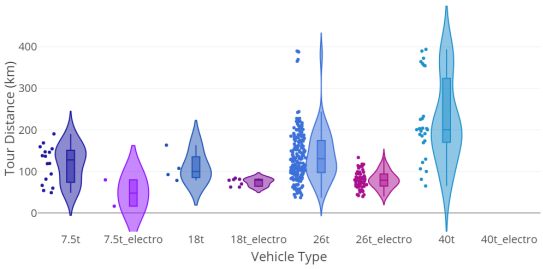
Figure C.2 shows the same, but now with BEVs that are *not restricted* in their range. Again, the results are compared to the (same) base case with only ICEVs available (Figure C.2a). These results belong to Section 8.5.1.



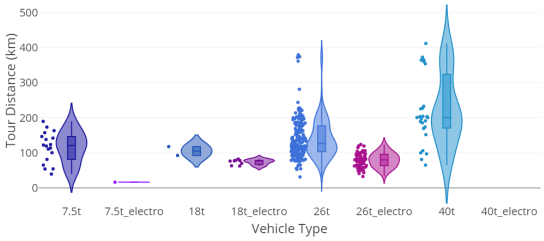
(a) Base case: no Tax, only ICEVs



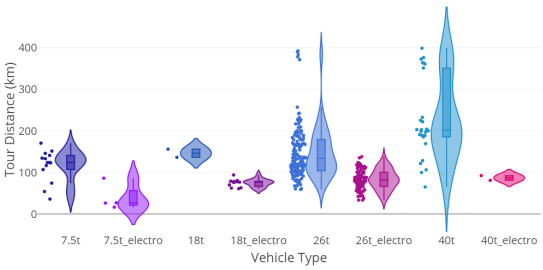
(b) No Tax



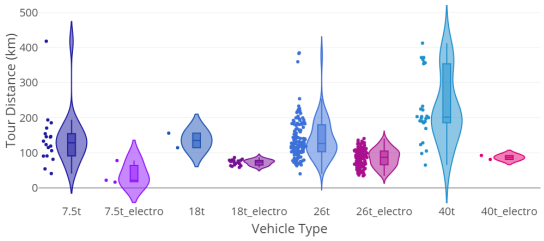
(c) Tax 25



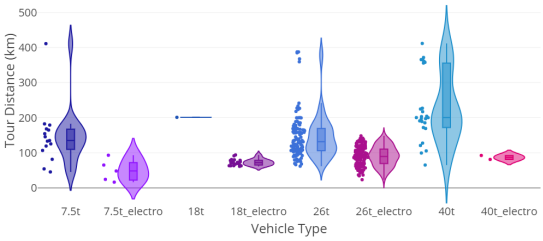
(d) Tax 50



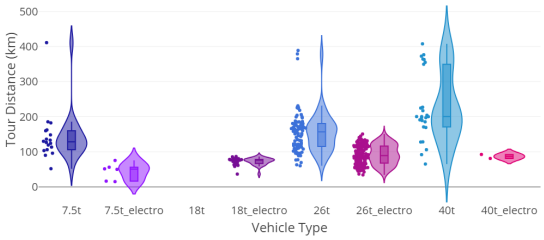
(e) Tax 100



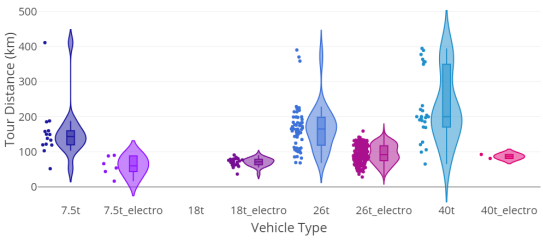
(f) Tax 150



(g) Tax 200

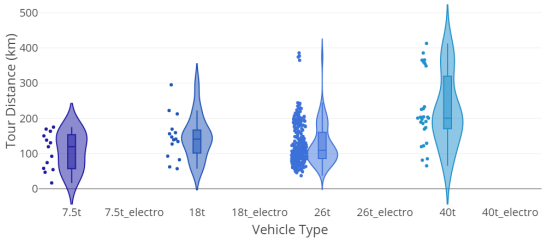


(h) Tax 250

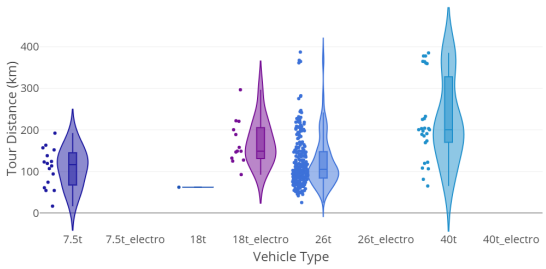


(i) Tax 300

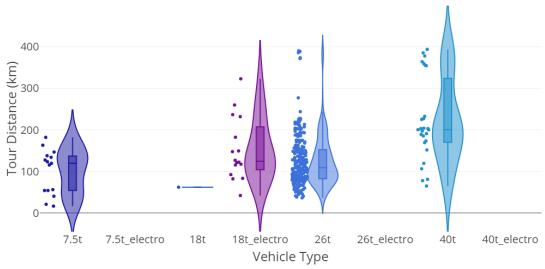
Figure C.1: Observed distances (vkm) driven by each vehicle sorted by their type and depending on the tax (€/t) on CO_2-emissions for the ICEVs. The BEVs are *restricted* in their range. Bluish colors represent the ICEVs and violet colors the BEVs.



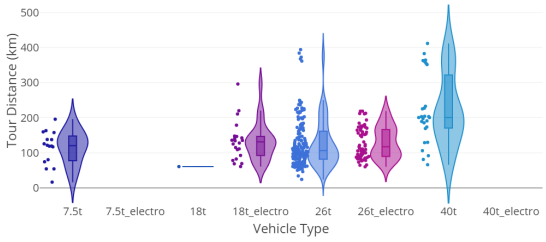
(a) Base case: no Tax, only ICEVs



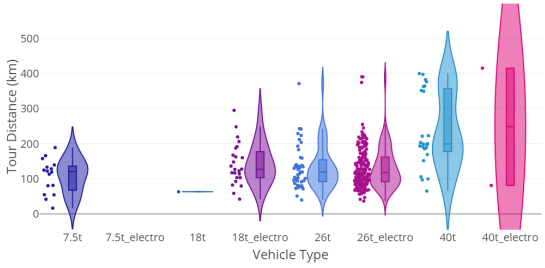
(b) No Tax



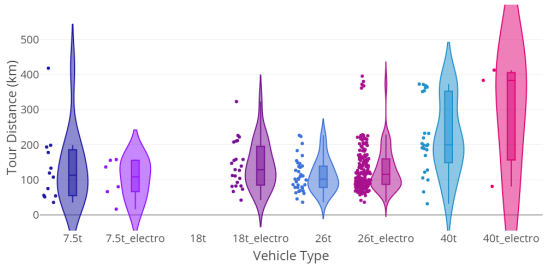
(c) Tax 25



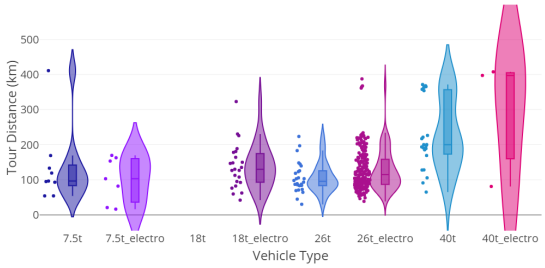
(d) Tax 50



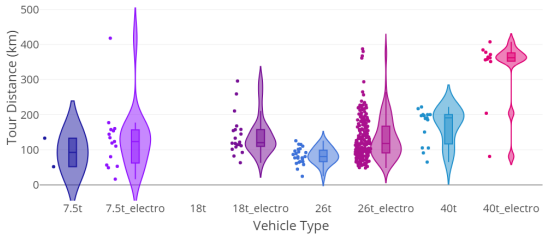
(e) Tax 100



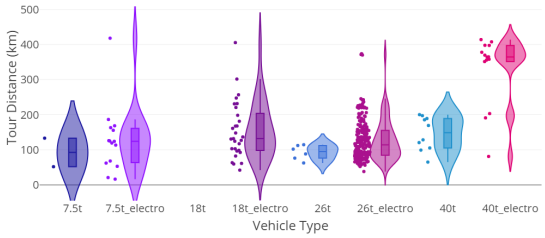
(f) Tax 150



(g) Tax 200



(h) Tax 250



(i) Tax 300

Figure C.2: Observed distances (vkm) driven by each vehicle type depending on the tax (€/t) on CO_2-emissions for the ICEVs. On top is the base case *without* BEVs available. The BEVs are *not restricted* in their range.

APPENDIX D

Detailed simulation outputs for the Logistics Service Provider runs

In this appendix some more-detailed results of the different runs for the LSP studies in Chapter 10 are given.

D.1 Carrier based runs

The following Tables D.1 and D.2 show the development of some key figures for the carrier-based simulation runs with the code from 2025.

Table D.1: Development of some key figures fo the simulations, depending on the number of iterations. New runs from 2025 *with* time-depended network.

(a) Kaufland)

# jsprit iterations	# veh.	distance (vkm)	travel time (h)	fixedCosts (€)	varCostsTime (€)	varCostsDist (€)	totalCosts (€)
1	9	2′778	44.56	1′139	1′595	1′917	4′651
10	9	2′773	44.34	1′139	1′591	1′913	4′643
50	10	2′603	42.20	1′266	1′548	1′796	4′610
100	10	2′603	42.20	1′266	1′548	1′796	4′610
250	10	2′603	42.20	1′266	1′548	1′796	4′610
500	10	2′598	42.36	1′266	1′551	1′793	4′609
1′000	10	2′598	42.36	1′266	1′551	1′793	4′609
2′500	10	2′598	42.36	1′266	1′551	1′793	4′609
5′000	10	2′598	42.36	1′266	1′551	1′793	4′609
10′000	10	2′598	42.36	1′266	1′551	1′793	4′609

(b) Edeka

# jsprit iterations	# veh.	distance (vkm)	travel time (h)	fixedCosts (€)	varCostsTime (€)	varCostsDist (€)	totalCosts (€)
1	18	3′276	67.90	1′485	2′777	2′192	6′454
10	17	3′227	66.90	1′404	2′760	2′162	6′326
50	17	3′227	66.90	1′404	2′760	2′162	6′326
100	17	3′227	66.90	1′404	2′760	2′162	6′326
250	17	3′227	66.90	1′404	2′760	2′162	6′326
500	17	3′182	66.38	1′404	2′751	2′132	6′287
1′000	17	3′182	66.27	1′404	2′749	2′132	6′285
2′500	16	3′175	66.77	1′322	2′757	2′127	6′206
5′000	16	3′180	66.32	1′322	2′749	2′131	6′202
10′000	16	3′122	65.43	1′322	2′734	2′092	6′147

Table D.2: Development of some key figures fo the simulations, depending on the number of iterarions. New runs from 2025 *without* time-depended network.

(a) Kaufland

# jsprit iterations	# veh.	distance (vkm)	travel time (h)	fixedCosts (€)	varCostsTime (€)	varCostsDist (€)	totalCosts (€)
1	9	2′751	40.51	1′139	1′514	1′898	4′551
10	10	2′576	38.39	1′266	1′471	1′777	4′514
50	10	2′577	38.30	1′266	1′469	1′778	4′513
100	10	2′577	38.30	1′266	1′469	1′778	4′513
250	10	2′577	38.30	1′266	1′469	1′778	4′513
500	10	2′577	38.30	1′266	1′469	1′778	4′513
1′000	10	2′577	38.30	1′266	1′469	1′778	4′513
2′500	10	2′577	38.30	1′266	1′469	1′778	4′513
5′000	10	2′577	38.30	1′266	1′469	1′778	4′513
10′000	10	2′577	38.30	1′266	1′469	1′778	4′513

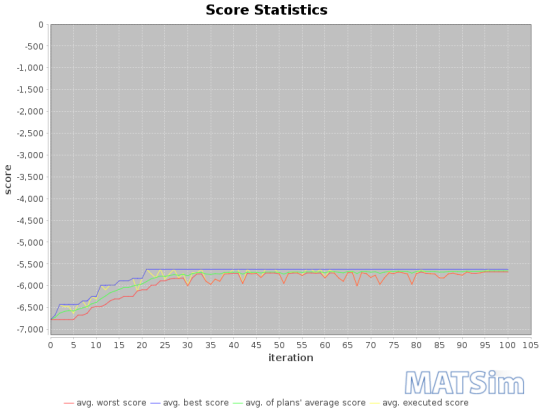
(b) Edeka

# jsprit iterations	# veh.	distance (vkm)	travel time (h)	fixedCosts (€)	varCostsTime (€)	varCostsDist (€)	totalCosts (€)
1	19	3′267	59.00	1′567	2′621	2′186	6′373
10	18	3′235	58.48	1′487	2′611	2′167	6′265
50	18	3′228	58.14	1′487	2′605	2′163	6′255
100	17	3′185	58.18	1′404	2′606	2′134	6′144
250	17	3′185	58.18	1′404	2′606	2′134	6′144
500	17	3′182	58.10	1′404	2′605	2′132	6′141
1′000	16	3′161	57.72	1′322	2′598	2′118	6′038
2′500	16	3′147	57.27	1′322	2′590	2′109	6′021
5′000	16	3′147	57.29	1′322	2′590	2′108	6′020
10′000	16	3′104	56.93	1′322	2′584	2′079	5′985

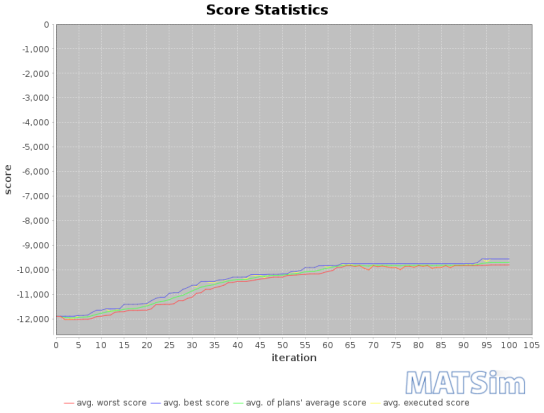
D.2 LSP scores development depending on the number of MATSim iterations

In the following Figure D.1, the score statistics for different numbers of MATSim iterations are shown. The plot with 500 iterations is the same as printed in the corresponding Figure 10.3 in Section 10.4.

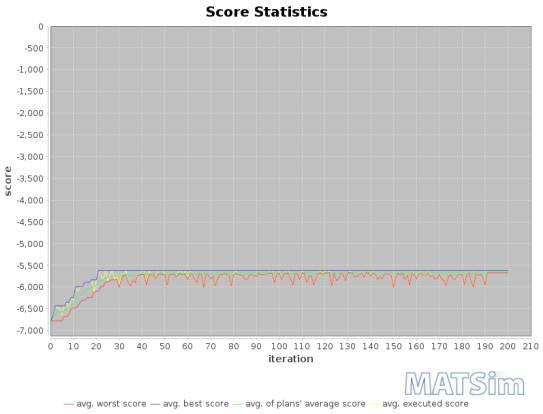
Figure D.1: Score development of the selected plan of the LSP over the MATSim iterations. The innovative strategies are switched off after 95 % of the number of iterations.



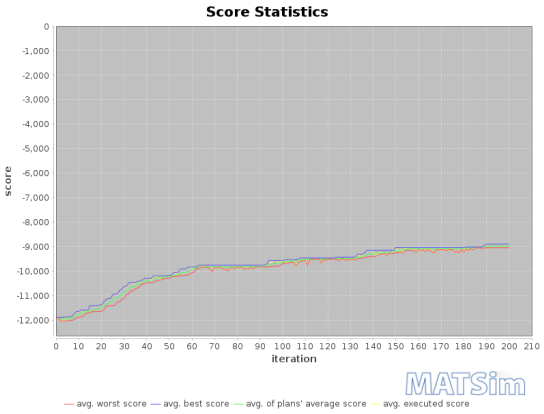
(a) Kaufland 100 iterations



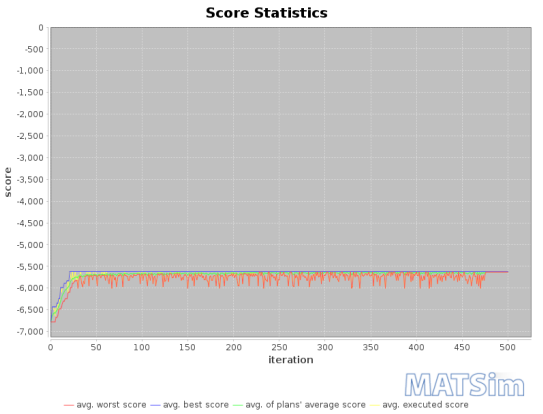
(b) Edeka 100 iterations



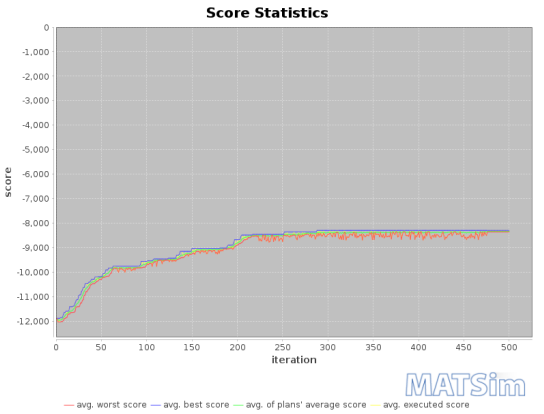
(c) Kaufland 200 iterations



(d) Edeka 200 iterations



(e) Kaufland 500 iterations



(f) Edeka 500 iterations

D.3 Vehicles usages LSP- vs. Carrier-based Approach

The following Tables D.3 and D.4 show more details on vehicle usage. It compares the results of the simulation using the carrier-based approach with those after the conversion to the LSP-based approach. The results belong to Section 10.4.2. The values differentiate between the different carriers of the logistics chains: For the *base* and *LSP: direct* cases, the values are for the only existing direct delivery carriers. In the *LSP: two-echelon* case, it is *main run carrier* + *delivery carrier*. For the case with *both chains*, the notation is *direct delivery carrier* + *main run carrier* + *delivery carrier*.

Table D.3: Results of vehicle usage per type for Kaufland carrier / LSP. The base scenario is calculated with the carrier-based approach, delivering all shipments directly to the customers. The other scenarios are calculated with the LSP-based approach: i) one direct chain, ii) one two-echelon chain, and iii) both chains allowing the LSP to choose for each shipment: direct and two-echelon delivery.

(a) Number of vehicles per day.

scenario	7.5 t ICEV	18 t ICEV	26 t ICEV	40 t ICEV	total ICEV
base: carrier-based	—	0	—	11	**11**
LSP: direct	—	0	—	11	**11**
LSP: two-echelon	—	0+1=1	—	14+7=21 =	**22**
LSP: both chains	—	0+0+1=1	—	3+8+5=16	**17**

(b) vehicle kilometer (vkm) driven per day.

scenario	7.5 t ICEV	18 t ICEV	26 t ICEV	40 t ICEV	total ICEV
base: carrier-based	—	0	—	2′188	**2′188**
LSP: direct	—	0	—	2′240	**2′240**
LSP: two-echelon	—	0+86=86	—	2′414+446=2′860	**2′946**
LSP: both chains	—	0+0+46=46	—	805+1′380+287=2′472	**2′518**

(c) vehicles travel time h per day.

scenario	7.5 t ICEV	18 t ICEV	26 t ICEV	40 t ICEV	total ICEV
base: carrier-based	—	0	—	32.87	**32.87**
LSP: direct	—	0	—	32.19	**32.19**
LSP: two-echelon	—	0+2.34=2.34	—	26.69+14.68=41.37	**43.71**
LSP: both chains	—	0+0+1.84=1.84	—	11.46+15.25+9.03=35.74	**37.58**

Table D.4: Results of vehicle usage per type for Edeka carrier / LSP. The base scenario is calculated with the carrier-based approach, delivering all shipments directly to the customers. The other scenarios are calculated with the LSP-based approach: i) one direct chain, ii) one two-echelon chain, and iii) both chains allowing the LSP to choose for each shipment: direct and two-echelon delivery.

(a) Number of vehicles per day.

scenario	7.5 t ICEV	18 t ICEV	26 t ICEV	40 t ICEV	total ICEV
base: carrier-based;	—	0	18	—	**18**
LSP: direct	—	2	21	—	**23**
LSP: two-echelon	—	0	49+17=66	—	**66**
LSP: both chains	—	1+0+0=1	10+17+8=35	–	**36**

(b) vehicle kilometer (vkm) driven per day.

scenario	7.5 t ICEV	18 t ICEV	26 t ICEV	40 t ICEV	total ICEV
base: carrier-based	—	0	3′300	—	**3′300**
LSP: direct	—	277	3′028	—	**3′505**
LSP: two-echelon	—	0	2′627+1′390=4′017	—	**4′017**
LSP: both chains	—	252+0+0=255	1′668+911+530=3′109	—	**3′361**

(c) travel time (h) driven per day.

scenario	7.5 t ICEV	18 t ICEV	26 t ICEV	40 t ICEV	total ICEV
base: carrier-based	—	0	59.9	—	**59.9**
LSP: direct	—	4.3	56.8	—	**61.1**
LSP: two-echelon	—	0	31.5+41.0=72.5	—	**72.5**
LSP: both chains	—	3.64+0+0=3.64	29.49+10.92+16.65=57.06	—	**60.71**

D.4 Well-to-Wheel Emissions

Table D.5 shows the aggregated W2W emissions in t CO_2eq per year for the baseline and different logistic chain scenarios.

Table D.5: Aggregated W2W emissions (only ICEVs) in t CO_2eq per year for the different scenarios. The values in parentheses are the relative changes compared to the base case.

scenario	Kaufland		Edeka	
	W2W (t CO_2eq/ year)	relative change	W2W (t CO_2eq year)	relative change
base: carrier-based	649	—	866	—
LSP: direct	665	(+2.4 %)	867	(+0.1 %)
LSP: two-echelon	871	(+34.2 %)	1′054	(+21.7 %)
LSP: both chains	746	(+14.8 %)	883	(+1.9 %)

List of Units and Acronyms

CO_2eq CO_2 equivalents.

BC black carbon.

CH_4 methane.

CO_2 carbon dioxide.

CO carbon monoxide.

$NMVOC$ non-methane volatile organic compounds.

NO_x nitrogen oxides.

N_2O nitrous oxide.

PM_{10} particulate matter $< 10\,\mu m$, PM with particle size <10 μm.

$PM_{2.5}$ particulate matter $< 2.5\,\mu m$, PM with particle size <2.5 μm.

PM particulate matter.

SO_2 sulfur dioxide.

μm micrometer, $1/10^6$ m.

km^2 square kilometer, km^2.

2E-CVRP Two-Echelon (capacitated) Vehicle Routing Problem. 28, 95

2E-EVRPTW-PR Two-Echelon Electric Vehicle Routing Problem with Time Windows and Partial Recharging. 28, 95

2E-FLRP Flexible Two-Echelon Location Routing Problem. 96

2E-TVRP Two-Echelon Time-Constrained Vehicle Routing Problem. 95

2E-VRP Two-Echelon Vehicle Routing Problem. 5, 22, 23, 28, 34, 49, 94–97, 104, 105, 109, 123, 126, 137, 139, 140, 163

2E-VRP-CO Two-Echelon Vehicle Routing Problem with Covering Options. 95

2E-VRPTW Two-Echelon Vehicle Routing Problem with Time Windows. 28

ABM Agent-Based Modeling. 17, 18

ABS Agent-Based Simulation. 17, 18

AFIR Alternative Fuels Infrastructure Regulation. 141

BEV Battery Electric Vehicle. ix–xi, xiii, xiv, xvi–xx, 1–3, 5, 13, 15, 32, 37–42, 48–50, 55–70, 72–75, 77–89, 93–95, 121, 127–137, 140, 141, 149–153

BVWP Bundesverkehrswegeplan, Federal Transport Infrastructure Plan. 37, 38, 58, 68

CEP Courier, Express, and Parcel. iii, xiv, 11, 33, 51–53

CVRP Capacitated Vehicle Routing Problem. 28

DC distribution center, also called "depot". 33, 51, 67, 68, 72

DRT Demand Responsive Transport. 47

DVS Direct Vision Standard. 94

E-FSMFTW Electric Fleet Size and Mix Vehicle Routing Problem with Time Windows and Recharging Stations. 28, 95

EC European Commission. 55, 65, 93

EU European Union. 12, 38, 141

FSMVRP Fleet Size and Mix Vehicle Routing Problem. 28, 87, 97, 106, 137, 164

g gram, 1/1'000 kg.

GHG greenhouse gas. xiv, 1, 3, 5, 12, 13, 15, 33, 55–57, 62, 65–67, 69–72, 75, 76, 79, 81, 83–85, 87–89, 93

GVWR Gross Vehicle Weight Rating. x, xi, xiii, xv, 11, 15, 26, 32, 38–41, 56, 67–69, 72, 76, 81, 84, 94, 112–114, 117, 118, 125–129, 131, 132

h hour, 60 min.

HBEFA Handbook on Emission Factors for Road Transport, see `www.hbefa.net`. xiv–xvi, 5, 13–15, 25, 26, 56, 57, 62, 63, 76, 78, 84, 86, 88, 119, 120, 128, 129, 133–135

HGV Heavy Goods Vehicle. 14, 26, 94, 102, 129, 142

ICEV Internal Combustion Engine Vehicle. ix–xi, xiii, xiv, xvi, xvii, xix, xx, 1–3, 5, 13, 15, 27, 32, 37–42, 48–50, 55–76, 78–89, 93, 95, 110, 115, 117, 121, 126–137, 140, 141, 148–153, 159–161

J joule, SI unit of energy.

kg kilogram, the SI base unit of mass.

km kilometer, 1'000 m.

kW kilowatt, unit of power, 1 $kW = 1'000\ W$.

kWh kilowatt hour, unit of energy, 1 $kW \times 1\ h$.

l liter, unit of volume, 1 $l = 10^{-3}\ m^3$.

LC-2E-HVRP Low-Carbon Two-Echelon Heterogeneous-Fleet Vehicle Routing Problem. 95

LCA Life Cycle Assessment. 13, 142

LCV Light Commercial Vehicle. 14, 26, 129

LEZ Low Emission Zone. 1, 2, 27, 48, 49, 94, 102, 106–108, 125, 126, 165

LSP Logistics Service Provider. x, xi, xv–xvii, xix, 2–5, 10, 18–20, 22–25, 94, 96–98, 100–105, 107–112, 114–119, 121–123, 127, 136, 137, 139, 140, 145, 146, 155, 158–161

m meter, the SI base unit of length.

MATSim Multi-Agent Transport Simulation, see `www.matsim.org`. ix–xi, xvii, xix, 4, 11, 13, 14, 17–29, 45–47, 52, 55–57, 66–68, 96–98, 107, 109–111, 115–118, 121–123, 126–128, 137, 139–142, 158, 165

MDVRP Multi-Depot Vehicle Routing Problem. 23, 28, 29, 32, 45–48, 52, 68, 97

MFVRP Mixed Fleet Vehicle Routing Problem. 28

MILP Mixed-Integer Linear Programming. 123

min minute, 60 s.

NCE network change event, an event in MATSim, that changes some properties of the network, e.g. the free-speed or capacity of a link, at the event's time. 19, 33, 110

s second, the SI base unit for time.

SBB Schweizerische Bundesbahnen, Swiss Federal Railway. 142

SDG Sustainable Development Goal. 1, 2, 93

t ton, 1'000 kg.

TCC transport cost calculation. 37, 38, 68, 69

TCO Total Cost of Ownership. 142

TSP Transport Service Provider. 94

UCC Urban Consolidation Center, also called "hub". 48–50, 107

ULEZ Ultra Low Emission Zone. 94, 102, 103

UN United Nations. 1, 2, 93

VAT Value Added Tax. 37, 38, 68

vkm vehicle km.

VRP Vehicle Routing Problem. ix, 2, 4, 5, 17, 20–25, 27, 28, 31, 37, 38, 40, 45–48, 51–53, 55–58, 64–68, 73, 79–81, 87, 96–98, 105, 106, 110–115, 117–119, 122, 123, 137, 140, 141, 163–165, 167

VRPPD Vehicle Routing Problem with Pickup and Delivery. 28, 29

VRPTW Vehicle Routing Problem with Time Windows. 28, 163

W watt, unit of power, 1 $W = 1\ J/s$.

W2W Well-to-Wheel. ix–xi, xiii, xvi, xvii, xx, 5, 11, 13, 15, 56, 57, 62–64, 66, 69, 79, 80, 87–89, 121, 122, 128, 129, 135–137, 140, 142, 161

ZEZ Zero Emissions Zone. xi, xvi, 3–5, 20, 27, 125–128, 130–136, 140

Glossary

Java JAVA programming language, see www.java.com. 46, 96

jsprit An open-source Vehicle Routing Problem – solver, see http://jsprit.github.io/. ix, xv, xvi, 17, 21, 22, 27–29, 45–47, 52, 53, 55, 56, 60, 66, 67, 72, 79, 97, 110–115, 117, 122, 127, 137, 156, 157

Bibliography

Anderluh, A., V. C. Hemmelmayr, and P. C. Nolz. Synchronizing vans and cargo bikes in a city distribution network. *Central European Journal of Operations Research*, 25:345–376, 2017. doi: 10.1007/s10100-016-0441-z. (cited on pp. 95, 123, 126).

Anderluh, A., P. C. Nolz, V. C. Hemmelmayr, and T. G. Crainic. Multi-objective optimization of a two-echelon vehicle routing problem with vehicle synchronization and 'grey zone' customers arising in urban logistics. *CIRRELT-2019-33*, 2019. https://www.cirrelt.ca/documentstravail/cirrelt-2019-33.pdf. (cited on pp. 95, 126).

Bakach, I., A. M. Campbell, and J. F. Ehmke. A two-tier urban delivery network with robot-based deliveries. *Networks*, 78(4):461–483, 2021. doi: 10.1002/net.22024. (cited on pp. 28, 95, 100).

Baldacci, R., M. Battarra, and D. Vigo. *Routing a Heterogeneous Fleet of Vehicles*, pages 3–27. Springer US, Boston, MA, 2008. ISBN 978-0-387-77778-8. doi: 10.1007/978-0-387-77778-8_1. (cited on p. 28).

Ballou, R. H. *Business Logistics Supply Chain Management*. Pearson, New Jersey, 5 edition, 2004. ISBN 978-8131705841. (cited on p. 10).

Battarra, M., J.-F. Cordeau, and M. Iori. *Chapter 6: Pickup-and-Delivery Problems for Goods Transportation*, chapter 6, pages 161–191. In Toth and Vigo (2014), 2014. doi: 10.1137/1.9781611973594.ch6. (cited on p. 28).

Bean, W. L. and J. W. Joubert. An agent-based implementation of freight receiver and carrier collaboration with cost sharing. *Transportation Research Interdisciplinary Perspectives*, 11:100416, 2021. ISSN 25901982. doi: 10.1016/j.trip.2021.100416. (cited on p. 18).

BEHG. Gesetz über einen nationalen Zertifikatehandel für Brennstoffemissionen (Brennstoffemissionshandelsgesetz). https://www.gesetze-im-internet.de/behg/BJNR272800019.html. Brennstoffemissionshandelsgesetz vom 12. Dezember 2019 (BGBl. I S. 2728; 2022 I S. 2098), das zuletzt durch Artikel 2 des Gesetzes vom 27. Februar 2025 (BGBl. 2025 I Nr. 70) geändert worden ist. (cited on p. 89).

Biemann, K., V. Bolte, H. Fehrenbach, C. Heidt, F. Spathelf, D. Kirsch, A. Bernsmann, A. Gade, K. Horstmann, and S. Stütz. Lokaler, nationaler und internationaler umweltschonender Güterverkehr – Datenbericht zum Transformationsdialog und UBA Forum mobil und nachhaltig. Technical Report Texte 89/2024, Umweltbundesamt, 2024. URL https://www.uba.de/n110418de. (cited on p. 11).

Bischoff, J. *Mobility as a Service and the transition to driverless systems*. PhD thesis, 2019. (cited on p. 18).

BMUB. Climate Action Plan 2050. http://www.https://www.bmu.de/fileadmin/Daten_BMU/Pools/Broschueren/klimaschutzplan_2050_en_bf.pdf, 2016. (cited on pp. 1, 12, 65, 93).

BMUB. Klimaschutz in Zahlen. Fakten, Trends und Impulse deutscher Klimapolitik. Ausgabe 2018, 2018. (cited on pp. 1, 12, 45, 55, 65, 93).

BMVI. Bundesverkehrswegeplan 2030. http://www.bmvi.de/DE/Themen/Mobilitaet/Infrastrukturplanung-Investitionen/Bundesverkehrswegeplan-2030/bundesverkehrswegeplan-2030.html, 2016. (cited on pp. 37, 58, 68).

Boysen, N., S. Schwerdfeger, and F. Weidinger. Scheduling last-mile deliveries with truck-based autonomous robots. *European Journal of Operational Research*, 271(3):1085–199, 2018. doi: 10.1016/j.ejor.2018.05.058. (cited on p. 95).

Caggiani, L., A. Colovic, L. P. Prencipe, and M. Ottomanelli. A green logistics solution for last-mile deliveries considering e-vans and e-cargo bikes. *Transportation Research Procedia*, 52:75–82, 2020. doi: 10.1016/j.trpro.2021.01.010. (cited on pp. 28, 93, 95, 123, 126).

Cerwenka, P. *Handbuch der Verkehrssystemplanung*. Österreichischer Kunst- und Kulturverlag, 2007. ISBN 9783854372653. (cited on pp. 27, 46).

Charlton, W. SimWrapper, 2026. URL https://github.com/simwrapper/simwrapper. accessed: 2026-07-15. (cited on pp. x, xi, 108, 130, 131).

Crainic, T. G., N. Ricciardi, and G. Storchi. Advanced freight transportation systems for congestedurban areas. *Transportation Research Part C: Emerging Technologies*, 12(2):119–137, 2004. doi: 10.1016/j.trc.2004.07.002. (cited on pp. 28, 95, 126).

Crainic, T. G., N. Ricciardi, and G. Storchi. Models for Evaluating and Planning City Logistics Transportation Systems. *Transportation science*, 43(4):432–454, 2009. doi: 10.1287/trsc.1090.0279. (cited on pp. 28, 95, 126).

Crainic, T. G., G. Perboli, and N. Ricciardi. City Logistics: New Opportunities and Challenges. *Transportation Research Procedia*, 1:1–10, 2012. (cited on p. 10).

Crippa, M., D. Guizzardi, F. Pagani, M. Banja, M. Muntean, E. Schaaf, F. Monforti-Ferrario, W. Becker, R. Quadrelli, A. Risquez Martin, P. Taghavi-Moharamli, J. Köykkä, G. Grassi, S. Rossi, J. Melo, D. Oom, A. Branco, J. San-Miguel, G. Manca, E. Pisoni, E. Vignati, and F. Pekar. GHG emissions of all world countries. Technical Report KJ-01-24-010-EN-N (online), KJ-01-24-010-EN-C (print), Luxembourg, 2024. (cited on pp. 1, 12).

Darvish, M., C. Archetti, L. C. Coelho, and M. G. Speranza. Flexible two-echelon location routing problem. *European Journal of Operational Research*, 277(3):1124–1136, 2019. ISSN 0377-2217. doi: 10.1016/j.ejor.2019.04.002. (cited on p. 96).

Desaulniers, G., O. B. Madsen, and S. Ropke. *Chapter 5: The Vehicle Routing Problem with Time Windows*, chapter 5, pages 119–159. In Toth and Vigo (2014), 2014. doi: 10.1137/1.9781611973594.ch5. (cited on p. 28).

Dethloff, J. Vehicle routing and reverse logistics: The vehicle routing problem with simultaneous delivery and pick-up. *OR-Spektrum*, 23(1):79–96, 2001. ISSN 1436-6304. doi: 10.1007/PL00013346. (cited on p. 28).

DIN EN 16258:2012. Methodology for calculation and declaration of energy consumption and GHG emissions of transport services (freight and passengers) (DIN EN 16258:2012); German version EN 16258:2012 [Methode zur Berechnung und Deklaration des Energieverbrauchs und der Treibhausgasemissionen bei Transportdienstleistungen (Güter- und Personenverkehr) (DIN EN 16258:2012); Deutsche Fassung EN 16258:2012]. Deutsches Institut für Normung e.V., 2013. 03/2013. (cited on pp. 15, 69, 129).

DIN EN ISO 14040. Environmental management – Life cycle assessment – Principles and framework (ISO 14040:2006 + Amd 1:2020); German version EN ISO 14040:2006 + A1:2020, 2021. (cited on p. 13).

DIN EN ISO 14044. Environmental management – Life cycle assessment – Requirements and guidelines (ISO 14044:2006 + Amd 1:2017 + Amd 2:2020); German version EN ISO 14044:2006 + A1:2018 + A2:2020, 2021. (cited on p. 13).

Domenteanu, A., C. Delcea, N. Chiriță, and C. Ioanăș. From Data to Insights: A Bibliometric Assessment of Agent-Based Modeling Applications in Transportation. *Applied Sciences*, 2023. doi: 10.3390/app132312693. (cited on p. 17).

Domschke, W., A. Drexl, R. Klein, and A. Scholl. *Einführung in Operations Research*. Springer, Berlin, 9 edition, 2017. ISBN 978-3662482155. (cited on p. 10).

EC. The European Green Deal, 2019. European Commission (EC), Brussels, COM(2019) 640 final. (cited on pp. 1, 12, 55, 93).

Ehmke, J. F. *Integration of information and optimization models for routing in city logistics*, volume 177 of *International Series in Operations Research & Management Science*. Springer Science+Business Media, 2012. (cited on pp. 10, 27, 46, 56).

Enthoven, D. L., B. Jargalsaikhan, K. J. Roodbergen, M. A. uit het Broek, and A. H. Schrotenboer. The two-echelon vehicle routing problem with covering options: City logistics with cargo bikes and parcel lockers. *Computers & Operations Research*, 118:104919, 2020. ISSN 0305-0548. doi: 10.1016/j.cor.2020.104919. (cited on p. 95).

European Environment Agency. *Transport and environment report 2022. Digitalisation in the mobility system: challenges and opportunities*. Number 07/2022 in EEA report. 2023. doi: 10.2800/47438. (cited on p. 12).

European Environment Agency. *Air quality status in Europe 2026*. European Environment Agency, 2026. doi: doi/10.2800/1334940. (cited on pp. 12, 13).

European Parliament and Council. Directive (EU) 2015/719 of the European Parliament and of the Council of 29 April 2015 amendingmending Council Directive 96/53/EC laying down for certain road vehicles circulating within the Community the maximum authorised dimensions in national and international traffic and the maximum authorised weights in international traffic. Official Journal of the European Union L 115, 6 May 2015, pp. 1–10, 2015. URL http://data.europa.eu/eli/dir/2015/719/oj. last accessed: 26 July 2025. (cited on pp. 38, 69).

European Parliament and Council of the European Union. Directive 2002/49/EC of the European Parliament and of the Council of 25 June 2002 relating to the assessment and management of environmental noise, 2021. URL http://data.europa.eu/eli/dir/2002/49/2021-07-29. (cited on p. 12).

European Parliament and Council of the European Union. Regulation (EU) 2023/1804 of the European Parliament and of the Council of 13 September 2023 on the deployment of alternative fuels infrastructure, and repealing Directive 2014/94/EU, 2026. URL https://eur-lex.europa.eu/eli/reg/2023/1804/2026-01-08. (cited on p. 141).

Europäische Kommission. Der europäische Grüne Deal. COM(2019) 640 final, 2019. COM(2019) 640 final. (cited on p. 65).

Eurotransport. Lastauto Omnibus Katalog 2018, 2017. (cited on pp. 38, 68).

Ewert, R., K. Martins-Turner, C. Thaller, and K. Nagel. Using a Route-based and Vehicle Type Specific Range Constraint for Improving Vehicle Routing Problems with Electric Vehicles. *Transportation Research Procedia*, 52:517–524, 2021a. ISSN 2352-1465. doi: 10.1016/j.trpro.2021.01.061. (cited on pp. 1, 11, 18, 20, 27, 37, 65, 66, 69, 126).

Ewert, R., K. Martins-Turner, C. Thaller, and K. Nagel. Using a Route-based and Vehicle Type specific Range Constraint for Improving Vehicle Routing Problems with Electric Vehicles. *Transportation Research Procedia*, 52:517–524, 2021b. doi: 10.1016/j.trpro.2021.01.061. (cited on pp. 29, 93, 141).

Ewert, R., K. Martins-Turner, A. Grahle, A. Syré, D. Göhlich, and K. Nagel. Showing the cost benefits for commercial electric vehicles – Case Study of Battery Electric Vehicles in Urban Food Distribution. *Transportation Research Procedia*, 86:532–539, 2025. ISSN 2352-1465. (cited on pp. 64, 69, 80, 126, 141).

Fadranski, D., T. Tietz, and D. Göhlich. Methodology for Optimizing Charging Infrastructure Distribution for Long-Haul Freight Traffic Based on Multi-Agent Simulation and Evolutionary Bi-Objective Optimization. *Procedia Computer Science*, 257:951–958, 2025. ISSN 18770509. doi: 10.1016/j.procs.2025.03.122. (cited on p. 141).

Fernandes, P., J. M. Bandeira, T. Fontes, S. R. Pereira, B. J. Schröder, N. M. Rouphail, and M. C. Coelho. Traffic restriction policies in an urban avenue: a methodological overview for a trade-off analysis of traffic and emission impacts using microsimulation. *International Journal of Sustainable Transportation*, 2014. doi: 10.1080/15568318.2014.885622. (cited on p. 13).

Fuessel, A. *Technische Potenzialanalyse der Elektromobilität: Stand der Technik, Forschungsausblick und Projektion auf das Jahr 2025*. Research. Springer Vieweg, Wiesbaden, 2017. ISBN 978-3-658-16695-3. URL http://www.springer.com/. (cited on pp. 39, 58, 69).

Gable, T., K. Martins-Turner, and K. Nagel. Enhanced Emission Calculation for Freight Transport. *Procedia Computer Science*, 201:601–607, 2022. doi: 10.1016/j.procs.2022.03.078. (cited on pp. 11, 14, 26, 76, 84).

Gabler, M., S. Schröder, H. Friedrich, and G. Liedtke. Generierung der Nachfragestrukturen für die mikroskopische Simulation des städtischen Distributionsverkehrs im Lebensmittelhandel. In Clausen, U. and C. Thaller, editors, *Wirtschaftsverkehr 2013*, pages 32–48. Springer Berlin Heidelberg, 2013. ISBN 978-3-642-37600-9. doi: 10.1007/978-3-642-37601-6_3. URL http://dx.doi.org/10.1007/978-3-642-37601-6_3. (cited on pp. xiii, 41, 42, 57, 67, 68, 117).

Gao, Z., Z. Lin, and O. Franzese. Energy Consumption and Cost Savings of Truck Electrification for Heavy-Duty Vehicle Applications. *Transportation Research Record: Journal of the Transportation Research Board*, 2628(1):99–109, 2017. ISSN 0361-1981. doi: 10.3141/2628-11. (cited on p. 38).

Garcia-Castro, A., A. Monzon, C. Valdes, and M. Romana. Modeling different penetration rates of eco-driving in urban areas: Impacts on traffic flow and emissions. *International Journal of Sustainable Transportation*, 11(4):282–294, 2016. doi: 10.1080/15568318.2016.1252972. (cited on p. 13).

German Environment Agency. Handbook on Environmental Value Factors — Methodological Convention 4.0 for the Assessment of Environmental Impacts. Technical report, 2026. URL https://www.uba.de/n306692de. (cited on p. 140).

Ghafghazi, G. and M. Hatzopoulou. Simulating the environmental effects of isolated and area-wide traffic calming schemes using traffic simulation and microscopic emission modeling. *Transportation*, 41: 633–649, Feb. 2014. (cited on p. 13).

Gleißner, H. and J. C. Femerling. *Transportplanung*, pages 35–53. Springer Fachmedien Wiesbaden, Wiesbaden, 2016. ISBN 978-3-658-10396-5. doi: 10.1007/978-3-658-10396-5_5. (cited on pp. ix, 10).

Göhlich, D., T.-A. Fay, and S. Park. Conceptual Design of Urban E-Bus Systems with Special Focus on Battery Technology. *Proceedings of the Design Society: International Conference on Engineering Design*, 1(1):2823–2832, 2019. doi: 10.1017/dsi.2019.289. (cited on pp. 39, 58).

Golden, B., A. Assad, L. Levy, and F. Gheysens. The Fleet Size and Mix Vehicle Routing Problem. *Computers & Operations Research*, 11(1):49–66, 1984. (cited on p. 28).

Grigoratos, T. and G. Martini. Non-exhaust traffic related emissions. Brake and tyre wear PM. Technical Report ISSN 1831-9424, European Commission, Joint Research Centre, Institute of Energy and Transport, 2014. URL https://ec.europa.eu/jrc. Luxembourg: Publications Office of the European Union. (cited on pp. 13, 129).

Gruber, J., A. Kihm, and B. Lenz. A new vehicle for urban freight? An ex-ante evaluation of electric cargo bikes in courier services. *Research in Transportation Business & Management*, 11:53–62, 2014. doi: 10.1016/j.rtbm.2014.03.004. (cited on p. 94).

Guimarães, T. A., L. C. Coelho, C. M. Schenekemberg, and C. T. Scarpin. The two-echelon multi-depot inventory-routing problem. *Computers & Operations Research*, 101:220–233, 2019. ISSN 0305-0548. doi: 10.1016/j.cor.2018.07.024. (cited on p. 96).

Guzman, L. A., D. de la Hoz, and A. Monzón. Optimization of transport measures to reduce GHG and pollutant emissions through a LUTI modeling approach. *International Journal of Sustainable Transportation*, 2015. doi: 10.1080/15568318.2015.1033039. (cited on p. 13).

Göhlich, D., K. Nagel, A. M. Syré, A. Grahle, K. Martins-Turner, R. Ewert, R. Miranda Jahn, and D. Jefferies. Integrated Approach for the Assessment of Strategies for the Decarbonization of Urban Traffic. *Sustainability*, 13(2), 2021. ISSN 2071-1050. doi: 10.3390/su13020839. (cited on pp. 3, 9).

Hesse, M. *Logistik und Transport: Grundlagen der Verkehrswissenschaft*. Oldenbourg, München, 3 edition, 2019. (cited on p. 9).

Hiermann, G., J. Puchinger, S. Ropke, and R. F. Hartl. The Electric Fleet Size and Mix Vehicle Routing Problem with Time Windows and Recharging Stations. *European Journal of Operational Research*, 252(3):995–1018, 2016. doi: 10.1016/j.ejor.2016.01.038. (cited on pp. 28, 95, 141).

Hiermann, G., R. F. Hartl, J. Puchinger, and T. Vidal. Routing a mix of conventional, plug-in hybrid, and electric vehicle. *European Journal of Operational Research*, 272(1):235–248, 2019. doi: 10.1016/j.ejor.2018.06.025. (cited on p. 93).

Horni, A. and K. Nagel. More About Configuring MATSim. In Horni, Nagel, and Axhausen (2016), chapter 4. doi: 10.5334/baw. (cited on p. 19).

Horni, A., K. Nagel, and K. W. Axhausen, editors. *The Multi-Agent Transport Simulation MATSim*. Ubiquity, London, 2016. doi: 10.5334/baw. (cited on pp. ix, x, 18, 19, 26, 46, 47, 56, 67, 96, 97, 98, 126, 173, 175, 176, 177, 180).

Huang, J., Y. Cui, L. Zhang, W. Tong, Y. Shi, and Z. Liu. An Overview of Agent-Based Models for Transport Simulation and Analysis. *Journal of Advanced Transportation*, 2022. doi: 10.1155/2022/1252534. (cited on p. 17).

Hülsmann, F., R. Gerike, B. Kickhöfer, K. Nagel, and R. Luz. Towards a multi-agent based modeling approach for air pollutants in urban regions. In *Conference on "Luftqualität an Straßen"*, pages 144–166. Bundesanstalt für Straßenwesen, FGSV Verlag GmbH, 2011. ISBN 978-3-941790-77-3. Also VSP WP 10-15, see http://www.vsp.tu-berlin.de/publications. (cited on pp. 13, 26).

Icha, P. and G. Kuhs. Entwicklung der spezifischen Kohlendioxid-Emissionen des deutschen Strommix in den Jahren 1990 – 2018. Technical Report Climate Change 10/2019, Umweltbundesamt, 2019. (cited on pp. 15, 129).

IKT für Elektromobilität. Gesamtbericht-Wirtschaftlichkeit-von-Elektromobilitaet, 2015. (cited on p. 39).

INFRAS. Handbuch Emissionsfaktoren des Strassenverkehrs 4.1. Technical report, INFRAS Zurich Switzerland, 2019. See http://www.hbefa.net. (cited on pp. 5, 13, 14, 25, 26, 76, 84, 128, 129).

Intergovernmental Panel on Climate Change (IPCC). *Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, 2023. doi: 10.1017/9781009157896. (cited on p. 12).

Intraplan and Trimode. Gleitende Langfrist-Verkehrsprognose für den Personen- und Güterverkehr in den Jahren 2021 — 2022. Technical report, 2023. URL https://www.bmv.de/SharedDocs/DE/Anlage/G/gleitende-langfrist-verkehrsprognose-personen-und-gueterverkehr-2021-2022.pdf?__blob=publicationFile. (cited on p. 11).

Irnich, S., P. Toth, and D. Vigo. *Chapter 1: The Family of Vehicle Routing Problems*, chapter 1, pages 1–33. In Toth and Vigo (2014), 2014. doi: 10.1137/1.9781611973594.ch1. (cited on pp. 27, 28, 46).

Iwan, S. and K. Małecki. Utilization of cellular automata for analysis of the efficiency of urban freight transport measures based on loading/unloading bays example. *Transportation Research Procedia*, 25: 1021–1035, 2017. ISSN 2352-1465. doi: https://doi.org/10.1016/j.trpro.2017.05.476. World Conference on Transport Research - WCTR 2016 Shanghai. 10-15 July 2016. (cited on p. 18).

Jakara, M. and N. Brnjac. Foliated Transport Networks in Intermodal Freight Transport. *Sustainability*, 15 (9), 2023. ISSN 2071-1050. doi: 10.3390/su15097384. (cited on pp. ix, 10).

Jayarathna, D. Survey on thirty years of vehicle routing problems: Mathematical models, solution methods, and real-life applications. *International Journal of Research and Scientific Innovation*, XI, 2024. ISSN 2321–2705. doi: 10.51244/ijrsi.2024.1107032. (cited on p. 28).

JRC, R. E., H. HASS, J.-F. LARIVÉ, L. L. JRC, H. MAAS, and D. Rickeard. WELL-TO-WHEELS Report Version 4. a JEC WELL-TO-WHEELS ANALYSIS. *Institute for Energy and Transport, Joint Research Centre, Luxembourg: Publications Office of the European Union*, 2014, 2014. (cited on pp. 15, 56, 79, 129).

jsprit. https://github.com/graphhopper/jsprit, 2024. accessed 23-jun-2024. (cited on pp. 27, 28, 46, 55, 56, 67, 97, 127).

Kaddoura, I. *Simulated Dynamic Pricing for Transport System Optimization*. PhD thesis, 2019. URL http://dx.doi.org/10.14279/depositonce-9316. (cited on pp. 18, 19).

Kaddoura, I., R. Ewert, and K. Martins-Turner. Exhaust and non-exhaust emissions from today's and future road transport: A simulation-based quantification for Berlin. *Transportation Research Procedia*, 62:696–702, 2022. doi: 10.1016/j.trpro.2022.02.086. (cited on pp. 11, 13, 18, 129, 134).

Kaddoura, I., D. Masson, T. Hettinger, and M. Unterfinger. An agent-based simulation approach to investigate the shift of Switzerland's inland freight transport from road to rail. *Transportation*, 51(5): 1701–1722, 2024a. ISSN 1572-9435. doi: 10.1007/s11116-023-10383-3. (cited on p. 142).

Kaddoura, I., M. Unterfinger, T. Hettinger, C. Rakow, and M. Rieser. A large-scale hybrid micro- and mesoscopic simulation approach for railway operation. *Procedia Computer Science*, 238:714–721, 2024b. ISSN 1877-0509. doi: 10.1016/j.procs.2024.06.082. URL https://www.sciencedirect.com/science/article/pii/S1877050924013188. (cited on p. 142).

Karolemeas, C., S. Tsigdinos, E. Moschou, and K. Kepaptsoglou. Shared autonomous vehicles and agent based models: a review of methods and impacts. *European Transport Research Review*, 2024. doi: 10.1186/s12544-024-00644-2. (cited on pp. 17, 18).

Kerriou, A. Road transport: a coveted German market. 2023. URL https://market-insights.upply.com/en/road-transport-a-coveted-german-market. last accessed: 27.08.2026. (cited on p. 11).

Kickhöfer, B. Emission Modeling. In Horni, Nagel, and Axhausen (2016), chapter 36, pages 247–252. doi: 10.5334/baw. (cited on p. 26).

Kickhöfer, B. and K. Nagel. Towards High-Resolution First-Best Air Pollution Tolls. *Networks and Spatial Economics*, 16(1):175–198, 2016. doi: 10.1007/s11067-013-9204-8. (cited on p. 13).

Laudan, J., S. Banzhaf, B. Khan, and K. Nagel. Coupling MATSim and the PALM Model System—Large Scale Traffic and Emission Modeling with High-Resolution Computational Fluid Dynamics Dispersion Modeling. *Atmosphere*, 15(10), 2024. ISSN 2073-4433. doi: 10.3390/atmos15101183. (cited on p. 14).

Li, H., J. Yuan, T. Lv, and X. Chang. The two-echelon time-constrained vehicle routing problem in linehaul-delivery systems considering carbon dioxide emissions. *Transportation Research Part D: Transport and Environment*, 49:231–245, 2016. ISSN 1361-9209. doi: 10.1016/j.trd.2016.10.002. (cited on p. 95).

Li, H., J. Chen, F. Wang, and M. Bai. Ground-vehicle and unmanned-aerial-vehicle routing problems from two-echelon scheme perspective: A review. *European Journal of Operational Research*, 294(3): 1078–1095, 2021. ISSN 0377-2217. doi: 10.1016/j.ejor.2021.02.022. (cited on p. 95).

Liimatainen, H., O. van Vliet, and D. Aplyn. The potential of electric trucks – An international commodity-level analysis. *Applied Energy*, 236:804 – 814, 2019. ISSN 0306-2619. doi: 10.1016/j.apenergy.2018.12.017. (cited on pp. 1, 65).

Liu, R. and S. Jiang. A variable neighborhood search algorithm with constraint relaxation for the two-echelon vehicle routing problem with simultaneous delivery and pickup demands. *Soft Computing - A Fusion of Foundations, Methodologies and Applications*, 2021. doi: 10.1007/s00500-021-06692-3. (cited on p. 28).

Lu, C., K. Martins-Turner, and K. Nagel. Creating an agent-based long-haul freight transport model for Germany. *Procedia Computer Science*, 201:614–620, 2022. doi: 10.1016/j.procs.2022.03.080. (cited on p. 21).

Mahmoud, A. H., T. Chouaki, S. Hörl, and J. Puchinger. Adapting JSprit for the Electric Vehicle Routing Problem with Recharging: Implementation and Benchmark. *INTERNATIONAL JOURNAL FOR TRAFFIC AND TRANSPORT ENGINEERING*, 12(3):340–351, 2022. doi: 10.7708/ijtte2022.12(3).04. (cited on p. 141).

Martins-Turner, K. and K. Nagel. How driving multiple tours affects the results of last mile delivery vehicle routing problems. *Procedia Computer Science*, 151:840–845, 2019. doi: 10.1016/j.procs.2019.04.115. (cited on pp. 18, 20, 27, 32, 45, 57, 68, 126).

Martins-Turner, K. and K. Nagel. Agent-based solving of the 2-echelon Vehicle Routing Problem. *Transportation Research Procedia*, 82:3912–3924, 2025. ISSN 2352-1465. doi: 10.1016/j.trpro.2024.12.005. Presented at WCTR conference 2023. (cited on pp. ix, 18, 20, 23, 27, 34, 93, 108, 109, 126).

Martins-Turner, K. and K. Nagel. Reactions to Zero-Emission and Safety Zone Restrictions in Urban Food Retail Logistics. Technical report, 2026. VSP-WP 26-07. (cited on pp. 20, 125).

Martins-Turner, K., A. Grahle, K. Nagel, and D. Göhlich. Electrification of Urban Freight Transport - a Case Study of the Food Retailing Industry. *Procedia Computer Science*, 170:757–763, 2020. doi: 10.1016/j.procs.2020.03.159. (cited on pp. 1, 11, 18, 20, 27, 29, 37, 55, 65, 66, 67, 68, 69, 126, 129).

Matteis, T., W. Wisetjindawat, and G. Liedtke. Modelling interactions between freight forwarders and recipients – An extension of the MATSim toolkit. In *15th World Conference on Transport Research*, May 2019. URL https://elib.dlr.de/134376/. (cited on pp. 18, 22, 23, 96, 97, 98, 106, 126).

McKinnon, A. *Decarbonising Logistics: Distributing Goods in a Low Carbon World*. Kogan Page, London, 2 edition, 2018. (cited on p. 9).

McNally, M. G. and C. R. Rindt. *The Activity-Based Approach*, chapter 4, pages 55–73. Emerald Group Publishing Limited, Oxford, 2nd edition, 2007. ISBN 9781836966876. doi: 10.1108/9780857245670-004. (cited on p. 17).

Meinhardt, S., T. Schlenther, K. Martins-Turner, and M. Maciejewski. Simulation of On-Demand Vehicles that Serve both Person and Freight Transport. *Procedia Computer Science*, 201:398–405, 2022. ISSN 1877-0509. doi: 10.1016/j.procs.2022.03.053. (cited on p. 47).

Menter, J., T.-A. Fay, A. Grahle, and D. Göhlich. Long-Distance Electric Truck Traffic: Analysis, Modeling and Desiging a Demand-Oriented Charging Network for Germany. *World Electric Vehicle Journal*, 14 (8):1–26, Jan. 2023. doi: 10.3390/wevj14080205. (cited on p. 141).

Milence, 2026. URL https://milence.com. last accessed: 01.08.2026. (cited on p. 141).

Ministère de la transition écologique et de la cohésion des territoires, 2022. URL https://www.certificat-air.gouv.fr/. (cited on pp. 2, 94, 125).

Miranda Jahn, R., A. M. Syré, A. Grahle, K. Martins-Turner, and D. Göhlich. Methodology for Determining Charging Strategies for Freight Traffic Vehicles based on Traffic Simulation Results. *Procedia Computer Science*, 184:656–661, 2021. doi: 10.14279/depositonce-10977,10.1016/j.procs.2021.03.082. (cited on pp. 3, 64).

Moltenbrey, M. *Einführung in Die Verkehrssimulation*. Essentials Ser. Springer Fachmedien Wiesbaden GmbH, Wiesbaden, 2020. ISBN 9783658287177. (cited on p. 18).

Nagel, K. Road Pricing. In Horni, Nagel, and Axhausen (2016), chapter 15. doi: 10.5334/baw. (cited on p. 26).

Nationale Leitstelle Ladeinfrastruktur, 2026. URL https://nationale-leitstelle.de/. last accessed: 02.08.2026. (cited on p. 142).

Oliveira, B., A. G. Ramos, and J. P. de Sousa. A generic mathematical formulation for two-echelon distribution systems based on mobile depots. *Transportation Research Procedia*, 52:99–106, 2020. (cited on p. 93).

Oliveira, B., A. Ramos, and J. de Sousa. A heuristic for two-echelon urban distribution systems. *Transportation Research Procedia*, 62:533–540, 2022. doi: 10.1016/j.trpro.2022.02.066. (cited on pp. 2, 28, 94, 95, 126).

OpenStreetMap, 2026. http://www.openstreetmap.org, last accessed 2026-05-19. (cited on pp. x, xi, 108, 130, 131).

Papis, A. and K. Nagel. Personal communication, 2025. (cited on p. 26).

Perboli, G., R. Tadei, and D. Vigo. The Two-Echelon Capacitated Vehicle Routing Problem: Models and Math-Based Heuristics. *CIRRELT-2008-55*, 2008. (cited on pp. 28, 95, 126).

Planco, ITP, and TUBS. Grundsätzliche Überprüfung und Weiterentwicklung der Nutzen-Kosten-Analyse im Bewertungsverfahren der Bundesverkehrswegeplanung. Endbericht FE Projekt Nr. 960974/2011, Planco GmbH, Intraplan Consult GmbH, TU Berlin Service GmbH, 2015. Im Auftrag des BMVI. Also VSP WP 14-12, see http://www.vsp.tu-berlin.de/publications. (cited on pp. 15, 37, 38, 62, 68, 76, 79, 85, 87, 119, 129, 133).

Prockl, G. Informationsmanagement. In Stölzle, W., editor, *Güterverkehr kompakt*, Lehrbuch kompakt, chapter Informationsmanagement, pages 151–165. Oldenbourg, 2010. ISBN 9783486590036. (cited on pp. 21, 27, 46).

Prodhon, C. and C. Prins. A survey of recent research on location-routing problems. *European Journal of Operational Research*, 238(1):1–17, 2014. ISSN 0377-2217. doi: 10.1016/j.ejor.2014.01.005. (cited on p. 95).

PTV, TCI, and H.-U. Mann. Methodenhandbuch zum Bundesverkehrswegeplan 2030. http://www.bmvi.de/DE/VerkehrUndMobilitaet/Verkehrspolitik/Verkehrsinfrastruktur/Bundesverkehrswegeplan2030/InhalteHerunterladen/inhalte_node.html, 2016. (cited on pp. 37, 38, 68).

Qiu, Y., D. Zhou, Y. Du, J. Liu, P. M. Pardalos, and J. Qiao. The two-echelon production routing problem with cross-docking satellites. *Transportation Research Part E: Logistics and Transportation Review*, 147:102210, 2021. ISSN 1366-5545. doi: 10.1016/j.tre.2020.102210. (cited on p. 96).

Rehman, M. M. U., F. Zhang, M. Evzelman, R. Zane, K. Smith, and D. Maksimovic. Advanced cell-level control for extending electric vehicle battery pack lifetime. In *2016 IEEE Energy Conversion Congress and Exposition (ECCE)*, pages 1–8. IEEE, 2016. ISBN 978-1-5090-0737-0. doi: 10.1109/ECCE.2016.7854827. (cited on p. 38).

Richter, N., K. Martins-Turner, and K. Nagel. Extension of an agent-based simulation for the optimized allocation of freight requests to differently structured supply chains. *Procedia Computer Science*, 238: 728–735, 2024. ISSN 1877-0509. doi: 10.1016/j.procs.2024.06.084. (cited on pp. 20, 23, 24, 98, 105, 109, 110, 123).

Rieser, M., A. Horni, and K. Nagel. Let's Get Started. In Horni, Nagel, and Axhausen (2016), chapter 2. doi: 10.5334/baw. (cited on p. 20).

Rieser, M., K. Nagel, and A. Horni. MATSim Data Containers. In Horni, Nagel, and Axhausen (2016), chapter 6, pages 55–60. doi: 10.5334/baw. (cited on pp. 19, 33, 57, 68).

Scheuerer, S. *Neue Tabusuche-Heuristiken für die logistische Tourenplanung bei restringierendem Anhängereinsatz, mehreren Depots und Planungsperioden*. phdthesis, Universität Regensburg, 2004. URL https://epub.uni-regensburg.de/10196/. (cited on pp. 21, 27, 28, 46).

Schlenther, T., K. Martins-Turner, J. F. Bischoff, and K. Nagel. Potential of Private Autonomous Vehicles for Parcel Delivery. *Transportation Research Record*, 0(0):0361198120949878, 2020. doi: 10.1177/0361198120949878. bmvi-pave. (cited on p. 47).

Schneidewind, U. *Nachhaltige Verkehrssysteme: Transformation und Dekarbonisierung*. Springer Gabler, Berlin, 2 edition, 2020. (cited on p. 9).

Schrimpf, G., J. Schneider, H. Stamm-Wilbrandt, and G. Dueck. Record Breaking Optimization Results Using the Ruin and Recreate Principle. *Journal of Computational Physics*, 159:139–171, 2000. doi: 10.1006/jcph.1999.6413. (cited on pp. 28, 97).

Schröder, S. and G. Liedtke. Modeling and analyzing the effects of differentiated urban freight measures – a case study of the food retailing industry. Annual Meeting Preprint 14-5015, Transportation Research Board, Washington D.C., 2014. (cited on pp. xiii, xvii, xix, 5, 31, 32, 37, 41, 42, 48, 57, 67, 68, 72, 117, 126).

Schröder, S., M. Zilske, G. Liedtke, and K. Nagel. Towards a Multi-Agent Logistics and Commercial Transport Model: The Transport Service Provider's View. *Procedia Social and Behavioral Sciences*, 39: 649–663, 2012. doi: 10.1016/j.sbspro.2012.03.137. (cited on pp. 23, 94).

Semet, F., P. Toth, and D. Vigo. *Chapter 2: Classical Exact Algorithms for the Capacitated Vehicle Routing Problem*, chapter 2, pages 37–57. In Toth and Vigo (2014), 2014. doi: 10.1137/1.9781611973594.ch2. (cited on p. 28).

Senatsverwaltung für Stadtentwicklung und Umwelt (SenStadt). Luftreinhalteplan 2011 bis 2017 für Berlin, 2013. (cited on pp. 1, 45, 55).

Senatsverwaltung für Umwelt, Verkehr und Klimaschutz Berlin (SenUVK). Umweltzone - bessere Luft für Berlin. see https://www.berlin.de/senuvk/umwelt/luftqualitaet/umweltzone/download/umweltzone_flyer_2017.pdf, 2017. (cited on pp. 1, 2, 94, 125, 126).

Simchi-Levi, D., P. Kaminsky, and E. Simchi-Levi. *Designing and Managing the Supply Chain. Concepts, Strategies and Case Studies*. McGraw-Hill, New York, 3 edition, 2008. ISBN 978-0071287142. (cited on p. 10).

Statistisches Bundesamt. Güterverkehr: Beförderungsmenge und Beförderungsleistung nach Verkehrsträgern, 2025. URL https://www.destatis.de/DE/Themen/Branchen-Unternehmen/Transport-Verkehr/Gueterverkehr/Tabellen/gueterbefoerderung-lr.html. last accessed: 27.08.2026. (cited on p. 11).

Steinmeyer, I. Definition und Bedeutung des Personenwirtschaftsverkehrs. Ein Sachstandsbericht aus dem Jahr 2005. In Arndt, W.-H. and Verkehrsplanungsseminar, editors, *Wirtschaftsverkehr in der Verkehrsplanung: Beiträge aus dem Verkehrsplanungsseminar 2005/2006*, Schriftenreihe des Instituts für Land- und Seeverkehr : Schriftenreihe A BV017076732 44. Springer Berlin Heidelberg, 2017. ISBN 9783798320604. (cited on p. 9).

Syré, A. M. *Assessment of decarbonization strategies in road transport - a comprehensive methodology*. PhD thesis, Technische Universität Berlin, 2026. (cited on p. 142).

Syré, A. M. and D. Göhlich. Decarbonization of Long-Haul Heavy-Duty Truck Transport: Technologies, Life Cycle Emissions, and Costs. *World Electric Vehicle Journal*, 16(2), 2025. ISSN 2032-6653. doi: 10.3390/wevj16020076. URL https://www.mdpi.com/2032-6653/16/2/76. (cited on p. 13).

Tietz, T., T.-A. Fay, T. Schlenther, and D. Göhlich. Electric Long-Haul Trucks and High-Power Charging: Modelling and Analysis of the Required Infrastructure in Germany. *World Electric Vehicle Journal*, 16 (2):96, Feb. 2025. ISSN 2032-6653. doi: 10.3390/wevj16020096. (cited on p. 141).

Toth, P. and D. Vigo, editors. *Vehicle Routing: Problems, Methods, and Applications*. Society for Industrial and Applied Mathematics (SIAM), 2014. doi: 10.1137/1.9781611973594. (cited on pp. 28, 46, 169, 170, 174, 178).

Transport for London (TfL). ULEZ: Where and when, 2022a. URL https://tfl.gov.uk/modes/driving/ultra-low-emission-zone/ulez-where-and-when. (cited on pp. 1, 94).

Transport for London (TfL). Direct Vision Standard and HGV Safety Permit, 2022b. URL https://tfl.gov.uk/info-for/deliveries-in-london/delivering-safely/direct-vision-in-heavy-goods-vehicles. (cited on pp. 94, 125).

Transport for London (TfL). Lorries, coaches and larger vehicles over 3.5 tonnes, 2022c. URL https://tfl.gov.uk/modes/driving/ultra-low-emission-zone/larger-vehicles. (cited on pp. 1, 2, 94, 102, 103, 125).

Turner, K. Agenten-basierte Modellierung und Simulation von Tourenplanung im städtischen Güterverkehr. Master's thesis, TU Berlin, 2015. (cited on pp. 23, 41, 97).

Umweltbundesamt. Methodenkonventionen 3.1 zur Ermittlung von Umweltkosten – Kostensätze. Technical report, 2020. (cited on p. 89).

Umweltbundesamt. Emissionen des Verkehrs. Technical report, Umweltbundesamt, 2026. URL https://www.uba.de/n11168de. last accessed: 01.08.2026. (cited on p. 12).

United Nations. Paris Agreement, 2015a. URL https://treaties.un.org/pages/ViewDetails.aspx?src=TREATY&mtdsg_no=XXVII-7-d&chapter=27&clang=_en. (cited on pp. 1, 12, 65, 93).

United Nations. Transforming our world: the 2030 Agenda for Sustainable Development. https://sdgs.un.org/sites/default/files/publications/21252030\Agenda\for\SustainableDevelopment\web.pdf, 2015b. (cited on pp. 1, 93).

Wang, D., H. Zhou, and R. Feng. A two-echelon vehicle routing problem involving electric vehicles with time windows. *Journal of Physics: Conference Series*, 1324(012071), 2019. doi: 10.1088/1742-6596/1324/1/012071. (cited on pp. 95, 126, 141).

Wang, Z. and P. Wen. Optimization of a Low-Carbon Two-Echelon Heterogeneous-Fleet Vehicle Routing for Cold Chain Logistics under Mixed Time Window. *Sustainability*, 12(5), 2020. ISSN 2071-1050. doi: 10.3390/su12051967. (cited on p. 95).

Washburn, S., H. C. Frey, and N. Rouphail. Final Report: Emissions Modeling and Implementation into CORSIM. Technical Report STRIDE 2012-014S, Southeastern Transportation Research, Innovation, Development and Education Center (STRIDE), 2016. (cited on p. 13).

Wermuth, M. Personen- und Personenwirtschaftsverkehr. In *Handbuch Verkehrspolitik*, pages 323–347. Springer Nature, 2007. doi: 10.1007/978-3-531-90337-8_15. (cited on p. 9).

Wiedemann, P. *Dekarbonisierung des Güterverkehrs: Technologische und systemische Ansätze*. Springer, Berlin, 2021. (cited on p. 10).

Wietschel, M., M. Kühnbach, and D. Rüdiger. Die aktuelle Treibhausgasemissionsbilanz von Elektrofahrzeugen in Deutschland. Technical report, Working Paper Sustainability and Innovation, 2019. (cited on pp. 15, 129).

Wikipedia. Dieselfahrverbot. https://de.wikipedia.org/wiki/Dieselfahrverbot, 2019. accessed 09-jan-2019. (cited on pp. 1, 45, 55).

Woxenius, J. Generic Framework for Transport Network Designs: Applications and Treatment in Intermodal Freight Transport Literature. *Transport Reviews*, 27(6):733–749, 2007. doi: 10.1080/01441640701358796. (cited on pp. ix, 10).

Yu, S., J. Puchinger, and S. Sun. Two-echelon urban deliveries using autonomous vehicles. *Transportation Research Part E: Logistics and Transportation Review*, 141(102018), 2020. doi: 10.1016/j.tre.2020.102018. (cited on pp. 28, 95, 100, 123).

Zhang, L., T. Matteis, C. Thaller, and G. Liedtke. Simulation-based Assessment of Cargo Bicycle and Pick-up Point in Urban Parcel Delivery. *Procedia Computer Science*, 130:18–25, 2018. ISSN 1877-0509. doi: 10.1016/j.procs.2018.04.007. (cited on pp. xiii, 33, 34, 41, 51).

Ziemke, D. *Person-centric integrated modeling of transport and urban systems.* PhD thesis, 2022. URL https://depositonce.tu-berlin.de/items/546d506c-4676-4cb1-8a7f-455d670dc0e7. (cited on p. 18).

Ziemke, D., I. Kaddoura, and K. Nagel. The MATSim Open Berlin Scenario: A multimodal agent-based transport simulation scenario based on synthetic demand modeling and open data. *Procedia Computer Science*, 151:870–877, 2019. ISSN 18770509. doi: 10.1016/j.procs.2019.04.120. (cited on pp. 21, 33, 57, 68).

Zilske, M. and J. W. Joubert. Freight Traffic. In Horni, Nagel, and Axhausen (2016), chapter 24, pages 155–156. doi: 10.5334/baw. (cited on pp. 18, 20, 21, 47, 55, 56, 97).

Zilske, M., S. Schröder, K. Nagel, and G. Liedtke. Adding freight traffic to MATSim. Technical Report 12-02, 2012. VSP working paper 12-02. See http://www.vsp.tu-berlin.de/publications. (cited on p. 97).

Statement on the use of AI Tools

In the preparation of this dissertation, the following AI-assisted tools were used:

- **ChatGPT (OpenAI)**: Assisted with programming analyses in R, support with LaTeX commands, and language corrections.
- **LanguageTool**: Used for checking and improving the linguistic and grammatical quality of the text.
- **DeepL**: Assisted with the translation.

The use of these tools was solely supportive and did not involve independent generation of content. All outputs generated by these tools were critically reviewed and incorporated into the dissertation in context.

This statement is provided for a transparency and follows current recommendations for disclosing the use of AI tools in academic work.