UNIVERSITÄT PADERBORN

Sequential Decision-Making in Urban Mobility And Logistics – Real-Time Optimization Under Uncertainty

der Fakultät für Wirtschaftswissenschaften
der Universität Paderborn
zur Erlangung des akademischen Grades
Doktor der Wirtschaftswissenschaften
- Doctor rerum politicarum -

vorgelegte Dissertation
von
Peter Dieter, M. Sc.
geboren am 01.11.1995 in Bad Nauheim

Paderborn, 2024

Dekan	Prof. Dr. Jens Müller
Gutachter	Prof. Dr. Guido Schryen
	Prof. Dr. Lin Xie
Termin der mündlichen Prüfung	25.02.2025

Acknowledgements

Diese Dissertation wäre nicht möglich gewesen ohne die Unterstützung vieler Personen, bei denen ich mich herzlich bedanken möchte:

Bei meinem Doktorvater Guido für sein Vertrauen in meine Arbeit, seine Unterstützung, wann immer ich Fragen hatte, und für die vielen netten und lustigen Momente.

Bei Lin für ihre Bereitschaft, meine Zweitgutachterin zu sein, und für ihr wertvolles Feedback.

Bei Herrn Stefan Betz und Oliver Müller für ihre Bereitschaft, Teil der Berufungskommission zu sein.

Bei meinen Kolleginnen und Kollegen Martina, Mitchi, Miriam, Philipp, Sascha, Stefan und Paul, die mich herzlich aufgenommen haben und mit denen ich viele schöne Momente erleben durfte – sei es beim Padeln, Darten, am Buffet im Phönix, im Büro oder bei Spieleabenden, an denen ich zu selten teilgenommen habe. Ebenso danke ich unseren SHKs und WHBs, die mich in der Lehre und Forschung tatkräftig unterstützt haben.

Bei Carina Uhde und Peter Volmich für ihre organisatorische und technische Hilfe.

Bei meinen Freunden in den Niederlanden (u.a. Kevin, Ruoshui, Matteo, Judith, Aravind, Giovanni, Dana, Lucas, Adi, Rosana), mit denen ich viele Momente teilen durfte und bei denen ich von der Arbeit abschalten konnte.

Bei Felix und Yannik für gemeinsame Urlaube und willkommene Ablenkungen vom Arbeitsalltag.

Bei Carina für die wunderschöne Zeit und die unvergesslichen Momente, die wir miteinander teilen konnten.

Bei allen weiteren Personen, die ich hier nicht explizit erwähnt habe, mit denen ich Zeit verbringen durfte und die mich auf meinem Weg unterstützt haben.

Zu guter Letzt möchte ich meiner Familie danken: Meinen Eltern, Brigitte und Walter, und meinen beiden Geschwistern, Elli und Bernd, die mich stets bedingungslos unterstützt haben.

Paderborn, November 2024 Peter Dieter

Contents

List of Figures

List of Tables

List of Algorithms

Acronyms

DVRP *Dynamic Vehicle Routing Problem.*

DVRPTW *Dynamic Vehicle Routing Problem With Time Windows.*

FFCS *Free-Floating Car Sharing.*

ILP *Integer Linear Programming.*

LMD *Last-Mile Delivery.*

MDPs *Markov Decision Processes.*

MIP *Mixed Integer Programming.*

ML *Machine Learning.*

MNL *Multinomial Logit.*

ODD *On-Demand Delivery.*

OR *Operations Research.*

P2P *Peer-to-Peer Ridesharing.*

SDD *Same-Day Delivery.*

TRS *Taxi Ridesharing.*

TSPTW *Traveling Salesman Problem With Time Windows.*

UN United Nations.

Part I

Introduction

1 Motivation

By the year 2050, it is projected that close to 7 billion people will live in urban areas (Ritchie & Roser, 2018). In relative numbers, this means that 68% of the total population is expected to live in urban areas by 2050, compared to 50% in 2018 (UN, 2019). This percentage is even higher in industrialized countries. In the United States, 86% of the population lives in urban areas in 2023. By 2050, this is expected to further increase to 89% (Ritchie & Roser, 2018). Naturally, this development also comes with an increased demand for urban mobility and logistics solutions, where urban logistics describes the movement of goods and urban mobility the movement of people. In addition to the growing urban population, both areas come with their own unique developments and challenges.

Concerning urban logistics, a major factor is the increased popularity of e-commerce systems. By 2025, the number of packages delivered worldwide is expected to climb to an amount of 200 billion, compared to less than 90 billion in 2018 (Szczepanski et al., 2021), leading to an increased demand for last-mile logistics and consequently, urban traffic. Regarding urban mobility, while many cities around the world have started initiatives aiming to reduce the use of cars (Nieuwenhuijsen & Khreis, 2016; Ortegon-Sanchez et al., 2017), a main concern is the fact that the most common transportation mode is still private cars, which according to a large-scale international survey of McKinsey in 2022, are used in 45 percent of all trips (Heineke et al., 2023). It is surpassing other modes such as public transport (23%), micro-mobility (16%), consisting of scooters, bikes, and other small vehicles, and walking (14%) (Heineke et al., 2023). Shared mobility services, including ride-hailing services like Uber, only account for around 2% (Heineke et al., 2023).

While providing essential services, today's urban mobility and logistic systems also cause increased traffic volumes which in turn have several adverse side effects. It leads to an increase in air pollution and greenhouse gas emissions and has a negative impact on public health, as it leads to an increase in respiratory problems, such as asthma (Anenberg et al., 2019). Further, it leads to traffic congestion which has economic costs for cities and individuals, including lost productivity. Alone in the EU, it is estimated that traffic congestion leads to a yearly loss of nearly 100 billion Euros, which corresponds to 1% of the EU's GDP (Savelsbergh & van Woensel, 2016). Moreover, it can also limit the development of cities by leading to inefficient use of urban space and increasing the risk of accidents and fatalities on the roads. In the US in 2021, 60% of deaths involving motor vehicle crashes occurred in urban areas (U.S. Department of Transportation, 2023). In 2000, this number was at just 40% and the same trend is visible in absolute numbers.

The two major trends, i.e., an increase in urban population and the growing number of packages delivered, coupled with their adverse side effects, stress the need for optimized urban mobility and logistics solutions. This is also underlined in the United Nations (UN) sustainability goals, where goal 11 is the development of *Sustainable Cities and Communities* (Colglazier, 2015). *Operations Research* (OR) has played an important role in improving the efficiency of logistics and mobility systems (Dekker et al., 2012; Laporte et al., 2018). An exemplary use case is the optimization of truck tours or companies' transportation networks. Another use case where OR methods have been extensively applied is mobility solutions such as optimizing bus schedules, intending to reduce the bus fleet size (L. Li et al., 2019).

In this thesis, to limit the scope of the dissertation, the focus is on two sub-domains of urban mobility and logistics that have gained importance in recent years due to the customers' desire for quicker delivery of goods and faster mobility, at reasonable costs. In the context of urban logistics, the focus is on *Last-Mile Delivery* (LMD) concepts where vehicle tours are optimized, that serve the final customers, such that e.g., driving distance or labor time is minimized (Boysen et al., 2021; Merchán et al., 2024). The reason for focusing on LMD is that its cost has risen significantly. In 2023, LMD was estimated to account for 53% of total delivery costs, compared to 41% in 2018 (Pohowalla et al., 2024), showing the economic potential in optimizing this segment of the logistics chain. This increase is mainly driven by labor costs, which have risen due to labor shortages (Pohowalla et al., 2024). This thesis aims to showcase how OR can help reduce these costs in various LMD use cases. Regarding urban mobility, the focus is on *Taxi Ridesharing* (TRS), where customers with similar itineraries share taxi rides. TRS has attracted more attention in both research (Santos & Xavier, 2015) and practical use (Heineke et al., 2023), as it aims to provide the speed and flexibility of taxis at lower costs. However, as stated above, in relative numbers, the market share of sharing services (less than 2%) compared to private cars (around 45%) is still very low. Therefore, another aim of this thesis is to improve the efficiency of TRS systems by reducing operational costs (e.g., by decreasing the needed taxi fleet size), or improve customer satisfaction through the reduction of waiting times, making it a more viable mobility option.

Coupled with these problem-specific challenges, come new (methodological) challenges, as many problems in the field of LMD and TRS are dynamic, i.e., problem environments change over time and decisions must be taken before all information is known, i.e., we deal with uncertainties. For example, in the case of LMD, a new trend is *Same-Day Delivery* (SDD), where the delivery of a good is performed the same day it has been ordered (Voccia et al., 2019). However, this also means that some customers arrive in the afternoon after some vehicles already left in the morning. To attain efficient planning, the planner must account for these initially unknown future customer requests. Similarly, in TRS, client requests arrive over the day and taxis need to be assigned to serve these requests in a short period. To account for these uncertainties, one can establish multiple time points, in which decisions must be taken.

Even within the OR community, multiple solution paradigms have been suggested to solve problems with multiple decision points. Among these paradigms are *Markov Decision Processes* (MDPs), where memorylessness of the stochastic process is assumed, i.e., the future state of the system depends only on the current state and the action taken, not on the sequence of events that preceded it. Further, in MDPs, transition probabilities (the probability the system moves from one state to another) are assumed to be known. This is in contrast to the modeling framework of *Stochastic Programming*, where probabilistic distributions characterize uncertain problem parameters (Jaillet & Wagner, 2010) that are gradually revealed in stages (Birge & Louveaux, 2011). Another framework is online optimization, which is not dependent on a priori assumptions about the structure of the problem data uncertainty (Jaillet & Wagner, 2010). As the aforementioned paradigms make certain problem assumptions, this thesis draws on the unifying framework of Powell (2019) for sequential decision problems, which provides a general modeling framework for problems with multiple decision points regardless of assumptions about the nature of uncertainty or memorylessness.

An important concept in sequential decision-making is decision points, i.e., the time decisions are taken. In static decision-making, there is only one decision point and it is not possible to react to system changes. Another option is to predetermine the times at which decisions are taken. A last option is to make decisions when events occur. This allows us to react to changes immediately. We can rank static problems, sequential problems with predetermined decision points, and event-driven decision points by what is further referred to as the *Level of Dynamism*, i.e., the degree to which we can react to changes within a system.

In both, LMD and TRS, sequential decision-making has attracted more research in recent years but still falls short compared to static decision-making. However, these two domains are suitable for sequential decision-making frameworks, due to their often uncertain environments (e.g., due to incoming orders), and the ability to allow planners to adapt to these using real-time data. Furthermore, previous research has paid little attention to the interplay between problem requirements (such as customer expectations of service speed) and the design choice on when decisions should be taken, i.e., the *Level of Dynamism*. In this thesis, novel problems in LMD and TRS are tackled, that deal with uncertainties and that have so far not been studied. Particularly, problems with different *Levels of Dynamism* are considered and it is shown how optimization can improve decision-making, irrespective of the decision points. Novel optimization heuristics are implemented, and computational evaluations for these selected problems are performed. These novel methods include a hybrid approach that combines traditional OR techniques with *Machine Learning* (ML) algorithms, and problem-specific heuristics. The overarching objective can therefore be framed as follows:

Develop optimization techniques to enhance the efficiency of urban mobility and logistics systems under uncertainty and varying Levels of Dynamism, with a particular emphasis on Last-Mile Delivery and Taxi Ridesharing.

The thesis is divided into three parts. The first part (I) consists of the Introduction. The remainder of this Introduction is structured in the following way. First, in Section 2, background information on the methodology, i.e., static and sequential decision-making, and the problem domain, i.e., urban mobility and logistics, is given. Also, in this section, research gaps are presented, resulting in two research questions. Further, a synthesis of challenges in both LMD and TRS is performed. This leads to the derivation of a research framework that allows for a classification of the papers, which is described in Subsection 3. Further, Section 3 includes a short summary of the research papers, and the papers are categorized within the framework.

The full research papers are given in Part II of the thesis. In total, it consists of five research papers, where three of them consider LMD, while two consider TRS systems.

Part III of this dissertation is a discussion. It consists of overall research and managerial implications (Sections 4.2 and 4.3), limitations (Section 5) as well as an outlook and suggestions for future work (Section 6).

2 Background

As stated in the motivation of this thesis, sequential decision-making is an emerging research area in the field of urban logistics and mobility. Therefore, literature along the problem domain, i.e., urban mobility and urban logistics, and the methodology used, i.e., sequential decision-making is scanned. This will lead to the building of a framework that is used to classify the research papers in Section 3, consisting of the two above-mentioned dimensions. Another goal of this section is to identify research areas that have received less attention and to derive research questions. Further, a goal is to provide the reader with the necessary knowledge about the problem domain and methodology used, to enhance the comprehension of the research papers presented in Part II of this thesis.

2.1 Methodological Background

In this subsection, first, a short tour d'horizon on sequential decision-making in the field of OR is given. This is done to substantiate the use of the unified modeling framework for sequential decision problems (Powell, 2019), which is presented further on. This is needed to achieve the second goal of this subsection, which is to explain the concept of decision points, and in doing so, the *Level of Dynamism*.

Sequential Decision-Making in Operations Research While the research community has long considered static decision-making and there exist accepted canonical forms (e.g., as a *Mixed Integer Programming* (MIP)), sequential decision-making is a far less beaten track and there exists a wide range of modeling approaches from different research communities, including OR, Reinforcement Learning, and Optimal Control. In the following, a short presentation about the most common paradigms in the field of OR that consider multiple decision epochs is given. It is noted that these paradigms overlap conceptually, i.e., some problems can be modeled by either paradigm. For an in-depth discussion on this topic, interested readers are referred to Powell (2014). Among these paradigms is the modeling framework of *Stochastic Programming*. Here, probabilistic distributions characterize uncertain problem parameters (Jaillet & Wagner, 2010). The most known example is two-stage stochastic programming with recourse. The first stage focuses on determining the optimal decisions based on known, certain information. In the second stage, decisions are made in response to uncertainty (known as recourse decisions), taking into account the first-stage decisions. The goal of the optimization is to minimize the total cost (in case of minimization), which includes the initial decisions and the expected costs arising from the recourse actions in the second stage (Birge & Louveaux, 2011). The classical two-stage problem can be extended to so-called multi-stage problems. Here, unlike two-stage stochastic programming, where decisions are divided into two phases (before and after the uncertainty is known), multi-stage models involve multiple decision points, with uncertainty being gradually revealed over time (Birge & Louveaux, 2011). Another modeling framework for sequential decision-making are *Markov Decision Processes* (MDPs). In MDPs, probabilities for the transition from one state to another (called transition probabilities), are assumed to be known. Further, the Markov property needs to hold, i.e., the probabilities of different outcomes are not dependent on past states, but only on the current state. This property is also called *memorylessness* (Puterman, 2014). A more recent paradigm for sequential decision-making is *Online Optimization* (Jaillet & Wagner, 2010). This approach does not rely on any prior assumptions about the nature or structure of the uncertainty in the problem data, i.e., defining distributions or sets to describe the uncertainty is omitted (Jaillet & Wagner, 2010). This leads to the development of policies, that do not incorporate possible future events but rather develop bounds on the performance compared to a solution with all information known (Powell, 2019).

To stress out the variety of different modeling and solution approaches, which makes it difficult to identify a standardized, cross-literature representation of problem characteristics and notations, Powell (2014) refers to it as a 'jungle'. Therefore, in this dissertation, the unifying framework for sequential decision-making of Powell (2019) is applied.

Modelling Sequential Decision Problems A Sequential Decision Problem is described by *States*, *Decision variables*, a *Exogenous information*, *Transition function* and an *Objective Function* (Powell, 2011). These components will now be explained in detail.

- *State* - The state s_t describes the system at a certain time t and includes all information that is available to the decision-maker to make a decision. In a *Dynamic Vehicle Routing Problem* (DVRP) context, this might be the customers that are already in the system and the position of vehicles.

- *Decision variables* - Decision variables are denoted by x_t and describe how we can interact with the system by making decisions. A decision could e.g., be a planned vehicle tour. Decisions are determined by a policy π that maps a state to a decision $x_t = X^{\pi}(s_t)$. Also here, the set of actions might be constrained and we thus should only consider feasible actions.

- *Exogenous information* - The exogenous information is denoted by ω_{t+1} and describes information that arrive after we take decision x_t, leading to state x_{t+1}. This could be, for example, a new incoming customer request.

- *Transition function* - The transition function $T(s_t, x_t, \omega_{t+1})$ determines how the system (and hence the states describing the system) evolves over time. It does so by taking into account the state at time t, the action taken at time t and the new exogenous information ω_{t+1}. The transition function therefore leads to the new state $s_{t+1} = T(s_t, x_t, \omega_{t+1})$.

- *Objective function* - The objective function $R(s_t, x_t)$ captures metrics that are used to evaluate the performance. This can be a reward function that we try to maximize, e.g., the number of customers we are able to serve (Meisel et al., 2011) or a cost function that we try to minimize, e.g., the distance traveled by all vehicles (Arslan et al., 2019).

The goal is to find an optimal policy π^* that satisfies the Bellman equation in each state. The Bellman equation consists of an immediate reward/cost and the expected sum over the future rewards/costs given state s_t and decision x_t and following optimal policy π^*. In the case of a cost minimization problem, the Bellman equation looks as follows:

$$X^{\pi^*}(s_t) = \underset{x_t \in X(s_t)}{\arg\min} \Big\{ R(s_t, x_t) + \mathbb{E}\Big[\sum_{j=t+1}^{T} R(s_j, X^{\pi^*}(s_j)) | (s_t, x_t) \Big] \Big\}. \tag{2.1}$$

We minimize the immediate costs plus the expected sum of future costs, as exogenous information arrives over time. Thus, we deal with a stochastic problem.

Decision Points & the Level of Dynamism We have now seen the mechanism of a Sequential Decision Problem and how it can be modeled. An important characteristic of Sequential Decision Problems is the decision points, i.e., the time when we make decisions. In static decision-making, there is only one decision point upfront. In Sequential Decision Problems, as seen previously, we have multiple decision points. These decision points can be predetermined or event-driven. An example of predetermined decision points is the Dynamic Dispatch Waves Problem for *Same-Day Delivery* (SDD) (Klapp et al., 2018; Van Heeswijk et al., 2019), where vehicles need to be dispatched in predetermined time steps, e.g., once per hour. An example of an event-driven decision problem is the work of X. Yang et al. (2016), where prices for time windows are offered to the customer when he/she arrives in the system. Sometimes the problem type determines whether decision points are event-driven or predetermined, e.g., in the treatment of chronic diseases where the doctor takes decisions at predefined decision points, to see if the treatment has been effective up to the given time (Denton, 2018). In other cases, the system/problem can be designed either way. For example, in the DVRP, we might dispatch vehicles once an hour, or we can decide upon dispatching when a customer arrives in the system/ a vehicle returns to the depot. Determining decision points should be done carefully: Frequent replanning, as is the case with event-driven decision points, allows for a quick and efficient response to evolving states while less frequent replanning may enable better decisions due to gained information (M. Ulmer et al., 2017).

We can rank static problems, sequential problems with predetermined decision points, and event-driven decision points by the *Level of Dynamism*, i.e., the degree to which we react to changes within a system. The term *Dynamism* (rather than *Sequentialism*) is chosen due to its usage in other works (see e.g., M. Ulmer et al., 2017). Naturally, the *Level of Dynamism* is lowest in static decision problems, as we do not react to any changes in the system by only having one decision point. When we have predetermined decision points, the *Level of Dynamism* can be classified as medium, as we have multiple decision points and can react to changes, however, we do not respond immediately when the system change occurs. In contrast, in event-driven systems, the *Level of Dynamism* is high as we can immediately react to those changes. The way to model a problem, including determining decision points, depends on various factors, such as problem-specific characteristics, information availability, and so on. There often exists no single right modeling choice. Also, the need for flexibility differs among different problems. In an ODD system, customers expect delivery within a few minutes, which requires quick decisions, while customers of traditional SDD systems, only expect delivery within the same day, making it possible to accumulate more information before taking a decision.

To summarize, the concept of *Level of Dynamism* helps identify the degree to which a system can respond to changes over time. The concept is independent of the specific modeling approaches (Stochastic Programming, Online Optimization, etc.) or solution techniques employed. It characterizes how much flexibility and responsiveness are available to adjust decisions as new information or uncertainties are revealed. A high *Level of Dynamism* indicates that decisions can be frequently updated in response to changes, while a low level suggests that adjustments are more limited or infrequent. This concept is important for understanding the adaptability of a system, independent of the methods used to optimize it.

In this thesis, it will be shown how selected problems can be modeled and solved as sequential decision problems with different *Levels of Dynamism*, aiming to demonstrate how varying degrees of real-time information affect decision-making processes and solution strategies.

Illustrative Example of Different Decision Points To further illustrate the role of different decision points, Figure 2.1 represents a timeline with incoming customer requests for a delivery system, e.g., an online grocery delivery system. In a static setting, all customers that arrived before time point 0 would be considered in the optimization, disallowing us to serve the five incoming customer requests on the same day. This would be the case in a classic LMD context, where a vehicle leaves a depot in the morning and returns in the evening. With predetermined decision points, it first needs to be decided at what time points vehicles should leave the depot, before determining the vehicle tours. For example, we might want to dispatch vehicles twice a day at 6:00 (serving customers 1 and 2) and at 12:00 (serving customers 3 to 5). With event-driven decision points, every time a customer arrives in the system, we can decide to either wait until more customers arrive in the system, or to dispatch a vehicle.

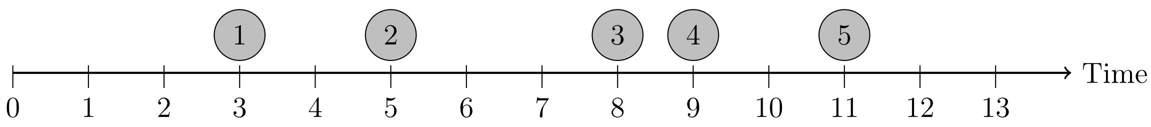

Figure 2.1: Timeline With Incoming Customer Requests

2.2 Problem Domain Background

In this subsection, an overview of current developments in the fields of urban logistics and mobility is provided. Solution methods that are used to solve challenges arising in this problem domain are not presented. Further, research gaps are described and two research questions are formulated. For more exhaustive overviews of current practices and trends in the field of urban mobility and logistics, interested readers are referred to Kaspi et al. (2022) and Cleophas and Meisel (2023). It is noted that in this thesis, the term urban logistics is used to specifically refer to the movement of goods and services, consistent with works such as Dahmardeh et al. (2018), Lagorio et al. (2016), and Savelsbergh and van Woensel (2016). The term urban mobility, on the other hand, will be used to denote the movement of people within urban areas. Additionally, using this terminology, hybrid forms of urban mobility and logistics exist, e.g., when public transport (such as buses and trams) is used to deliver goods (De Maio et al., 2024; Mandal & Archetti, 2023). Some research even proposes to view the transportation of goods and people as one single system and design it accordingly (De Sousa & Mendes-Moreira, 2015).

2.2.1 Urban Logistics

Urban logistics focuses on the efficient and effective transportation of goods in urban areas (Savelsbergh & van Woensel, 2016) and is also referred to as city logistics, urban (freight) distribution, last-mile logistics, or city distribution (Savelsbergh & van Woensel, 2016). It should not be confused with LMD, which describes the delivery of goods to the final customer (Boysen et al., 2021). A current pressing problem for companies in LMD is the uncertainty in driver behavior, i.e., drivers often deviate from the tour suggested by the planner (Merchán et al., 2024). A research gap is to develop methods that account for this uncertainty. Further, two emerging trends of LMD considered in this thesis are described: *Same-Day Delivery* (SDD) and *On-Demand Delivery* (ODD).

Same-Day Delivery *Same-Day Delivery* (SDD) describes the delivery of goods on the same day they have been purchased (Voccia et al., 2019). Besides the routing of vehicles, a key problem aspect is the decision of when to dispatch a vehicle to which customers. This is described by the Dynamic Wave Dispatching Problem (Baty et al., 2024; Klapp et al., 2018; Van Heeswijk et al., 2019), where a planner needs to dispatch and route a set of vehicles to serve customer requests that are incoming throughout the day. The goal is usually to minimize travel distance while maximizing the number of customers served on the same day. Through late dispatching, customers can be aggregated, potentially leading to more efficient vehicle tours. However, as customers often have time windows and couriers need to return to the depot at a certain time of the day, dispatching too late might lead to infeasibility or fewer customers that we can serve. Therefore, the planner must find the right balance between these two conflicting rationales. To foster research in this area, the *EURO Meets NeurIPS 2022 Vehicle Routing Competition* has been organized (Kool et al., 2022) together with the Dutch company *ORTEC* in which participants were asked to develop algorithms to solve the Dynamic Wave Dispatching Problem. This underlines the relevance of the problem in research and practice.

On-Demand Delivery A new trend in urban logistics where customers are served in a few minutes is referred to as *On-Demand Delivery* (ODD) by Waßmuth et al. (2023). It can be seen as a subtype of SDD. For example, the German ODD provider *Flink* used to promise their customer a delivery in only 10 minutes. To ensure such a fast delivery, the service provider operates multiple depots in a city where couriers with e-bikes depart. Research is sparse as ODD is a relatively new topic. Much of the existing research has focused on narrower subproblems, such as order acceptance (Kavuk et al., 2022), order bundling (Chen & Hu, 2024), or the assignment of orders to couriers (Dehghan et al., 2023; Guo et al., 2021), without accounting for the presence of multiple warehouses. Kronmueller et al. (2023b) address this gap by introducing the *Flash Delivery Problem* where customers are served from multiple depots in a short time and Kronmueller et al. (2023a) determine the optimal fleet size for such a system. The authors solve the problem using a rolling-horizon approach and solving an ILP in each horizon (every 100 seconds), disregarding depot workloads. A research gap here is to develop an event-driven system where customer arrivals trigger decision epochs, as this allows us to serve customers more quickly. Further, and similar to TRS, another gap is to develop methods that anticipate future customer requests considering the depots' current workload.

Considering the above-mentioned research gaps, the first research question that is tried to be answered in this thesis is:

> **RQ1**: *How can optimization methods be applied to improve the efficiency of Last-Mile Delivery services, considering uncertainties such as driver behavior or dynamically occurring customer orders?*

2.2.2 Urban Mobility

Urban mobility encompasses various modes of transportation such as walking, cycling, public transit, private vehicles, and shared mobility services. It is usually centered around two paradigms: public and private transport. In recent years, a mix between these two paradigms has gained more attraction, namely ridesharing services, where multiple users share a ride or vehicle. In the following, each of these three classes of urban mobility is presented.

Public Transport Public transport is characterized by high-capacity vehicles with fixed tours and schedules (Hörcher & Tirachini, 2021). In an urban setting, the most common public transport types are buses, trams, and metros. Due to high volume, these are characterized by relatively low costs for customers and are also seen as a sustainable means of transportation. However, compared to private transport, they lack flexibility and usually offer less comfort. Due to the high volumes of passengers transported and the Corona pandemic, research started investigating how the safety of public transport in terms of virus spread can be increased (Gutiérrez et al., 2021). Another new development of public transport systems is the electrification of buses, which is not only a challenging task from an engineering perspective but also from a planning perspective. From a planning perspective, it encompasses the joint optimization of strategic infrastructure tasks such as the building of charging stations and tactical planning of vehicle tours, including charging operations (Stumpe et al., 2021).

Private Transport Traditionally, private transportation means include private cars, taxis, and bikes. Motorized means, namely cars and taxis, are a major hurdle for sustainable cities.

They lead to traffic jams, air pollution, and road accidents (Borck, 2019). Companies such as Uber and Lyft have disrupted the taxi market by establishing a platform that matches drivers with customers (Grabher & van Tuijl, 2020). Services like Taxis and Uber are also known as ridehailing in the scientific literature (Feng et al., 2021). Here, strategic challenges are determining an optimal fleet size (Wallar et al., 2019; Zhang & Ukkusuri, 2016) while operational challenges are the optimal dispatching of cars to customer requests, and the rebalancing of vehicles to account for future demand (Jungel et al., 2023). More recently, e-bikes and e-scooters have become more prominent in many cities. Often, these bikes and scooters are offered by service providers and shared by users (Gössling, 2020; Teixeira et al., 2021). Also here, a main operational challenge is the rebalancing of these vehicles, while considering the battery level and charging processes (Osorio et al., 2021; Zhou et al., 2023).

Ridesharing Ridesharing is often seen as a hybrid between public and private transport. More specifically, it is a mode of transport in which individual travelers share a vehicle for a trip and share travel costs such as gas, tolls, and parking with others who have similar itineraries and schedules (Furuhata et al., 2013). It has been developed to combine the advantages of both public and private transport, i.e., offering a flexible and comfortable mobility system at relatively low costs. There exist a variety of different ridesharing systems. *Free-Floating Car Sharing* (FFCS) is a service model in which multiple users pay a fee to access a shared vehicle for transportation from one location to another. After using the car, they leave it at their destination for the next user to pick up, creating a flexible and dynamic system of shared mobility (Schiffer et al., 2021). *Peer-to-Peer Ridesharing* (P2P) describes systems where drivers share their personal trips with riders who have similar itineraries (Tafreshian et al., 2020). Therefore, drivers in P2P are not driving only for serving requests but have their own destination (Tafreshian et al., 2020). *Taxi Ridesharing* (TRS) (also referred to as ridepooling) systems are commercial ride services whose vehicles are used by several passengers at the same time for different ride requests (Ke et al., 2020; Ma et al., 2013). A key challenge in TRS is to optimally group customer requests to a single ride. Previous research in New York City has shown that TRS has the potential to reduce the fleet size by more than 50% (Lokhandwala & Cai, 2018). While TRS systems are seen as a promising means of urban mobility, they also have some disadvantages, such as relatively long travel times that arise due to detours that are driven to pick up each client at their origin and bring them to their destination (Barann et al., 2017). These long travel times might also result in a lower acceptance of such systems. Previous research has shown that shared pick-up and drop-off locations (also called meeting points), to which clients need to walk, can substantially improve the efficiency of such systems, by avoiding detours and increasing the possibilities of grouping multiple requests to one ride (Stiglic et al., 2015). However, two areas where the existing literature falls short are identified. First, when these systems are employed in real life, a common method is to apply a rolling-horizon approach, in which customer requests are collected during a horizon and then grouped. The service provider needs to determine several parameters, such as, among others, the maximally allowed walking distance or the horizon length. However, recent literature did not investigate the impact of these parameters on the efficiency of the system and the effects on customers. A second area in the literature that has not received attention yet is methods for TRS that anticipate future customer requests. This is a promising direction as anticipatory methods have proven useful in other problem areas such as meal-delivery (M. W. Ulmer et al., 2021) or energy storage (Cheng & Powell, 2016). This leads to the following research question:

> **RQ2**: *How can Taxi Ridesharing with meeting points services be designed to ensure high sharing rates, considering dynamically occurring customer requests?*

2.3 Synthesizing Needs in TRS and LMD

In both, TRS and LMD, the need for quicker service has led to the emergence of novel services and consequently, new decision problems. While there are problems that are solely relevant in one of the two areas, such as the lack of integrated driver behavior modeling in LMD, gaps have been identified, that concern both areas. These problems are coupled with the concept of sequential decision-making. For example, previous research has paid little attention to developing anticipatory methods for TRS and ODD, that account for future customer requests. Further, the interplay between problem requirements (such as the speed of service or data availability) and the design choice on decision points (*Level of Dynamism*) is often not reflected. This leads to the contributions of this thesis, which will be presented in the next chapter.

3 Framework and Contributions

In this section, first, a framework is presented, that aims to provide a structure for classifying the presented papers along their key dimensions, i.e., the research area (TRS and LMD) and the *Level of Dynamism*. Second, the research papers that are part of the thesis are shortly introduced and classified in the framework. Third, it is explained how each paper contributes to the overarching goal of the thesis, i.e., improving decision-making under uncertainty in urban mobility and logistics.

3.1 Framework

A two-dimensional framework is shown in Figure 3.1. This framework classifies the research papers that form this dissertation. For visual reasons, the research papers are already mentioned in this Figure, but a summary of the papers and their classification within the framework is presented in the following subsection. The framework consists of two dimensions which are explained in the following.

In the previous subsection, by presenting work on urban mobility and logistics, background on the problem domain was provided and some research trends have been shown. This discussion highlights the key themes and challenges that have shaped the research direction of this dissertation. This is reflected on the x-axis of the framework, where the two categories (urban logistics and urban mobility), are given. As already mentioned, to narrow the scope of this thesis to a manageable size, within the two categories, only LMD and TRS are considered. For a more detailed justification of why these two areas are chosen, we refer to Chapter 1. The nature of the problem domain is *categorical*. Therefore, the x-axis should not be seen as a quantitative scale, but rather as delineating variations across different categories within the problem domain. Consequently, many other problem domains in both urban logistics and mobility not covered in this thesis exist, such as inventory management, bus scheduling, vehicle charging location planning, etc.. These domains, though outside the scope of this thesis, represent interesting areas for future research.

The y-axis represents the *Level of Dynamism* (as explained in Section 2.1) of the considered research papers. This variable can be seen as *ordinal*, as different levels of dynamism exist. *Event-driven* systems have the highest *Level of Dynamism* since we are able to react to changes in the state (caused by events) immediately. When applying *rolling-horizon* approaches, we can react to state changes, however not immediately, but in set time intervals. Therefore its *Level of Dynamism* is lower than for *event-driven* systems. In *static* decision-making, we do not react to any state change. Also here, it needs to be stressed, that further levels of dynamism exist. For example, two-stage stochastic programming examines exactly two decision epochs (stages). It can therefore be seen as being situated between *static* and *rolling-horizon*. Further, the space

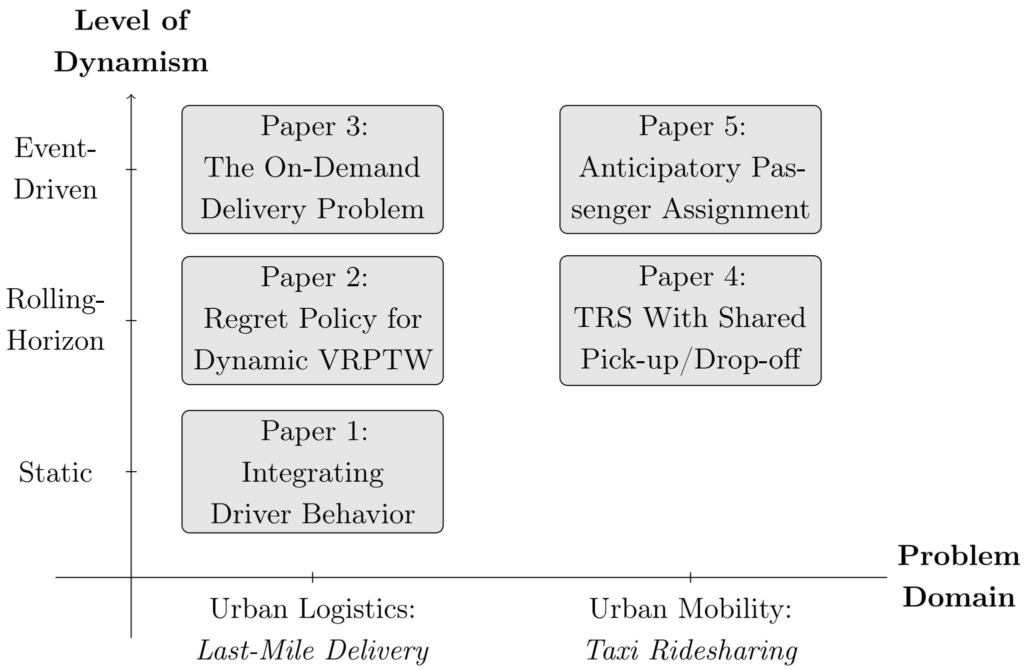

Figure 3.1: Research Framework to Classify Research Papers

beneath *static* in Figure 3.1 has been intentionally included to improve readability and there does not exist any class with less dynamism than *static* decision-making, i.e., there must be at least one decision epoch. Moreover, it should be highlighted that no *Level of Dynamism* should be regarded as superior to one another. As mentioned in Chapter 2, each level represents a different approach with its own strengths and weaknesses depending on the context of the decision-making process and is independent of the specific modeling approaches or solution techniques employed.

3.2 Summary of Research Papers

The thesis consists of five research papers. Four of them have been published and one is a working paper. An overview is given in Table 3.1. The first three papers are in the field of LMD. The fourth and fifth papers are in the field of *Taxi Ridesharing* (TRS). A summary of these five research papers is now presented.

Paper 1: *Integrating Driver Behavior into Last-Mile Delivery Routing: Combining Machine Learning and Optimization in a Hybrid Decision Support Framework*
A main challenge of LMD service providers is integrating driver knowledge and behavior. The relevance of the problem is illustrated by a research challenge organized by Amazon and the MIT Center for Transportation and Logistics in 2021 (Merchán et al., 2024), with the goal of developing novel methods for incorporating driver behavior into routing algorithms, as so far, this integration has hardly been exploited. This phenomenon is reflected in two

Table 3.1: Research Papers of the Dissertation

No.	Title	Authors	Status	Outlet
RQ1: How can optimization methods be applied to improve the efficiency of *Last-Mile Delivery* services, considering uncertainties such as driver behavior or dynamically occurring customer orders?				
1	*Integrating Driver Behavior into Last-Mile Delivery Routing: Combining Machine Learning and Optimization in a Hybrid Decision Support Framework*	**Peter Dieter**, Matthew Caron, Guido Schryen	Published	European Journal of Operational Research
2	*A Regret Policy for The Dynamic Vehicle Routing Problem with Time Windows*	**Peter Dieter**	Published	International Conference on Computational Logistics
3	*The On-Demand Delivery Problem: Assignment of Orders to Warehouses and Couriers*	**Peter Dieter**, Philipp Speckenmeyer, Guido Schryen	Under Review	Computers & Industrial Engineering
RQ2: How can Taxi Ridesharing with meeting points services be designed to ensure high sharing rates, considering dynamically occurring customer requests?				
4	*Designing Taxi Ridesharing Systems with Shared Pick-up and Drop-off Locations: Insights from a Computational Study*	Miriam Stumpe, **Peter Dieter**, Guido Schryen, Oliver Müller, Daniel Beverungen	Published	Transportation Research Part A: Policy and Practice
5	*Anticipatory Assignment of Passengers to Meeting Points for Taxi Ridesharing*	**Peter Dieter**, Miriam Stumpe, Marlin Ulmer, Guido Schryen	Published	Transportation Research Part D: Transport and Environment

distinct and largely independent research areas: logistics planning and driver behavior. In this paper, we attempt to bridge this gap by using and integrating historical data from actually driven tours into LMD planning. However, this also results in complex and large-scale routing challenges that necessitate an overarching methodology extending beyond traditional optimization techniques. This approach must encompass a multi-stakeholder perspective, integrate a hybrid-analytical strategy by including tour prediction and prescription, and utilize both data science and optimization methods. We propose a hybrid decision support framework for the *Traveling Salesman Problem With Time Windows* (TSPTW) that integrates ML techniques with conventional optimization methods. This framework takes into account the discrepancies between the suggested tours (derived using OR techniques) and the predicted tours (generated using ML). We demonstrate the applicability of the framework through a case study utilizing real-world logistics data. By conducting a sensitivity analysis, we explore and illustrate the trade-off between the level of deviation between predicted and suggested tours and the associated tour costs. We argue that the suggested hybrid ML and OR approach can mitigate the uncertainty of driver behavior, leading to improved decision-making by proposing tours to drivers, that they eventually will follow and thereby improving the efficiency, contributing to RQ1.

Paper 2: *A Regret Policy For The Dynamic Vehicle Routing Problem With Time Windows*
In this paper, I present a regret policy for the *Dynamic Vehicle Routing Problem With Time Windows* (DVRPTW) where customer order arrivals are revealed over the course of a day. The problem requires two types of decisions: Dispatching orders and planning vehicle tours. The aim is to minimize travel distance while fulfilling all orders within their specified time windows throughout the day. The core concept of this policy involves assessing a regret value for each order, indicating potential improvements foregone by dispatching the order immediately, i.e., the regret if we should dispatch the customer immediately. To determine this regret value, we leverage customer distribution data from which orders are drawn. If the calculated value falls below a predefined threshold, the order is dispatched, and tours are planned using a state-of-the-art VRPTW solver. The proposed regret policy outperforms two benchmark policies from the literature, thereby contributing to RQ1.

Paper 3: *The On-Demand Delivery Problem: Online Assignment of Orders to Warehouses and Couriers*
As presented in Section 2, *On-Demand Delivery* (ODD) describes systems where delivery is performed in only a few minutes (Waßmuth et al., 2023) by operating multiple micro-warehouses in a service region and employing a fleet of couriers with e-bikes. In this third paper, we mathematically describe the ODD as a Sequential Decision Problem with the aim of minimizing total tardiness. When an order arrives in the system, we need to assign it to a warehouse and a courier. To solve the modeled problem, we suggest anticipatory and data-driven assignments based on the current workload and capacity of warehouses, as well as previously assigned orders to couriers. We apply the policies to problem instances on a stylized grid as well as to instances derived from real-world data of Chicago. The methods are benchmarked to current practices from the industry, where statically defined spatial areas (polygons) are defined for each

micro-warehouse and all customers within this polygon are assigned to the respective warehouse. The paper contributes to RQ1 as we show that an anticipatory assignment can substantially reduce tardiness and improve the efficiency of the system, compared to the described industry benchmark.

Paper 4: *Designing Taxi Ridesharing Systems with Shared Pick-up and Drop-off Locations: Insights from a Computational Study*
In the fourth paper, a TRS system featuring shared pick-up and drop-off locations is considered, where passengers may need to cover a brief distance on foot from their origin or to their destination. More precisely, we propose a system where for each set of shared requests, one of those requests is selected as the main ride, and other customers need to walk to the origin location of the main ride and later need to walk from the destination of the main ride to their own final destination. We introduce a novel mathematical framework that conceptualizes this TRS problem with shared pick-up and drop-off points. To account for dynamically incoming customer requests, we employ a rolling-horizon strategy and conduct extensive computational trials using real-world data from New York City and Porto. Through these experiments, we manipulate various environmental and design factors, revealing their significant impact on rejection rates, sharing rates, and overall service quality. Lastly, the guidelines provide actionable insights for TRS operators, emphasizing the critical role of system design in leveraging extended waiting periods to achieve low rejection rates and foster high levels of ridesharing, thereby, contributing to RQ2.

Paper 5: *Anticipatory Assignment of Passengers to Meeting Points for Taxi Ridesharing*
As previously mentioned, literature shows that introducing meeting points in ridesharing systems, where customers are picked up and dropped off, significantly increases its performance by facilitating the aggregation of requests (Stiglic et al., 2015). In this fifth paper, we focus on the anticipatory assignment of customers to such meeting points. We approach the problem by framing it as a Sequential Decision Problem aimed at maximizing the distance conserved through allocating requests to previously scheduled trips. The proposed solution involves an anticipatory approach to trip planning, which integrates two key elements: forecasting future customer demands using historical data and employing a policy function approximation that minimizes unnecessary redundancy, thereby enhancing service area coverage. The paper contributes to RQ2, as we perform an extensive evaluation using real-world data from New York, demonstrating the efficacy of the proposed policy by showcasing substantial improvements in distance saved compared to a myopic benchmark policy.

3.3 Framework-Based Classification of Papers

Recall that the overarching research objective is the development of optimization techniques to enhance the efficiency of urban mobility and logistics systems under uncertainty with varying *Levels of Dynamism*, with a particular emphasis on LMD and TRS. In all the papers mentioned above, we are dealing with uncertainties. In Paper 1, the uncertainty lies in the unknown driver's behavior. In Papers 2 and 3, the main uncertainty lies in the unknown customer orders.

Similarly, in Papers 4 and 5, it lies in unknown taxi requests. However, the papers regard distinct use cases that require various modeling approaches regarding the *Level of Dynamism*. Paper 1 regards a traditional LMD problem where customer orders have arrived on previous days. Therefore, even though uncertainty exists in driver behavior, and in contrast to the other papers, we deal with a static problem, since we do not re-optimize the tour online. In Paper 2, a SDD case is considered, where customers expect delivery the same day it has been ordered. Therefore, a rolling-horizon approach is applied, in which an optimization model is run every hour. This is also the case in Paper 4, for a TRS use case. However, instead of optimizing every hour, an optimization is performed every few minutes (the horizon length is varied in experiments), which allows for faster decision-making, which is needed in the TRS context, as customers cannot wait for hours for a taxi to arrive. A rolling-horizon approach is useful, since in both these papers, decisions do not need to be taken immediately and the approach allows us to gather information before deciding. A quicker decision is needed in Papers 3 and 5, as customers expect delivery within minutes (Paper 3) or immediate feedback on their request (Paper 5). Therefore, both these papers include event-driven decision points, allowing immediate decision-making.

Part II

Research Papers

Part III

Discussion

4 Conclusion

The goal of this chapter is to derive conclusions from Part I of this thesis as well as from papers that were presented in Part II. To achieve this, first, the research questions are addressed. Further, research and managerial implications are discussed.

4.1 Addressing Research Questions

The first research question is how optimization methods can be applied to improve the efficiency of LMD services, considering uncertainties such as driver behavior or dynamically occurring customer orders. Considering uncertain driver behavior, in Paper 1 we argue that a hybrid ML and OR method can increase driver obedience, where driver behavior is predicted by a ML method (learned from historical data), which then serves as input to an optimization (OR) model and thereby, increasing the system efficiency. Concerning dynamically occurring customer orders, in Papers 2 and 3 optimization approaches have been developed that outperformed existing methods from literature (Paper 2) or industry (Paper 3). While the *Level of Dynamism* is different in both Papers (Paper 2 adopted a rolling-horizon approach and Paper 3 an event-triggered approach), in both cases, the anticipation of future orders proved useful.

The second research question is how services for taxi-ridesharing with meeting points can be designed to ensure high sharing rates, considering dynamically occurring customer requests. Two potential designs have been suggested in Papers 4 and 5. Both these designs, i.e., a rolling-horizon approach (Paper 4) and an event-driven system (Paper 5), show large sharing potential. Moreover, it could be seen in Paper 4, that a horizon length of 5 minutes led to high sharing rates, as this allowed for sufficient information accumulation. In contrast, the system in Paper 5 did not allow for information accumulation, since customer requests had to be responded to instantly. However, the anticipation of future customer orders, based on historical data and the incorporation of previously implemented decisions, proved highly beneficial.

4.2 Research Implications

From the papers in Part II, several implications for research can be derived. It is visible that sequential decision-making plays a significant role in the field of LMD as well as TRS, as many problems in this domain can be modeled as Sequential Decision Problems. However, from reviewing related literature in the individual papers, it is also visible that it received considerably less attention in research. It can be hypothesized that this is also the case for other problem areas outside of LMD and TRS. Therefore, sequential decision-making could also be applied in other problem areas of urban mobility and logistics where it has not been studied yet. For example, in *Free-Floating Car Sharing* (FFCS), users of this service usually arrive over the day, and decisions, such as the rebalancing of cars, need to be taken sequentially.

However, to the best of my knowledge, all research papers considering FFCS so far assume perfect information.

Sequential decision-making can also play a role in areas beyond mobility and logistics. Areas that traditionally received a lot of attention from the OR community, such as scheduling and production planning, could also benefit from the lense of sequential decision-making as also here, it is reasonable to assume that at least some orders/jobs arrive during an ongoing production process and need to be inserted into an existing schedule.

From a methodological point of view, other characteristics of the problems considered can be relevant to research. For example, the value of anticipating future events, i.e., in the papers considered in this thesis, customer requests. As Papers 2,3 and 5 in this dissertation show, such anticipation often results in significant improvement compared to methods where no anticipation is present. This observation is also in line with previous research (see e.g., M. Ulmer, 2019). Such an anticipation does not need to be overly complicated. Papers 3 and 5 of this dissertation show that adjusting a cost/reward function to account for future events can improve a system's performance significantly. Another finding made across papers, is the importance of parametrization of the suggested methods, as usually, the suggested methods have parameters that need to be determined upfront and there is a significant influence of these parameters on the system performance. While parameter tuning is an existing research area, the results support the importance and relevance of this area. Furthermore, an important implication is the need for robust validation methodologies for the proposed methods. Validating these anticipatory methods rigorously against real-world data remains a critical challenge. The findings underscore the importance of developing and applying robust validation frameworks, i.e., simulation environments, that can reliably assess the performance and reliability of predictive methods in practical settings. Preferably, the validation of the methods is done with real-world data (see e.g., Papers 1,2,4 and 5) but in case this is not possible, data can also be generated, e.g., by estimating the demand for a service based on the population density (see Paper 3).

4.3 Managerial Implications

Several managerial implications partly overlap with research implications. In the following, implications from a service operator perspective (TRS or LMD company) are given, before giving implications from a customer perspective.

For Service Operators

First, instead of relying on myopic decision rules, companies should incorporate more advanced methods in their operational decision-making, if they deal with, e.g., on-demand services. Preferably, the applied methods should be able to ex- or implicitly anticipate future events and not only consider the best short-term decision. The studies showed that, compared to non-anticipating methods, this can greatly increase service quality with the same amount of resources needed. Vice versa, this also means that service quality can be kept constant with fewer resources, consequently leading to a cost reduction for the operating company. This is especially relevant when these companies operate at relatively low margins, such as is the case in On-Demand Delivery services (Simmons et al., 2022). To be able to develop new methods, companies need to create simulation environments in which such methods can be safely evaluated. A challenge is to create simulation environments that are detailed enough such that all major problem characteristics are sufficiently addressed. However, a too high degree of detail can lead to overly complex simulation models which make it difficult to understand and maintain the software. Therefore, the right balance between simplicity and level of detail needs to be found, such that a valid evaluation of solution methods can be performed.

Another managerial implication derives from a problem faced in some of the presented research papers, namely data availability. For example, in the case of TRS (Papers 4 and 5), lead times (the time when customers make a request) were unavailable, which forced us to make assumptions about this time. Similarly, in the case of ODD (Paper 3), customer locations were drawn from a theoretical distribution based on the population density, rather than empirical data. Therefore, companies should collect such data to be able to incorporate empirical distributions, or distributions derived from empirical data, in the simulation models for all kinds of parameters. When customer behavior is to be incorporated into the simulation environments, this also includes data on customer preferences, which can be used to adjust customer-choice models. However, it also needs to be mentioned that acquiring data might be costly and it should be considered carefully if it is necessary in case data is costly to obtain. Interested readers on simulation guidelines are referred to Carson (2005) and Law (2015).

Furthermore, throughout the papers, it could be seen that the results are strongly dependent on resource availability, which were treated as given parameters. Examples are the taxi fleet size or the number of couriers available, in case of ODD. Ideally, this should be treated as a tactical decision that should be optimized together with the operational planning. Tactical planning is essential for the efficient and effective operation of businesses. For a taxi company, determining the optimal fleet size is crucial to meet customer demand while minimizing operational costs. Similarly, for a delivery company, deciding on the right number of couriers is vital to ensure timely deliveries and maintain customer satisfaction.

For Customers

From a customer perspective, the research can lead to an increase in service quality, as we have shown that e.g., waiting times (Paper 3 and 4) and rejection rates (Paper 4) can be decreased. Further, as mentioned previously, a cost decrease for the service provider might also lead to lower prices for customers. These effects could increase the demand for the mentioned service (e.g., ODD or TRS). In the case of TRS, an increase in demand might lead to a positive network effect cycle (B. Yang et al., 2020), as more participating users will lead to an increase in ride-sharing opportunities, reducing wait times and costs per trip, which can further attract new users, creating a cycle of enhanced efficiency and user growth. In the case of SDD (and its special case ODD), indirect network effects could emerge, i.e., companies could start investing more money in these services if they prove to be more profitable (e.g., by applying the methods presented in Papers 2 and 3), resulting in an offer increase.

For Society

The research conducted in this thesis can also have an impact on a broader, societal level. For example, as shown in Papers 4 and 5, TRS can reduce traffic and its accompanying side effects (e.g., congestion, pollution, accidents), by reducing the taxi fleet needed to serve all customer requests. Also regarding SDD, more efficient planning can reduce traffic and have positive impacts. However, increased demand due to more efficient operations can have a negative side effect, as it can lead to people who would not have considered SDD now using this service, moving away from traditional, less resource-intensive, multi-day delivery.

5 Limitations

The studies presented in this thesis come with certain general limitations. One limitation arises from the methods used in the research papers. While it is generally agreed upon that stochastic and dynamic real-world sized problem instances are intractable to solve with exact methods (H. Li & Womer, 2015; Topaloglu & Powell, 2006; Woerner et al., 2015), in the presented research papers, it is not attempted to develop such exact methods, but it has been relied on heuristics and approximations. Therefore, rather than providing a measure of how closely the solutions approach theoretical optimality, the solutions are rather practical approaches that trade off computational efficiency for feasible implementation within realistic constraints and time limits. This is even the case for Paper 4, where a rolling-horizon approach is applied and each planning horizon is solved with an exact matching/grouping method. This is because the size of planning horizons is predetermined and horizons that allow for different and better matchings/groupings most likely exist.

Another limitation is that all problems studied are just a representation of real-world problems but cannot fully reflect all real-world characteristics and requirements. Therefore, more details can be added, which could potentially alter the results to some extent. Examples of this model detail are driving times, which are assumed to be deterministic in all the studies, while in the real world, they are stochastic. Another example is employee availability, which is assumed to be a deterministic parameter, neglecting possible absences due to e.g., due to illness. In the papers presented in this thesis, the advice of Law (2015) was followed, who states: ‘Do not have more detail in the model than is necessary to address the issues of interest, subject to the proviso that the model must have enough detail to be credible.’ Therefore, the models presented in the papers are expected to be realistic (detailed) enough, such that the key statements remain valid.

Closely related to the detail of the model is another limitation of the studies, namely the neglect of customer choice models. More precisely, in the presented studies, it is assumed that all customers are homogeneous and accept the offers at any time. For example, the choice of accepting an offered shared taxi ride. In the real world, however, customers are heterogeneous and might reject the service in the short or also long term (i.e., the customer now accepts the service but forgoes in the future). Neglecting these customer choices therefore might distort the findings and their real-life generalisability.

The limitations of this work lead to the next section, in which possible avenues for future work related to the papers in this thesis are presented.

6 Future Work

There exist several possible future directions. Regarding the previously mentioned model complexity, the presented models could be extended by a higher level of detail in general. More specifically, stochasticity of many parameters (driving times, service times) could be included, where it is not done already. This could strengthen the validity of the studies. However, it might also lead to the requirement for specialized solution approaches that account for these stochasticities and make use of probability distributions regarding the parameters. For example, regarding uncertain driving time, a common approach in the literature is to artificially add safety slack to the times, to make sure that customers are reached within their time window (Gorissen et al., 2015; Kok et al., 2012). Further, the previously mentioned customer choice models could be incorporated into the problem environments and models. Also here, one could draw on the choice model to steer customer demand and consequently, to make better decisions. Common ways to do this are either by adjusting offer availabilities (i.e., determining which service options to offer to a customer), dynamic pricing, or both (Akkerman et al., 2024; Fleckenstein et al., 2023). The most frequently used choice model is the *Multinomial Logit* (MNL) choice model (Feldman et al., 2022; Lin et al., 2020), where choice probabilities are expressed as a linear combination of exponential terms (Strauss et al., 2018) (attributes of an option) and parameters need to be tuned based on available, preferably real-world, choice data. In the case of TRS, one might directly reject customer requests when a service would result in an unacceptable waiting time, offer the customer options with different waiting times and prices, or offer customers a single option with an individual price (see, e.g. Luo & Saigal, 2017; Yan et al., 2020). Also in LMD, dynamic pricing has attracted attention in both practice and research (Akkerman et al., 2024; X. Yang et al., 2016) and could be incorporated into the problems studied in this dissertation.

Another possible future direction is to include the concept of fairness in the considered problems. For example, in the case of TRS, customers in busy areas can be shared more often with other rides, compared to customers who live in less busy areas, potentially leading to benefits for those customers, such as lower rejection rates and/or lower prices. A reallocation of resources (in that case, taxis), can potentially reduce this unfairness by assigning more taxis to less populated regions. In the context of LMD, customers living in central areas will likely have lower delivery times, which could be balanced by adjusting the objective function to accommodate for unbalanced waiting times, e.g., by minimizing the maximal waiting time instead of the average waiting time. However, including fairness will likely result in an efficiency loss of the systems (Bertsimas et al., 2011, 2012).

A further direction for future research is based on the limitation of having only developed heuristic methods for the considered problems. While exact methods are intractable for dynamic real-world sized problem instances (Powell, 2019), they still might be used for small artificial instances. A possible approach is to apply classical dynamic programming to solve the problems at hand (using value and/or policy iteration). Besides deriving optimal policies, another approach to strengthen the theoretical value of the work is to derive performance guarantees for certain developed policies. An interesting approach from the literature is to draw on queuing theory to derive theoretical performance guarantees. Interested readers are referred to Fatehi and Wagner (2022) who derive performance guarantees for policies in the context of Crowd-Sourced Delivery. Another example is the work of Chen and Hu (2024), who analyze when customer bundling is beneficial in the case of ODD, assuming there is one warehouse located at the center of a disk-shaped region.

Another possible avenue is related to an implication given in Section 4.3, stating that companies should carefully plan the number of used resources, as it could be seen that resource availability strongly affects operational planning. This is by no means a trivial task, since usually, multiple conflicting objectives are involved on a strategic, tactical, and operational level. For example, when deciding on the taxi fleet size, a small taxi fleet leads to lower costs, but might also lead to longer waiting times and more customer rejects, negatively influencing both revenue and customer satisfaction. A related problem arising is the time horizon of different planning levels. Strategic planning focuses on a time frame of months to years, tactical planning covers weeks to a few months, and operational planning deals with periods from a few hours to a day (Zeltyn et al., 2011). For instance, when buying a taxi, it can be used for multiple years. A question arising is therefore how to align the long-term investment of purchasing a taxi with the shorter-term decisions involved in tactical and operational planning, ensuring that all planning levels are integrated effectively to maximize overall efficiency and profitability. An example of an approach integrating tactical and operational planning is the work of Hasturk et al. (2024) who consider an inventory routing problem for hydrogen. The authors develop an algorithm that jointly optimizes tactical repetitive schedules for vehicle transportation and the operational buying and selling decisions in case of underproduction or overproduction, by iteratively solving the tactical and operational problem. Drawing on this approach, in the case of ODD, the planning of warehouse locations (strategic level), the courier fleet size (tactical level), and the customer-warehouse/courier assignment (operational level) could be jointly optimized. Similarly in TRS systems, methods could be developed that jointly optimize the number of taxis owned by the service provider (strategic level), the schedule for taxi drivers (tactical planning), and the taxi-customer assignment (operational level).

Bibliography

Akkerman, F., Dieter, P., & Mes, M. (2024). Learning dynamic selection and pricing of out-of-home deliveries. *Transportation Science*. https://doi.org/10.1287/trsc.2023.0434

Anenberg, S., Miller, J., Henze, D., & Minjares, R. (2019). A global snapshot of the air pollution-related health impacts of transportation sector emissions in 2010 and 2015. *International Council on Clean Transportation: Washington, DC, USA*, 1–48.

Arslan, A. M., Agatz, N., Kroon, L., & Zuidwijk, R. (2019). Crowdsourced delivery—a dynamic pickup and delivery problem with ad hoc drivers. *Transportation Science*, *53*(1), 222–235. https://doi.org/10.1287/trsc.2017.0803

Barann, B., Beverungen, D., & Müller, O. (2017). An open-data approach for quantifying the potential of taxi ridesharing. *Decision Support Systems*, *99*, 86–95. https://doi.org/10.1016/j.dss.2017.05.008

Baty, L., Jungel, K., Klein, P. S., Parmentier, A., & Schiffer, M. (2024). Combinatorial optimization-enriched machine learning to solve the dynamic vehicle routing problem with time windows. *Transportation Science*. https://doi.org/10.1287/trsc.2023.0107

Bertsimas, D., Farias, V. F., & Trichakis, N. (2011). The price of fairness. *Operations research*, *59*(1), 17–31. https://doi.org/10.1287/opre.1100.0865

Bertsimas, D., Farias, V. F., & Trichakis, N. (2012). On the efficiency-fairness trade-off. *Management Science*, *58*(12), 2234–2250. https://doi.org/10.1287/mnsc.1120.1549

Birge, J. R., & Louveaux, F. (2011). *Introduction to stochastic programming*. Springer Science & Business Media. https://doi.org/10.1007/978-1-4614-0237-4

Borck, R. (2019). Public transport and urban pollution. *Regional Science and Urban Economics*, *77*, 356–366. https://doi.org/10.1016/j.regsciurbeco.2019.06.005

Boysen, N., Fedtke, S., & Schwerdfeger, S. (2021). Last-mile delivery concepts: A survey from an operational research perspective. *OR Spectrum*, *43*(1), 1–58. https://doi.org/10.1007/s00291-020-00607-8

Carson, J. S. (2005). Introduction to modeling and simulation. *Proceedings of the Winter Simulation Conference, 2005.*, 8–pp.

Chen, M., & Hu, M. (2024). Courier dispatch in on-demand delivery. *Management Science*, *70*(6), 3789–3807. https://doi.org/10.1287/mnsc.2023.4858

Cheng, B., & Powell, W. (2016). Co-optimizing battery storage for the frequency regulation and energy arbitrage using multi-scale dynamic programming. *IEEE Transactions on Smart Grid*, *9*(3), 1997–2005. https://doi.org/10.1109/TSG.2016.2605141

Cleophas, C., & Meisel, F. (2023). Urban mobility and logistics-past, present, and future. *Logistics Management Conference*, 115–130. https://doi.org/10.1007/978-3-031-38145-4_7

Colglazier, W. (2015). Sustainable development agenda: 2030. *Science*, *349*(6252), 1048–1050.

Dahmardeh, M., Telhada, J., Carvalho, M. S., & Paisana, A. (2018). Urban logistics: A systematic literature review. *Proc. 7th Int. Conf Industrial Technology and Management (ICITM)*, 279–283. https://doi.org/10.1109/ICITM.2018.8333961

De Maio, A., Ghiani, G., Laganà, D., & Manni, E. (2024). Sustainable last-mile distribution with autonomous delivery robots and public transportation. *Transportation Research Part C: Emerging Technologies*, *163*, 104615. https://doi.org/10.1016/j.trc.2024.104615

De Sousa, J. F., & Mendes-Moreira, J. (2015). Urban logistics integrated in a multimodal mobility system. *2015 IEEE 18th International Conference on Intelligent Transportation Systems*, 89–94. https://doi.org/10.1109/ITSC.2015.23

Dehghan, A., Cevik, M., & Bodur, M. (2023). Neural approximate dynamic programming for the ultra-fast order dispatching problem. *arXiv preprint arXiv:2311.12975*. https://doi.org/10.48550/arXiv.2311.12975

Dekker, R., Bloemhof, J., & Mallidis, I. (2012). Operations research for green logistics–an overview of aspects, issues, contributions and challenges. *European journal of operational research*, *219*(3), 671–679. https://doi.org/10.1016/j.ejor.2011.11.010

Denton, B. T. (2018). Optimization of sequential decision making for chronic diseases: From data to decisions. In *Recent advances in optimization and modeling of contemporary problems* (pp. 316–348). INFORMS. https://doi.org/10.1287/educ.2018.0184

Dieter, P. (2023). A Regret Policy for the Dynamic Vehicle Routing Problem with Time Windows. *International Conference on Computational Logistics*, 235–247. https://doi.org/10.1007/978-3-031-43612-3_14

Dieter, P., Caron, M., & Schryen, G. (2023). Integrating Driver Behavior Into Last-Mile Delivery Routing: Combining Machine Learning and Optimization in a Hybrid Decision Support Framework. *European Journal of Operational Research*, *311*(1), 283–300. https://doi.org/10.1016/j.ejor.2023.04.043

Dieter, P., Speckenmeyer, P., & Schryen, G. (2024). The On-Demand Delivery Problem: Assignment of Orders to Warehouses and Couriers. *Available at SSRN*. https://doi.org/10.2139/ssrn.5039888

Dieter, P., Stumpe, M., Ulmer, M., & Schryen, G. (2023). Anticipatory Assignment of Passengers to Meeting Points For Taxi-Ridesharing. *Transportation Research Part D: Transport and Environment*, *121*, 103832. https://doi.org/10.1016/j.trd.2023.103832

Fatehi, S., & Wagner, M. R. (2022). Crowdsourcing last-mile deliveries. *Manufacturing & Service Operations Management*, *24*(2), 791–809. https://doi.org/10.1287/msom.2021.0973

Feldman, J., Zhang, D. J., Liu, X., & Zhang, N. (2022). Customer choice models vs. machine learning: Finding optimal product displays on alibaba. *Operations Research*, *70*(1), 309–328. https://doi.org/10.1287/opre.2021.2158

Feng, G., Kong, G., & Wang, Z. (2021). We are on the way: Analysis of on-demand ride-hailing systems. *Manufacturing & Service Operations Management*, *23*(5), 1237–1256. https://doi.org/10.1287/msom.2020.0880

Fleckenstein, D., Klein, R., & Steinhardt, C. (2023). Recent advances in integrating demand management and vehicle routing: A methodological review. *European Journal of Operational Research*, *306*(2), 499–518. https://doi.org/10.1016/j.ejor.2022.04.032

Furuhata, M., Dessouky, M., Ordóñez, F., Brunet, M.-E., Wang, X., & Koenig, S. (2013). Ridesharing: The state-of-the-art and future directions. *Transportation Research Part B: Methodological*, *57*, 28–46. https://doi.org/10.1016/j.trb.2013.08.012

Gorissen, B. L., Yanıkoğlu, İ., & Den Hertog, D. (2015). A practical guide to robust optimization. *Omega*, *53*, 124–137. https://doi.org/10.1016/j.omega.2014.12.006

Gössling, S. (2020). Integrating e-scooters in urban transportation: Problems, policies, and the prospect of system change. *Transportation Research Part D: Transport and Environment*, *79*, 102230. https://doi.org/10.1016/j.trd.2020.102230

Grabher, G., & van Tuijl, E. (2020). Uber-production: From global networks to digital platforms. *Environment and Planning A: Economy and Space*, *52*(5), 1005–1016. https://doi.org/10.1177/0308518X20916507

Guo, B., Wang, S., Ding, Y., Wang, G., He, S., Zhang, D., & He, T. (2021). Concurrent order dispatch for instant delivery with time-constrained actor-critic reinforcement learning. *2021 IEEE Real-Time Systems Symposium (RTSS)*, 176–187. https://doi.org/10.1109/RTSS52674.2021.00026

Gutiérrez, A., Miravet, D., & Domènech, A. (2021). Covid-19 and urban public transport services: Emerging challenges and research agenda. *Cities & Health*, *5*(sup1), S177–S180. https://doi.org/10.1080/23748834.2020.1804291

Hasturk, U., Schrotenboer, A. H., Ursavas, E., & Roodbergen, K. J. (2024). Stochastic cyclic inventory routing with supply uncertainty: A case in green-hydrogen logistics. *Transportation Science*, *58*(2), 315–339. https://doi.org/10.1287/trsc.2022.0435

Heineke, K., Laverty, N., Ziegler, F., & Möller, T. (2023). The future of mobility [Accessed on 05.10.2024]. https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/the-future-of-mobility-mobility-evolves

Hörcher, D., & Tirachini, A. (2021). A review of public transport economics. *Economics of transportation*, *25*, 100196. https://doi.org/10.1016/j.ecotra.2021.100196

Jaillet, P., & Wagner, M. R. (2010). Online optimization—an introduction. In *Risk and optimization in an uncertain world* (pp. 142–152). INFORMS. https://doi.org/10.1287/educ.1100.0072

Jungel, K., Parmentier, A., Schiffer, M., & Vidal, T. (2023). Learning-based online optimization for autonomous mobility-on-demand fleet control. *arXiv preprint arXiv:2302.03963*. https://doi.org/10.48550/arXiv.2302.03963

Kaspi, M., Raviv, T., & Ulmer, M. W. (2022). Directions for future research on urban mobility and city logistics. *Networks*, *79*(3), 253–263. https://doi.org/10.1002/net.22092

Kavuk, E. M., Tosun, A., Cevik, M., Bozanta, A., Sonu, S. B., Tutuncu, M., Kosucu, B., & Basar, A. (2022). Order dispatching for an ultra-fast delivery service via deep reinforcement learning. *Applied Intelligence*, *52*(4), 4274–4299. https://doi.org/10.1007/s10489-021-02610-0

Ke, J., Yang, H., & Zheng, Z. (2020). On ride-pooling and traffic congestion. *Transportation Research Part B: Methodological*, *142*, 213–231. https://doi.org/10.1016/j.trb.2020.10.003

Klapp, M. A., Erera, A. L., & Toriello, A. (2018). The dynamic dispatch waves problem for same-day delivery. *European Journal of Operational Research*, *271*(2), 519–534. https://doi.org/10.1016/j.ejor.2018.05.032

Kok, A. L., Hans, E. W., & Schutten, J. M. (2012). Vehicle routing under time-dependent travel times: The impact of congestion avoidance. *Computers & operations research*, *39*(5), 910–918. https://doi.org/10.1016/j.cor.2011.05.027

Kool, W., Bliek, L., Numeroso, D., Zhang, Y., Catshoek, T., Tierney, K., Vidal, T., & Gromicho, J. (2022). The euro meets neurips 2022 vehicle routing competition. *NeurIPS 2022 Competition Track*, 35–49.

Kronmueller, M., Fielbaum, A., & Alonso-Mora, J. (2023a). Fleet sizing for the flash delivery problem from multiple depots a case study in amsterdam. *arXiv preprint arXiv:2311.03869*. https://doi.org/10.48550/arXiv.2311.03869

Kronmueller, M., Fielbaum, A., & Alonso-Mora, J. (2023b). Online flash delivery from multiple depots. *Transportation Letters*, *0*(0), 1–17. https://doi.org/10.1080/19427867.2023.2278859

Lagorio, A., Pinto, R., & Golini, R. (2016). Research in urban logistics: A systematic literature review. *International Journal of Physical Distribution & Logistics Management*, *46*(10), 908–931. https://doi.org/10.1108/IJPDLM-01-2016-0008

Laporte, G., Meunier, F., & Wolfler Calvo, R. (2018). Shared mobility systems: An updated survey. *Annals of Operations Research*, *271*, 105–126. https://doi.org/10.1007/s10479-018-3076-8

Law, A. M. (2015). *Simulation modeling & analysis* (5th ed.). McGraw-Hill.

Li, H., & Womer, N. K. (2015). Solving stochastic resource-constrained project scheduling problems by closed-loop approximate dynamic programming. *European Journal of Operational Research*, *246*(1), 20–33. https://doi.org/10.1016/j.ejor.2015.04.015

Li, L., Lo, H. K., & Xiao, F. (2019). Mixed bus fleet scheduling under range and refueling constraints. *Transportation Research Part C: Emerging Technologies*, *104*, 443–462. https://doi.org/10.1016/j.trc.2019.05.009

Lin, Y. H., Wang, Y., He, D., & Lee, L. H. (2020). Last-mile delivery: Optimal locker location under multinomial logit choice model. *Transportation Research Part E: Logistics and Transportation Review*, *142*, 102059. https://doi.org/10.1016/j.tre.2020.102059

Lokhandwala, M., & Cai, H. (2018). Dynamic ride sharing using traditional taxis and shared autonomous taxis: A case study of nyc. *Transportation Research Part C: Emerging Technologies*, *97*, 45–60. https://doi.org/10.1016/j.trc.2018.10.007

Luo, Q., & Saigal, R. (2017). Dynamic pricing for on-demand ride-sharing: A continuous approach. *Available at SSRN 3056498*.

Ma, S., Zheng, Y., & Wolfson, O. (2013). T-share: A large-scale dynamic taxi ridesharing service. *2013 IEEE 29th International Conference on Data Engineering (ICDE)*, 410–421. https://doi.org/10.1109/ICDE.2013.6544843

Mandal, M. P., & Archetti, C. (2023). A decomposition approach to last mile delivery using public transportation systems. *arXiv preprint arXiv:2306.04219*. https://doi.org/10.48550/arXiv.2306.04219

Meisel, S., Suppa, U., & Mattfeld, D. (2011). Serving multiple urban areas with stochastic customer requests. *Dynamics in Logistics: Second International Conference, LDIC 2009, Bremen, Germany, August 2009, Proceedings*, 59–68. https://doi.org/10.1007/978-3-642-11996-5_6

Merchán, D., Arora, J., Pachon, J., Konduri, K., Winkenbach, M., Parks, S., & Noszek, J. (2024). 2021 Amazon last mile routing research challenge: Data set. *Transportation Science*, *58*(1), 8–11. https://doi.org/10.1287/trsc.2022.1173

Nieuwenhuijsen, M. J., & Khreis, H. (2016). Car free cities: Pathway to healthy urban living. *Environment international*, *94*, 251–262. https://doi.org/10.1016/j.envint.2016.05.032

Ortegon-Sanchez, A., Popan, C., & Tyler, N. (2017). Car-free initiatives from around the world: Concepts for moving to future sustainable mobility. *TRB 96th Annual Meeting Compendium of Papers, Washington, DC*.

Osorio, J., Lei, C., & Ouyang, Y. (2021). Optimal rebalancing and on-board charging of shared electric scooters. *Transportation Research Part B: Methodological*, *147*, 197–219. https://doi.org/10.1016/j.trb.2021.03.009

Pohowalla, F., Collins, T., & Chang, J. (2024). Supply chain technology market update [Accessed on 08.09.2024]. https://www.cascadiacapital.com/wp-content/uploads/Supply-Chain-Technology-Winter-Spring-2024.pdf

Powell, W. (2011). *Approximate dynamic programming - solving the curses of dimensionality*. John Wiley & Sons. https://doi.org/10.1002/9781118029176

Powell, W. (2014). Clearing the jungle of stochastic optimization. In *Bridging data and decisions* (pp. 109–137). Informs. https://doi.org/10.1287/educ.2014.0128

Powell, W. (2019). A unified framework for stochastic optimization. *European Journal of Operational Research*, *275*(3), 795–821. https://doi.org/10.1016/j.ejor.2018.07.014

Puterman, M. L. (2014). *Markov decision processes: Discrete stochastic dynamic programming*. John Wiley & Sons. https://doi.org/10.1002/9780470316887

Ritchie, H., & Roser, M. (2018). Urbanization. *Our world in data*. https://ourworldindata.org/urbanization

Santos, D. O., & Xavier, E. C. (2015). Taxi and ride sharing: A dynamic dial-a-ride problem with money as an incentive. *Expert Systems with Applications*, *42*(19), 6728–6737. https://doi.org/10.1016/j.eswa.2015.04.060

Savelsbergh, M., & van Woensel, T. (2016). 50th anniversary invited article—city logistics: Challenges and opportunities. *Transportation Science*, *50*(2), 579–590. https://doi.org/10.1287/trsc.2016.0675

Schiffer, M., Hiermann, G., Rüdel, F., & Walther, G. (2021). A polynomial-time algorithm for user-based relocation in free-floating car sharing systems. *Transportation Research Part B: Methodological*, *143*, 65–85. https://doi.org/10.1016/j.trb.2020.11.001

Simmons, V., Spielvogel, J., Timelin, B., & Tjon Pian Gi, M. (2022). Instant grocery: Will it stay or will it go? [Accessed on 05.07.2024]. *McKinsey Report: The State of Grocery Retail 2022*. https://www.mckinsey.com/industries/retail/our-insights/instant-grocery-will-it-stay-or-will-it-go#

Stiglic, M., Agatz, N., Savelsbergh, M., & Gradisar, M. (2015). The benefits of meeting points in ride-sharing systems. *Transportation Research Part B: Methodological*, *82*, 36–53. https://doi.org/10.1016/j.trb.2015.07.025

Strauss, A. K., Klein, R., & Steinhardt, C. (2018). A review of choice-based revenue management: Theory and methods. *European journal of operational research*, *271*(2), 375–387. https://doi.org/10.1016/j.ejor.2018.01.011

Stumpe, M., Dieter, P., Schryen, G., Müller, O., & Beverungen, D. (2024). Designing Taxi-Ridesharing Systems With Shared Pick-up and Drop-off Locations: Insights From a Computational Study. *Transportation Research Part A: Policy and Practice*, *183*, 104063. https://doi.org/10.1016/j.tra.2024.104063

Stumpe, M., Rößler, D., Schryen, G., & Kliewer, N. (2021). Study on sensitivity of electric bus systems under simultaneous optimization of charging infrastructure and vehicle schedules. *EURO Journal on Transportation and Logistics*, *10*, 100049. https://doi.org/10.1016/j.ejtl.2021.100049

Szczepanski, K. v., Wagener, C., Mooney, T., McDaniel, L., Mathias, O., & Sharp, L. (2021). Only an ecosystem can solve last-mile gridlock in package delivery [Accessed on 08.09.2024]. https://www.bcg.com/publications/2021/solving-the-package-delivery-system-problems-with-a-new-ecosystem

Tafreshian, A., Masoud, N., & Yin, Y. (2020). Frontiers in service science: Ride matching for peer-to-peer ride sharing: A review and future directions. *Service Science*, *12*(2-3), 44–60. https://doi.org/10.1287/serv.2020.0258

Teixeira, J. F., Silva, C., & Moura e Sá, F. (2021). Empirical evidence on the impacts of bikesharing: A literature review. *Transport reviews*, *41*(3), 329–351. https://doi.org/10.1080/01441647.2020.1841328

Topaloglu, H., & Powell, W. (2006). Dynamic-programming approximations for stochastic time-staged integer multicommodity-flow problems. *INFORMS Journal on Computing*, *18*(1), 31–42. https://doi.org/10.1287/ijoc.1040.0079

Ulmer, M. (2019). Anticipation versus reactive reoptimization for dynamic vehicle routing with stochastic requests. *Networks*, *73*(3), 277–291. https://doi.org/10.1002/net.21861

Ulmer, M., Heilig, L., & Voß, S. (2017). On the value and challenge of real-time information in dynamic dispatching of service vehicles. *Business & Information Systems Engineering*, *59*, 161–171. https://doi.org/10.1007/s12599-017-0468-2

Ulmer, M. W., Thomas, B. W., Campbell, A. M., & Woyak, N. (2021). The restaurant meal delivery problem: Dynamic pickup and delivery with deadlines and random ready times. *Transportation Science*, *55*(1), 75–100. https://doi.org/10.1287/trsc.2020.1000

UN. (2019). World urbanization prospects: The 2018 revision. https://population.un.org/wup/Publications/Files/WUP2018-Report.pdf

U.S. Department of Transportation. (2023). Highway statistics 2021 [Accessed on 12.11.2024]. https://www.fhwa.dot.gov/policyinformation/statistics/2021/

Van Heeswijk, W. J., Mes, M. R., & Schutten, J. M. (2019). The delivery dispatching problem with time windows for urban consolidation centers. *Transportation Science*, *53*(1), 203–221. https://doi.org/10.1287/trsc.2017.0773

Voccia, S. A., Campbell, A. M., & Thomas, B. W. (2019). The same-day delivery problem for online purchases. *Transportation Science*, *53*(1), 167–184. https://doi.org/10.1287/trsc.2016.0732

Wallar, A., Alonso-Mora, J., & Rus, D. (2019). Optimizing vehicle distributions and fleet sizes for shared mobility-on-demand. *2019 International Conference on Robotics and Automation (ICRA)*, 3853–3859. https://doi.org/10.1109/ICRA.2019.8793685

Waßmuth, K., Köhler, C., Agatz, N., & Fleischmann, M. (2023). Demand management for attended home delivery—a literature review. *European Journal of Operational Research*, *311*(3), 801–815. https://doi.org/10.1016/j.ejor.2023.01.056

Woerner, S., Laumanns, M., Zenklusen, R., & Fertis, A. (2015). Approximate dynamic programming for stochastic linear control problems on compact state spaces. *European Journal of Operational Research*, *241*(1), 85–98. https://doi.org/10.1016/j.ejor.2014.08.003

Yan, C., Zhu, H., Korolko, N., & Woodard, D. (2020). Dynamic pricing and matching in ride-hailing platforms. *Naval Research Logistics (NRL)*, *67*(8), 705–724. https://doi.org/10.1002/nav.21872

Yang, B., Ren, S., Legara, E. F., Li, Z., Ong, E. Y., Lin, L., & Monterola, C. (2020). Phase transition in taxi dynamics and impact of ridesharing. *Transportation Science*, *54*(1), 250–273. https://doi.org/10.1287/trsc.2019.0915

Yang, X., Strauss, A. K., Currie, C. S., & Eglese, R. (2016). Choice-based demand management and vehicle routing in e-fulfillment. *Transportation Science*, *50*(2), 473–488. https://doi.org/10.1287/trsc.2014.0549

Zeltyn, S., Marmor, Y. N., Mandelbaum, A., Carmeli, B., Greenshpan, O., Mesika, Y., Wasserkrug, S., Vortman, P., Shtub, A., Lauterman, T., et al. (2011). Simulation-based models of emergency departments: Operational, tactical, and strategic staffing. *ACM Transactions on Modeling and Computer Simulation (TOMACS)*, *21*(4), 1–25. https://doi.org/10.1145/2000494.2000497

Zhang, W., & Ukkusuri, S. V. (2016). Optimal fleet size and fare setting in emerging taxi markets with stochastic demand. *Computer-Aided Civil and Infrastructure Engineering*, *31*(9), 647–660. https://doi.org/10.1111/mice.12203

Zhou, Y., Lin, Z., Guan, R., & Sheu, J.-B. (2023). Dynamic battery swapping and rebalancing strategies for e-bike sharing systems. *Transportation Research Part B: Methodological*, *177*, 102820. https://doi.org/10.1016/j.trb.2023.102820