Optimization Approaches for Sustainable Public Transportation

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Miriam Stumpe
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List of Abbreviations

ALNS	Adaptive Large Neighborhood Search
BEB	Battery Electric Bus
CLEVSP	Charging Location and Electric Vehicle Scheduling Problem
EB	Electric Bus
EVSP	Electric Vehicle Scheduling Problem
GA	Genetic Algorithm
HFCB	Hydrogen Fuel Cell Bus
ICT	Information and Communications Technology
ILP	Integer Linear Program
LCC	Life Cycle Cost
MILP	Mixed Integer Linear Program
MIP	Mixed Integer Program
ODR	On-Demand Ridesharing
OR	Operations Research
P2P	Peer to Peer
PT	Public Transportation
SDG	Sustainable Development Goal
TCO	Total Cost of Ownership
TRS	Taxi Ridesharing
UN	United Nations
VNS	Variable Neighborhood Search
VSP	Vehicle Scheduling Problem

Part I

Introduction

1 Motivation

The rapid pace of urbanization in recent decades has led to a growing demand for urban mobility. According to the United Nations (UN), more than 55% of the world's population resides in cities nowadays, a trend that is expected to continue (UN, 2019). As a consequence, transportation networks in urban environments face significant challenges, ranging from economic and social pressures to environmental concerns (Sultana et al., 2019). Among the most pressing of these issues are the rising levels of congestion and pollution, primarily due to the heavy reliance on private automobiles for commuting and travel (Ceder, 2021). These challenges have profound implications for quality of life in urban centers, contributing to air quality deterioration, increased greenhouse gas emissions, and inefficient use of space and resources (Shah et al., 2021).

Public transportation (PT), long considered a key solution to these challenges, plays a critical role in reducing dependence on private vehicles and mitigating congestion and emissions. Studies highlight the need to transition from auto-dependence to more sustainable urban mobility solutions, with public transportation reducing per capita energy use, emissions, and traffic congestion (Winkler et al., 2023). Traditionally, public transportation referred to systems with fixed routes and schedules, like buses, light rail, and metros, while paratransit described more flexible, on-demand services such as taxis and dial-a-ride. Today, both traditional PT and paratransit are recognized as public transportation systems, defined broadly as transport available for public use, in contrast to private modes (Ceder, 2021; Vuchic, 2007). In this context, sustainable public transportation emerges as a cornerstone of urban development, addressing the three pillars of sustainability by offering equitable mobility options, fostering environmental preservation, and contributing to economic resilience in cities (Miller et al., 2016).

Driven by the UN's Sustainable Development Goals (SDGs), particularly SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action), two key trends are shaping the future of public transportation: decarbonization and flexibility (Cao et al., 2024; Kuo et al., 2023). Specifically, SDG 11 emphasizes creating inclusive, safe, resilient, and sustainable urban environments, while SDG 13 focuses on urgent actions to combat climate change and its impacts (UN, 2015). Public transportation systems, ranging from light rail and metro services to traditional buses, are evolving in response to the SDGs, with emerging modes like Electric Bus (EB) systems and On-Demand Ridesharing (ODR) systems. EB systems are recognized for their decarbonization potential and suitability for high-demand routes (Manzolli et al., 2022), while ODR systems offer flexibility and enhance first-mile/last-mile connectivity in areas where fixed-route services are not practical (Zhu et al., 2023). As such, these two systems have been selected as normative representatives in this thesis due to their growing relevance in addressing urban sustainability challenges, and their increasing prominence in discussions on sustainable urban public transportation.

Electric buses, including Battery Electric Buses (BEBs) and Hydrogen Fuel Cell Buses

(HFCBs), are key solutions for reducing emissions and reliance on fossil fuels in public transportation. Both eliminate local CO_2 and NO_x emissions and reduce noise pollution compared to diesel buses (Muñoz et al., 2022). HFCBs offer longer range and faster refueling, but their high procurement costs and reliance on a decarbonized hydrogen supply chain limit widespread adoption (Ajanovic et al., 2021). BEBs, by contrast, are more widely adopted due to lower costs and higher energy efficiency (Deliali et al., 2021; Hensher et al., 2022). However, BEBs have disadvantages such as limited range, long charging times, and the need for sufficient charging infrastructure (J.-Q. Li, 2016). Optimization approaches for the design and operation of battery electric bus systems are therefore critical to overcoming these issues and enhancing their sustainability.

On-demand ridesharing, on the other hand, provides flexible transportation by enabling passengers to book shared rides in real time through mobile applications, meaning bookings are handled instantly rather than requiring advance scheduling (Zhu et al., 2023). Leveraging modern Information and Communication Technologies (ICT), these services include ridesourcing, taxi ridesharing and microtransit. Ridesourcing connects passengers with drivers of personal vehicles like Uber and Lyft, taxi ridesharing, allows multiple passengers to share a taxi on similar routes and microtransit employs small customized buses with flexible schedules based on real-time demand (Shaheen & Cohen, 2019). These services can offer advantages such as improved accessibility and convenience compared to traditional public transport, while decreasing the number of trips taken by private cars (Alonso-González et al., 2018). However, the dynamic nature of on-demand ridesharing systems presents challenges, including long detours and inefficient vehicle utilization due to fluctuating demand (Agatz et al., 2012). Therefore, optimization approaches for the design and operation of on-demand ridesharing systems are essential to address these issues and ensure that they support sustainable public transportation.

This thesis explores decision problems municipalities and transport operators face in the design and operation of BEB and ODR systems, all arising from the goal of achieving sustainable public transportation. Adopting a prescriptive approach, it provides optimization models to guide these decisions, in contrast to descriptive or predictive approaches, which focus on understanding or forecasting trends. Therefore, the overarching objective of this thesis is the following:

Development and application of optimization approaches for the design and operation of sustainable urban public transportation systems, with a specific focus on battery electric buses and on-demand ridesharing.

The thesis is organized into three main parts. Part I is the introduction, which provides the motivation and includes two additional chapters. Chapter 2 offers background information on battery electric bus systems and on-demand ridesharing. Chapter 3 presents an overview of the research papers included in this thesis, highlighting their individual contributions to the overall research objective. The full papers are provided in Part II, which comprises five chapters, with Chapter 4 to 6 dedicated to battery electric bus systems and Chapters 7 and 8 to on-demand ridesharing. Part III, the conclusion, summarizes the key findings across all research papers in Chapter 9, points out implications for research and practice in Chapter 10, and concludes with an outlook on future research in Chapter 11.

2 Background

This chapter provides an overview of the background on battery electric bus systems and on-demand ridesharing, focusing on key planning problems, modeling aspects, and common solution methods in both domains. The aim is to identify research gaps in each area, highlighting how they relate to the optimization problems addressed in this thesis. Each section ends with a research question that ties to the primary objective of developing optimization approaches for sustainable urban public transportation.

2.1 Battery Electric Bus Systems

Traditionally, research on urban bus networks has focused on planning transportation systems with diesel buses, establishing an important domain in Operations Research (OR) (Perumal et al., 2022). Since the entire bus planning process is computationally intractable and cannot be solved in a single step, it is typically broken down into several sub-problems, each tackled sequentially (Desaulniers & Hickman, 2007). As Ibarra-Rojas et al. (2015) outline, these sub-problems include *transit network design*, which defines the layout of lines and the space between stops to minimize operator and user costs; *timetabling*, which determines arrival and departure times at each stop to align with demand patterns, optimize transfers, and minimize waiting times; *vehicle scheduling*, which assigns vehicles to cover planned trips efficiently; *crew scheduling*, which creates daily duties that meet all trip requirements while minimizing labor costs and adhering to regulations on work hours and breaks; and *crew rostering*, which assigns generic duties to available drivers over a longer period (e.g., monthly) to minimize wage costs while ensuring regulatory compliance. The frequency with which these problems are executed increases, from long-term tasks like transit network design, updated every few years, to tasks like crew scheduling and rostering, carried out multiple times a year.

Battery electric buses introduce several restrictions compared to diesel buses, including limited range, long recharging times, and the need for specialized charging infrastructure. As a result, the traditional bus planning process requires significant adaptation. This is highlighted in the reviews by Perumal et al. (2022) on electric bus scheduling and by Zhou et al. (2024) on charging infrastructure planning. The impact on the planning process varies depending on the chosen charging technology (Häll et al., 2019).

Currently, there are four main technologies in use for charging electric buses (Zhou et al., 2024). One option is *overnight charging* at bus depots, where buses are slowly recharged using plug-in chargers. Another approach, called *opportunity charging*, employs fast plug-in or pantograph chargers at terminals or bus stops, enabling buses to top up their batteries quickly during brief stops. *Battery swapping* offers a different solution by replacing discharged batteries with fully charged ones, minimizing downtime. Additionally, some systems use *in-motion charging*, allowing buses to recharge while driving through overhead contact lines or wireless inductive chargers embedded in the

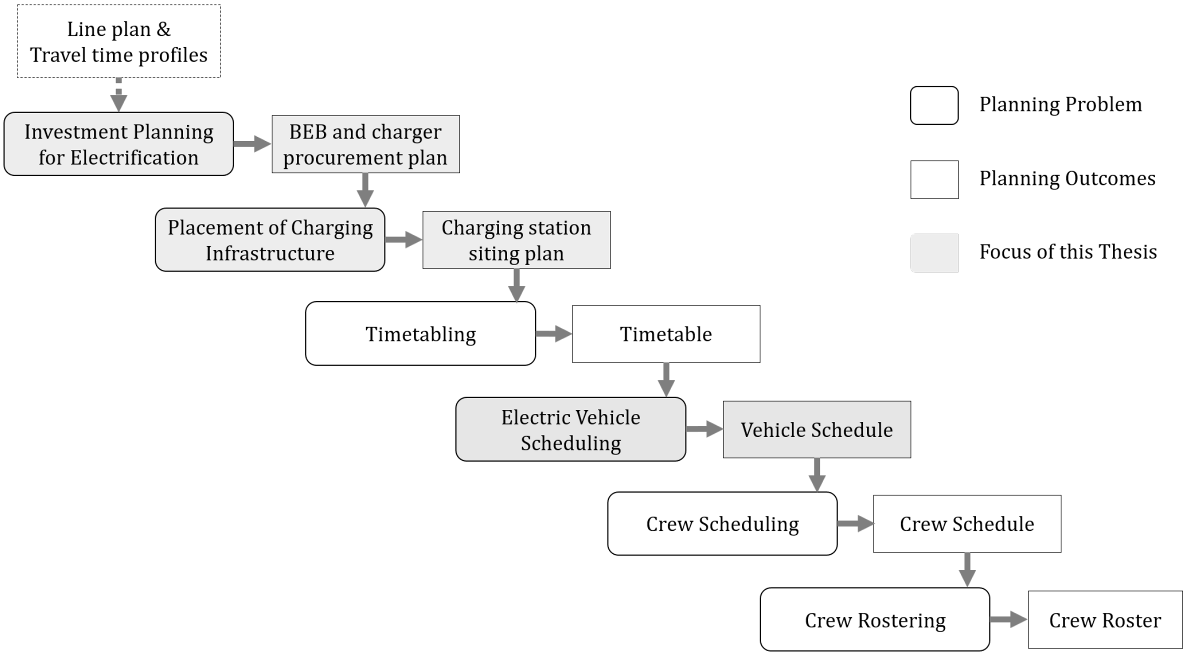

Figure 2.1: Electric bus planning process

road. Due to their lower upfront costs compared to battery swapping or in-motion charging, overnight and opportunity charging systems dominate the market (Zhou et al., 2024) and will be the focus of this thesis. However, it is worth noting that the OR literature also includes some optimization studies on battery swapping (e.g. An et al., 2020) and in-motion charging (e.g. Z. Liu & Song, 2017). Further research on cost comparisons provides insight into the cost competitiveness of the different charging concepts. Chen et al. (2018), for instance, compare all four charging technologies, while Lajunen (2018) specifically analyze overnight and opportunity charging.

The planning process for BEBs with overnight and opportunity charging differs from the traditional process by introducing two new planning problems: *investment planning for electrification* and *placement of charging infrastructure*. It also extends vehicle scheduling to the *electric vehicle scheduling problem*, incorporating charging times and limited driving range. Figure 2.1 illustrates the resulting sequential planning process, similar to that proposed by Perumal et al. (2022), and highlights three key planning problems – marked in grey – that are central to BEBs and this thesis.

Investment Planning for Electrification The electrification of a bus network requires developing a multi-period procurement strategy for electric buses and charging infrastructure, primarily due to the high upfront costs, which exceed the bus operators' annual budget. Respective planning problems can be categorized as fleet replacement problems, where decisions are made regarding the purchase or leasing of vehicles over a specified planning horizon (Pelletier et al., 2019). These problems use transit network design outputs – such as the line plan and travel times – to develop a gradual transformation strategy for BEB and charger procurement. Early studies incorporating electric vehicles focus primarily on the timing and quantity of electric bus purchases, often ignoring or making simplifying assumptions regarding the procurement of charging facilities (Islam & Lownes, 2019; L. Li et al., 2018; Pelletier et al., 2019). Additionally, many studies incorporate Total Cost of Ownership (TCO) and Lifecycle Cost (LCC) approaches to provide a comprehensive analysis of the long-term costs associated with electric vehicle fleets (Dirks et al., 2022; Islam & Lownes, 2019). These methods account for not only the initial purchase price but also other cost components, such as maintenance and operation costs, which are considered over the entire lifespan of the vehicles and infrastructure, enabling a more holistic view of the financial impacts over long planning horizons.

In general, pure fleet replacement planning problems can be optimally solved for large-scale, real-world applications using standard methods. Consequently, the state-of-the-art solution approach in addressing these kinds of problems, as seen across all cited studies, involves formulating a model – most often an Integer linear Program (ILP) or Mixed Integer Linear Program (MILP) – that is subsequently solved with standard optimization software.

Placement of Charging Infrastructure Determining the optimal placement of charging infrastructure is a key challenge, particularly for opportunity charging, as overnight charging infrastructure is typically located exclusively in bus depots. This involves decisions on charger numbers, locations, and technical configurations to meet the charging demand from the BEB procurement plan and the timetable or vehicle schedule. Candidate locations for installing charging infrastructure are usually bus stops along the bus lines or terminal bus stops. Most studies focus on single-period planning, developing optimization models that involve both electric and non-electric buses (Hsu et al., 2021; Xylia et al., 2017), or address battery capacity sizing (He et al., 2019; Kunith et al., 2017). More recent work addresses uncertainties concerned with time-of-use electricity prices, battery degradation, variable energy consumption (An, 2020; Azadeh et al., 2022; Zhou, Ong, Meng, & Cui, 2023). Another aspect explored in this research stream is the impact of power grid restrictions on the placement of charging infrastructure (Guschinsky et al., 2021; Lin et al., 2019).

Charging infrastructure placement is typically addressed by formulating optimization models, which are solved using standard solvers. Recent studies develop more problem-specific approaches, such as two-stage stochastic programming to handle uncertainties in travel time and battery degradation (Zhou, Ong, Meng, & Cui, 2023), or Lagrangian relaxation for optimizing decisions under time-of-use electricity pricing (An, 2020).

Electric Vehicle Scheduling Building upon the traditional Vehicle Scheduling Problem (VSP), the electric vehicle scheduling problem (EVSP) incorporates additional constraints specific to electric buses, such as limited driving range, charging requirements, and recharging times. Similar to the VSP, the EVSP considers features like multiple depots, multiple vehicle types, and route constraints like maximum route durations. The primary objective of the EVSP is to determine a minimum-cost schedule that assigns each timetabled trip to a suitable vehicle while ensuring all operational and resource constraints, including those imposed by pre-defined charging infrastructure, are met

(Reuer et al., 2015). However, the combinatorial nature of the EVSP leads to significant complexity. As demonstrated by Bodin and Golden (1981), any path-length-constrained VSP is NP-hard – including the EVSP. Consequently, early approaches to the EVSP rely on several simplifying assumptions to keep the problem computationally manageable. They include fixed recharging durations, full charges only, and a linearized battery charging behavior (Adler & Mirchandani, 2017; Chao & Xiaohong, 2013; H. Wang & Shen, 2007). While these assumptions enabled early progress, they limit practical applicability by neglecting real-world factors like partial and non-linear charging. Recent advancements now account for these issues (T. Liu & Ceder, 2020; Olsen & Kliewer, 2020; van Kooten Niekerk et al., 2017).

A wide array of solution approaches has been developed for the EVSP, extending classical VSP methods to address the added complexities of electric fleets. Exact methods, such as mixed integer programming and column generation, have been applied, particularly for small to medium problem instances (e.g. Janovec & Kohàni, 2019; J.-Q. Li, 2014). Expanding upon its use in the VSP, the column generation method has been refined to address larger EVSP instances, as demonstrated by van Kooten Niekerk et al. (2017). However, to improve scalability, several heuristic and metaheuristic approaches are developed. Olsen et al. (2022) present a decomposition heuristic, building on an exact method for the VSP, to efficiently solve large EVSP instances with up to 10,000 trips. The approach combines an aggregated time-space network, flow decomposition methods, and a novel algorithm for incorporating charging procedures. In addition to local search methods, population based methods increase in popularity to solve complex EVSP problems. While Wen et al. (2016) introduce an Adaptive Large Neighborhood Search (ALNS) for partial recharging and multi-depot scenarios, genetic algorithms (GAs) are commonly used, as shown by Rogge et al. (2018) and Yao et al. (2020).

Research gap: Need for Integrated Planning Approaches Fleet replacement, charging infrastructure placement, and vehicle scheduling are interdependent but often treated separately, leading to suboptimal outcomes. For example, investment decisions affect the timing and availability of charging infrastructure, while charging infrastructure directly impacts vehicle scheduling. In turn, vehicle scheduling influences the number of buses and chargers needed for the electrification of the bus network. Some studies, such as Rogge et al. (2018), integrate vehicle scheduling and charging infrastructure planning, but focus solely on depot charging and take a single-period approach. Others, like He et al. (2023), Zhou, Ong, and Meng (2023), and Lin et al. (2019), explore multi-period investment planning and charging infrastructure placement, but exclude vehicle scheduling. However, a holistic approach that accounts for the interdependencies of all three problems – ensuring an efficient transition by minimizing costs and resources, while enabling a gradual transition through a multi-period approach – is still lacking. This gap leads to the first central research question of this thesis:

RQ1: *How can optimization approaches integrate investment planning, placement of charging infrastructure and electric vehicle scheduling to ensure an efficient, gradual transition to a fully electrified bus network?*

2.2 On-Demand Ridesharing

Ridesharing refers to a transportation mode where multiple travelers share a vehicle for a trip and split associated costs, such as fuel and toll fees, while traveling along similar itineraries. At its core, ridesharing seeks to combine the flexibility and speed of private cars with the reduced costs of fixed-line systems (Furuhata et al., 2013). The practice originated informally, with *Carpooling* emerging during fuel crises in the mid-20th century, as a way for peers or employees to share regular, recurring trips, often taking turns driving each other to work (Chan & Shaheen, 2012). Over the years, advances in ICT, particularly mobile apps and GPS, have enabled on-demand ridesharing systems. These systems allow real-time matching of passengers and drivers with minimal pre-arrangement. Unlike traditional systems that require prior coordination, on-demand ridesharing adjusts to participants' needs as they arise, offering greater flexibility (Agatz et al., 2012). On-demand ridesharing systems include various types, with Peer-to-Peer Ridesharing (P2P) and Taxi Ridesharing being among the most flexible, operating without preplanned routes or schedules (Shaheen & Cohen, 2019). *Peer-to-Peer Ridesharing* involves drivers sharing personal trips with passengers on similar routes while traveling to their own destinations. A matching platform connects drivers and passengers in real time, making it a two-sided matching system. *Taxi Ridesharing*, on the other hand, involves a central operator who owns the vehicles and manages the drivers. It is a one-sided matching system that connects passengers with available taxis, allowing multiple ride requests to be served by the same vehicle at the same time (Tafreshian et al., 2020).

The main planning problem in on-demand ridesharing is efficiently matching requests to available rides, i.e., optimizing waiting times and vehicle utilization, with two key challenges: First, the dynamic nature of incoming requests, where ride requests arrive unpredictably throughout the day. Unlike static systems, which rely on pre-arranged schedules, dynamic systems must process ride requests as they arrive. This introduces a significant computational challenge, as decisions must balance responsiveness with overall system efficiency (Ulmer et al., 2017). Second, long detours caused by sharing rides while offering a door-to-door service. The first challenge is handled through two types of solution approaches – rolling horizon and event-based methods. In rolling horizon approaches, requests are handled in batches, whereas event-based methods respond to requests as they come in. To tackle the second challenge, meeting points are introduced, requiring clients to walk short distances to join rides. Accordingly, literature on dynamic ride-matching can be structured along these two dimensions, as shown in Figure 2.2. The gray areas highlight research on ridesharing with meeting points, which is central to this thesis. The following section presents the literature in more detail based on these two dimensions.

Rolling Horizon Approaches for Door-to-Door Ridesharing One common approach to address dynamically incoming requests is the use of rolling-horizon optimization. In this method, customer requests are collected over a predefined time window, or horizon, and processed in batches. This enables the grouping of compatible requests and allows to optimize assignments. However, the effectiveness of rolling-horizon approaches depends on the selection of key parameters like time window length and the computation

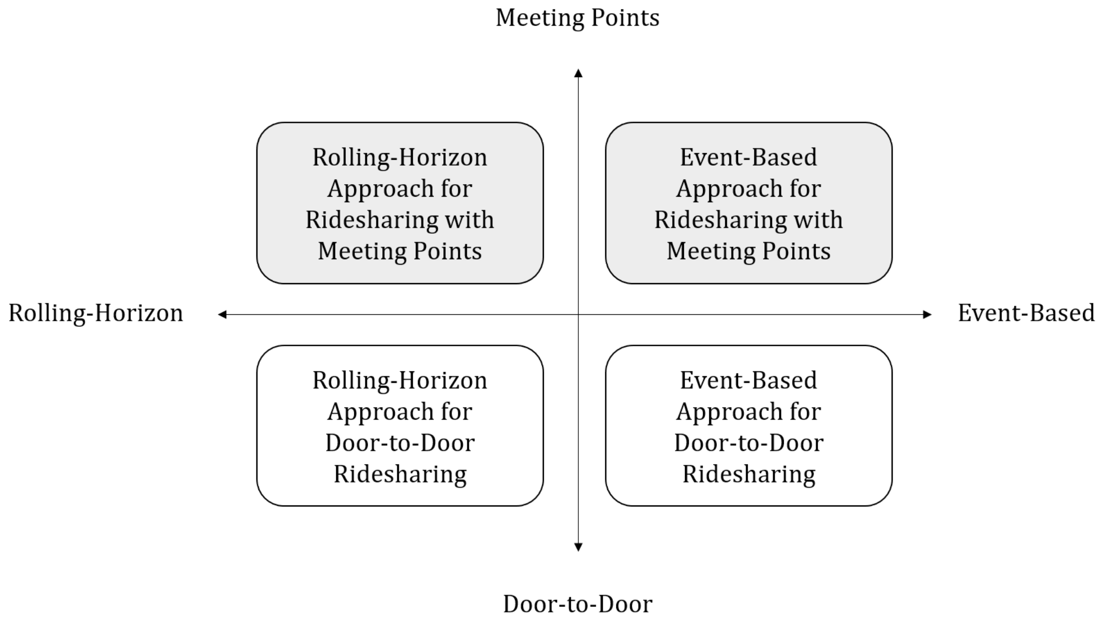

Figure 2.2: Approaches for on-demand ridesharing

time for each batch, typically solved with standard solvers.

Several prominent studies have explored this method for door-to-door ridesharing, where passengers are picked up and dropped off exactly at their specified locations. For instance, Najmi et al. (2017) focus on minimizing vehicle miles traveled by postponing trip confirmations as late as possible, thereby maximizing the opportunity for new requests to be incorporated into existing matches. Other approaches prioritize responsiveness by optimizing earlier, with more frequent re-optimization cycles, to reduce passenger wait times (Agatz et al., 2011) or optimize matching time intervals using reinforcement learning to balance efficiency and responsiveness (Qin et al., 2021). Some studies, such as X. Wang et al. (2018) and Kucharski and Cats (2020), focus on two-sided matching in P2P ridesharing, where routing is handled implicitly by matching customer requests to predefined shared routes, considering driver-passenger preferences and route compatibility. In contrast, methods for one-sided systems like taxi ridesharing, as developed by Santi et al. (2014) and Alonso-Mora et al. (2017), focus on optimizing fleet utilization and minimizing idle vehicle time.

Event-Based Approaches for Door-to-Door Ridesharing To manage continuously arriving ride requests, event-based approaches for ridesharing trigger a planning operation whenever a new request is received. Unlike rolling-horizon methods, which process requests in batches over predefined intervals, event-based systems prioritize immediate responsiveness. This characteristic ensures that passengers receive rapid feedback on ride availability, enhancing user satisfaction and service perception. The core advantage of event-based approaches lies in their ability to quickly match passengers with vehicles by leveraging advanced computational structures. For instance, Ma et al. (2014) accelerate the matching process in a taxi ridesharing system by utilizing spatiotemporal indices, which efficiently organize and query the locations of available vehicles. However, a key challenge of event-based approaches lies in making well-informed decisions without the extensive data collection typical of rolling-horizon methods. In practice, ridesharing systems often use myopic decision rules, such as matching requests with the nearest vehicles, but these strategies can lead to suboptimal matching due to imbalanced and time-varying demand (Hyland & Mahmassani, 2018; Özkan & Ward, 2020).

To address this, ride-matching methods have been evolved from reactive to proactive approaches. Reactive approaches make decisions based only on current information, while proactive methods anticipate future demand or travel patterns to improve system efficiency. For instance, Masoud and Jayakrishnan (2017) propose a dynamic programming algorithm to determine the best itinerary for riders in P2P ridesharing, modeling feasible travel options over time for context-aware assignments – an example of a more proactive approach. Similarly, Yu and Shen (2019) present an integrated decomposition and approximate dynamic programming approach to match multiple passenger requests and vehicles efficiently, considering future states, which also leans towards proactive planning. Another promising approach involves using high-quality demand predictions to optimize real-time system throughput, as shown in Van Engelen et al. (2018), improving performance by proactively predicting demand patterns. Although effective in fields like meal delivery (Ulmer et al., 2021), so far, anticipatory strategies have seen limited application in dynamic ride matching.

Ridesharing with Meeting Points Traditional ridesharing systems typically offer door-to-door service, which is convenient for passengers but often leads to significant inefficiencies due to long detours and extended vehicle travel times. Meeting points have emerged as a practical alternative to mitigate these inefficiencies. By requiring passengers to walk to shared pick-up and drop-off locations, meeting points reduce vehicle detours and improve the opportunities for consolidating requests into shared rides (Barann et al., 2017).

The concept of meeting points was first introduced in the context of two-sided matching systems. Several studies, such as Stiglic et al. (2015) and Qian et al. (2017) demonstrated that incorporating even small walking distances into ridesharing models can significantly reduce vehicle travel distances and improve overall system performance. However, these studies generally assume a static setting where all demand is known in advance and do not involve dynamic decision-making. As a result, they cannot be classified into either the rolling-horizon or event-based categories, which are dynamic approaches to handling requests. Research on dynamic approaches in this context remains limited, though a few studies explore dynamic settings for ridesharing with meeting points, such as a rolling-horizon method proposed by Fielbaum et al. (2021) and an event-based approach introduced by Lotze et al. (2022).

Research gap: Ride matching for on-demand ridesharing with meeting points Despite their advantages, the integration of meeting points introduces new trade-offs that must be carefully managed. These include balancing passenger walking distances against vehicle travel time savings and ensuring that meeting points are accessible and equitably distributed across the service area. The dynamic nature of ride matching further complicates this problem, as meeting point assignments must adapt to real-time changes in demand and system conditions. In particular, decisions need to balance responsiveness, ensuring passengers receive timely ride assignments, and efficiency, which involves optimizing waiting times of passengers and utilization of vehicles. Understanding these trade-offs and designing effective strategies for their management remains an important area of research, resulting in the second central research question of this thesis:

RQ2: *How can optimization approaches for ride matching in an on-demand ridesharing system with meeting points be designed to ensure system efficiency and responsiveness, considering both rolling-horizon and event-based approaches?*

3 Overview of Research Papers

This thesis comprises five research papers. These papers are organized according to the two primary research questions presented above. The first three papers address topics within the field of battery electric bus systems, contributing to the first research question. The fourth and fifth papers focus on the field of on-demand ridesharing, aligning with the second research question. A summary of each paper follows below, and Table 3.1 provides an overview, followed by a list of the included research papers.

Paper 1. *Study on Sensitivity of Electric Bus Systems under Simultaneous Optimization of Charging Infrastructure and Vehicle Schedules.* This paper addresses the simultaneous optimization of charging infrastructure placement and electric vehicle scheduling for battery electric bus systems with opportunity charging technology. Recognizing the intertwined nature of these planning problems, the study introduces a new mathematical model that integrates both aspects. To tackle the challenge of solving large-scale problem instances, a VNS-based heuristic is employed, enabling the computation of solutions for realistic problem sizes and providing a foundation for detailed experimental analysis. Sensitivity analysis is conducted through numerical experiments using real-world data. The experiments demonstrate that persistent structures for charging locations cannot be identified through a priori analysis of the problem instances, highlighting the necessity of simultaneous optimization. Additionally, the results reveal that the configuration of electric bus systems is highly sensitive to changes in parameters, such as battery capacity and energy consumption. To sum up, this paper contributes to RQ1 by employing a heuristic approach that incorporates problem-specific neighborhood operators to simultaneously solve the interdependent planning problems of charging infrastructure placement and electric vehicle scheduling for battery electric bus systems.

Paper 2. *A New Mathematical Formulation for the Simultaneous Optimization of Charging Infrastructure and Vehicle Schedules for Electric Bus Systems.* This paper presents a new MILP formulation for the simultaneous optimization of charging infrastructure placement and electric vehicle schedules, referred to as the Charging Location and Electric Vehicle Scheduling Problem (CLEVSP). The proposed MILP, building on the model from Paper 1, incorporates a two-index formulation based on the assumption of a homogeneous vehicle fleet. This formulation significantly enhances the model's scalability, making it solvable for real-world instances in small and medium-sized cities. It provides near-optimal solutions while allowing for the estimation of solution quality. Computational experiments show that the model, solved with Gurobi optimization software, is competitive with state-of-the-art methods for CLEVSP, such as the previously mentioned VNS, even for instances with several thousand service trips. However, the experiments demonstrate that the model's convergence behavior is highly sensitive to problem difficulty, which is influenced not only by the number of service trips but also by the available battery capacity of the electric buses. To sum up, this paper contributes to RQ1 by developing an exact approach for the integration of charging location placement and electric vehicle scheduling.

Paper 3. *Gradual Transition to Zero-Emission Bus Systems: Impact of Vehicle Scheduling on Charging Infrastructure and Fleet Replacement.* This paper proposes a holistic framework for the gradual transition to fully electrified bus networks, focusing on three key planning problems: investment planning for electrification, charging infrastructure placement, and electric vehicle scheduling. The framework employs a two-phase solution approach: first, solving the CLEVSP to generate vehicle schedules for full electrification; second, tackling the multi-period investment planning problem to minimize the total cost of ownership for the gradual transition. Computational experiments show that solving CLEVSP produces vehicle schedules that outperform traditional methods, guaranteeing full electrification and significant cost savings. The results highlight that vehicle rotations with long distances and sufficient idle time are prioritized for electrification, enabling earlier emission reductions and cost savings. To sum up, this paper contributes to RQ1 by developing a comprehensive framework that aligns vehicle scheduling with charging infrastructure placement and investment strategies to support a cost-efficient transition to the fully electrified bus networks.

Paper 4. *Designing Taxi Ridesharing Systems with Shared Pick-up and Drop-off Locations: Insights from a Computational Study.* This study explores the design of a rolling-horizon approach for dynamic ride-matching in taxi ridesharing systems with shared pick-up and drop-off locations, where customers might be required to walk a short distance from their origin/to their destination. A mathematical model is formulated, and computational experiments using real-world data from New York City and Porto are conducted. The experiments employ the rolling-horizon approach to study the effects of environmental and design factors on rejections, sharing rates, and service quality. Practical guidelines for TRS design are provided, focusing on leveraging extended waiting times to reduce rejection rates and increase sharing. To sum up, this paper contributes to RQ2 by applying a rolling-horizon approach to derive design guidelines for efficient ride-matching in a taxi ridesharing system with meeting points.

Paper 5. *Anticipatory Assignment of Passengers to Meeting Points for Taxi-Ridesharing.* This paper presents an event-based, anticipatory solution method for dynamic ride-matching in a taxi ridesharing system with meeting points, focusing on the assignment of customers to these meeting points to maximize the distance saved through sharing. The problem is modeled as a sequential decision process, and computational experiments using real-world data show that the proposed method significantly increases the saved distance and reduces CO_2 emissions compared to a myopic benchmark policy. Parameter analysis demonstrates that anticipatory methods further enhance the economic and ecological advantages of ridesharing. To sum up, this paper contributes to RQ2 by developing an event-based approach for dynamic ride-matching in a taxi ridesharing system with meeting points.

Table 3.1: Overview of research papers

RQ 1: How can optimization approaches integrate investment planning, placement of charging infrastructure and electric vehicle scheduling to ensure an efficient, gradual transition to a fully electrified bus network?			
No.	**Title**	**Authors**	**Outlet**
P1	Study on Sensitivity of Electric Bus Systems under Simultaneous Optimization of Charging Infrastructure and Vehicle Schedules	**Miriam Stumpe**, David Rößler-von Saß, Guido Schryen, Natalia Kliewer	EURO Journal on Transportation and Logistics
P2	A New Mathematical Formulation for the Simultaneous Optimization of Charging Infrastructure and Vehicle Schedules for Electric Bus Systems	**Miriam Stumpe**	Transportation Research Procedia
P3	Gradual Transition to Zero-Emission Bus Systems: Impact of Vehicle Scheduling on Charging Infrastructure and Fleet Replacement	**Miriam Stumpe**, David Rößler-von Saß, Natalia Kliewer, Guido Schryen	Under Review at EURO Journal on Transportation and Logistics
RQ 2: How can optimization approaches for ride matching in an on-demand ridesharing system with meeting points be designed to ensure system efficiency and responsiveness, considering both rolling-horizon and event-based approaches?			
No.	**Title**	**Authors**	**Outlet**
P4	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	Transportation Research Part A: Policy and Practice
P5	Anticipatory Assignment of Passengers to Meeting Points for Taxi-Ridesharing	Peter Dieter, **Miriam Stumpe**, Marlin Ulmer, Guido Schryen	Transportation Research Part D: Transport and Environment

Research Papers

P1 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

P2 Stumpe, M. (2024). A new mathematical formulation for the simultaneous optimization of charging infrastructure and vehicle schedules for electric bus systems. *Transportation Research Procedia*, *78*, 402–409. https://doi.org/10.1016/j.trpro.2024.02.051

P3 Stumpe, M., Rößler, D., Kliewer, N., & Schryen, G. (2024). Gradual transition to zero-emission bus systems: Impact of vehicle scheduling on charging infrastructure and fleet replacement. *Under Review at EURO Journal on Transportation and Logistics*

P4 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*. https://doi.org/10.1016/j.tra.2024.104063

P5 Dieter, P., Stumpe, M., Ulmer, M. W., & 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

Part II

Research Papers

4 Study on Sensitivity of Electric Bus Systems under Simultaneous Optimization of Charging Infrastructure and Vehicle Schedules

Abstract: The transition from traditional fuel-based bus transportation towards electric bus systems is regarded as a beacon of hope for emission-free public transport. In this study, we focus on battery electric bus systems, in which charging is possible at a variety of locations distributed at terminal stations over the entire bus network. In such systems, two intertwined planning problems to be considered are charging location planning and electric vehicle scheduling. We account for the interdependent nature of both planning problems by adopting a simultaneous optimization perspective. Acknowledging the existence of parameter uncertainty in such complex planning situations, which is rooted in potential changes of values of several environmental factors, we analyze the solution sensitivity to several of these factors in order to derive methodological guidance for decision makers in public transportation organizations. Based on the formulation of a new mathematical model and the application of a variable neighborhood search metaheuristic, we conduct sensitivity analysis by means of numerical experiments drawing on real-world data. The experiments reveal that it is not possible to identify persistent structures for charging locations by an a priori analysis of the problem instances, so that rather a simultaneous optimization is necessary. Furthermore, the experiments show that the configuration of electric bus systems reacts sensitively to parameter changes.

Keywords: Electric bus system; Sensitivity analysis; Charging station location; Variable neighborhood search; Simultaneous optimization

Full Citation: 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

5 A New Mathematical Formulation for the Simultaneous Optimization of Charging Infrastructure and Vehicle Schedules for Electric Bus Systems

Abstract: This paper presents a new mixed integer program (MIP) formulation for the Charging Location and Electric Vehicle Scheduling Problem (CLEVSP). The CLEVSP aims at minimizing the investment costs for charging infrastructure and electric buses as well as the operational costs resulting from the vehicle schedule of an electric bus system applying opportunity charging. Leveraging the assumption of a homogeneous vehicle fleet, the presented MIP is based on two-index decision variables for vehicle scheduling. The formulation allows finding near-optimal solutions for real-world instances of small and medium-sized cities and estimating their solution quality. The computational experiments show that the model, when solved with the Gurobi optimization software, is competitive with state-of-the-art solution methods for the CLEVSP even for problem instances with several thousand service trips. The model's convergence behavior strongly depends on the difficulty of the problem, which is not only influenced by the number of service trips but also by the available battery capacity of the electric buses.

Keywords: Electric bus; Charging infrastructure; Vehicle scheduling; Simultaneous planning; Optimization model

Full Citation: Stumpe, M. (2024). A new mathematical formulation for the simultaneous optimization of charging infrastructure and vehicle schedules for electric bus systems. *Transportation Research Procedia*, *78*, 402–409. https://doi.org/10.1016/j.trpro.2024.02.051

6 Gradual Transition to Zero-Emission Bus Systems: Impact of Vehicle Scheduling on Charging Infrastructure and Fleet Replacement

Abstract: This paper presents a holistic framework for the transition from diesel to electric bus networks, crucial for meeting EU regulations targeting 100% zero-emission urban buses by 2035. We employ a two-phase solution approach: first, solving the Charging Location and Electric Vehicle Scheduling Problem (CLEVSP) to generate vehicle schedules for full electrification; second, addressing the multi-period transition planning problem to minimize the total cost of ownership for the electrified fleet. Our experiments show that CLEVSP-generated schedules significantly outperform traditional methods, resulting in lower costs. Additionally, gradual transition plans reduce emissions by up to 85% compared to a diesel-only scenario. We find that vehicle rotations with long distances and sufficient idle time are prioritized for electrification, enabling earlier emission reductions and cost savings. This highlights the importance of adopting vehicle scheduling tailored for electric buses, rather than relying on legacy diesel schedules.

Keywords: Electric bus; Multi-period planning; Electric vehicle scheduling; Fleet replacement; Charging infrastructure

Full Citation: Stumpe, M., Rößler, D., Kliewer, N., & Schryen, G. (2024). Gradual transition to zero-emission bus systems: Impact of vehicle scheduling on charging infrastructure and fleet replacement. *Under Review at EURO Journal on Transportation and Logistics*

7 Designing Taxi Ridesharing Systems with Shared Pick-up and Drop-off Locations: Insights from a Computational Study

Abstract: Taxi ridesharing (TRS) systems are considered one means towards more sustainable transportation by increasing car occupancy rates and thereby significantly improving the efficiency of urban transportation systems. In this study, we consider TRS with shared pick-up and drop-off locations, where customers of a shared trip might be required to walk a short distance from their origin/to their destination. Related research has discussed the advantages of this approach over other TRS variants, including shorter travel times, lower fuel consumption and fewer emissions. However, these studies do not investigate how a TRS ought to be designed under different environmental conditions to maximize its effectiveness in terms of rejection and sharing rate. We contribute to closing this gap with three achievements. First, we propose a new mathematical model that provides a conceptualization of the TRS problem with shared pick-up and drop-off locations. Second, we implement a rolling horizon approach and conduct extensive computational experiments based on empirical data from New York City and Porto. In our experiments, we vary and combine several exogeneous (environmental) and design-oriented factors and show that both exert considerable influence on the rejection rate, sharing rate and service quality. Third, for practitioners considering a TRS with shared pick-up and drop-off locations, our guidelines highlight the importance of system design, particularly in leveraging extended waiting times to attain low rejection rates and foster high sharing rates.

Keywords: Taxi ridesharing; Sustainable transport; System design

Full Citation: 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.* https://doi.org/10.1016/j.tra.2024.104063

8 Anticipatory Assignment of Passengers to Meeting Points for Taxi-Ridesharing

Abstract: Taxi-ridesharing systems are considered an important means for sustainable urban transport. Previous literature shows that introducing meeting points in ridesharing, where customers are picked up and dropped off, increases its performance. We consider an on-demand taxi-ridesharing system, where the focus lies on the anticipatory assignment of customers to meeting points. We model the problem as a sequential decision process with the objective to maximize the distance saved through sharing. We suggest an anticipatory solution method for the planning of trips which assigns passengers to meeting points. We evaluate the suggested method on instances arising from real-world data and show that it leads to a significant increase in saved distance, and consequently CO_2 emissions when compared to a benchmark. We analyze the problem's and method's parameters and show that anticipatory methods further leverage the economical and ecological advantages of ridesharing.

Keywords: Ridesharing; Meeting points; Sequential decision process

Full Citation: Dieter, P., Stumpe, M., Ulmer, M. W., & 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

Part III

Conclusion

9 Summary of Findings

First Research Question (RQ1) The first research question explores how optimization approaches can integrate investment planning, placement of charging infrastructure, and electric vehicle scheduling to ensure an efficient, gradual transition to a fully electrified bus network. To address it, this thesis presents a comprehensive framework built upon three studies. The first study introduces the Charging Location and Electric Vehicle Scheduling Problem (CLEVSP) and tackles it using a metaheuristic approach to simultaneously optimize charging infrastructure locations and electric vehicle schedules, with a focus on sensitivity of charging infrastructure to environmental parameters (P1). Building on this, the second study develops a novel MILP formulation for the CLEVSP, enabling exact and near-optimal solutions for medium-sized cities (P2). The third study extends these insights with a two-phase solution approach: first, solving the CLEVSP model from P2 to generate vehicle schedules that are well suited for electrification, followed by an optimization model for multi-period investment planning to minimize the total cost of ownership during a gradual transition to electrification. This two-phase approach prioritizes long-distance vehicle rotations for electrification, achieving cost efficiency, early emission reductions, and alignment with zero-emission targets (P3). To sum up, heuristic and exact solution approaches for the CLEVSP, combined with multi-period investment planning, can effectively integrate investment planning, charging infrastructure placement, and vehicle scheduling, facilitating a holistic approach for a gradual, cost-efficient transition to a fully electrified bus network.

Second Research Question (RQ2) The second research question explores how optimization approaches for ride matching in an on-demand ridesharing system with meeting points can ensure system efficiency and responsiveness, considering both rolling-horizon and event-based approaches. To address this, the thesis presents two complementary approaches. The first study (P4) applies a rolling-horizon approach for dynamic ride-matching in taxi ridesharing systems with meeting points. Computational experiments show that managing waiting times strategically reduces rejection rates and increases sharing, leading to improved service quality and vehicle utilization. The second study (P5) focuses on an event-based, anticipatory approach, optimizing the assignment of passengers to meeting points to maximize the distance saved through sharing. By modeling the problem as a sequential decision process, the approach uses foresight to combine policies that exploit popularity and ensure coverage of meeting points. This method significantly increases operational efficiency compared to myopic approaches. To sum up, the rolling-horizon approach (P4) and event-based, anticipatory approach (P5) demonstrate how optimization approaches enhance system efficiency and responsiveness in taxi ridesharing systems with meeting points, balancing both objectives in complementary ways.

10 Implications for Research and Practice

This chapter presents implications for research and practice, contextualizing the results across the five papers. The chapter is divided into the domains of battery electric bus systems (P1-P3) and on-demand ridesharing (P4-P5). Each domain covers research implications, which highlight the theoretical contributions, and managerial implications, which present actionable strategies for practitioners.

Battery Electric Bus Systems Papers P1 and P2 highlight that charging infrastructure placement and electric vehicle scheduling are highly sensitive to technological (e.g., battery capacity) and economic (e.g., investment costs) parameters. The first paper demonstrates that persistent charging infrastructure structures cannot be determined through topological or timetable analyses alone. Instead, integrated optimization approaches – whether heuristic (VNS) or exact (two-index formulation) – are required to navigate the mutual dependencies between charging infrastructure and vehicle scheduling. The sensitivity analysis in P1 contributes to the literature by explicitly quantifying robustness across varying parameter settings and illustrating how persistent structures emerge under specific scenarios. This process could be further enriched by leveraging the two-index formulation proposed in P2. By applying the two-index formulation to the sensitivity analysis framework from P1, it would be possible to assess the influence of the VNS heuristic on the robustness of results.

Paper P3 introduces a holistic framework that leverages the optimization model developed in P2 as the foundation for its two-phase approach. By employing this model, P3 highlights the alignment of short-term electric vehicle scheduling with long-term multi-period transition planning for electric bus networks. This methodological alignment showcases the strength of the CLEVSP model in addressing not only short-term scheduling challenges but also the long-term planning necessary for full fleet electrification. The experiments conducted in P3 validate the effectiveness of the CLEVSP model by demonstrating its ability to generate vehicle schedules that outperform traditional scheduling methods in terms of cost efficiency and emissions reduction. This reinforces the methodological insight that using a dedicated electric vehicle scheduling approach, rather than adapting diesel-based schedules, is critical for effective fleet electrification. Moreover, all three papers P1-P3 highlight the need for more holistic approaches that integrate several planning problems of the electric bus planning process to account for their strong interdependence.

The methodology presented in paper P1 provides a valuable tool for assessing the robustness of charging infrastructure in the context of parameter variations, such as battery capacity, charging power, and energy consumption. While it does not guarantee the identification of a universally optimal charging infrastructure, it allows practitioners to test the resilience of different charging station locations against a range of technological and economic scenarios. This helps in determining which locations are more likely to remain effective under varying conditions, thus offering insights for more adaptable infrastructure planning.

For long-term planning, paper P3 presents a more comprehensive framework that practitioners should adopt. This approach aligns both vehicle scheduling and charging infrastructure placement within a multi-period planning model, enabling transit operators to make strategic decisions that align with long-term objectives, such as complete fleet electrification and zero-emissions. By considering the interplay between vehicle rotations, idle times, and charging station deployment, transit agencies can develop more effective transition plans, ensuring cost savings and emissions reductions over time. The CLEVSP model, presented in paper P2 and employed in this framework, helps prioritize vehicle rotations for electrification based on their operational characteristics, providing a systematic way to approach fleet conversion and infrastructure deployment.

On-Demand Ridesharing Papers P4 and P5 emphasize that meeting points play a pivotal role in the efficiency of on-demand ridesharing systems, improving sharing rates and reducing vehicle-miles traveled. Both papers allude to how customer flexibility (e.g., willingness to accept longer waits or walking distances) influences system performance, which could be addressed by incorporating dynamic pricing or incentives, potentially leading to more efficient fleet utilization and increased sharing rates. Papers P4 and P5 demonstrate two different approaches to balancing overall system efficiency and responsiveness in ridesharing systems. The rolling horizon approach used in paper P4 and the anticipatory assignment of taxis in paper P5 both fall under the category of approximate dynamic programming. These methods, leveraging preemptive planning to varying degrees, aim to minimize operational inefficiencies, reduce customer waiting times, and increase ride-sharing opportunities.

Managers designing on-demand ridesharing systems should consider the guidelines in paper P4 when applying a rolling horizon approach. Specifically, they should prioritize setting appropriate optimization intervals and minimize customer waiting times by adjusting pick-up and drop-off locations dynamically. Operators should incentivize walking to shared pick-up points and explore dynamic pricing models to encourage longer walking distances, enhancing ride-sharing potential and cost savings for both the system and customers. Both papers P4 and P5 highlight the importance of anticipatory planning for fleet management. Managers should use preemptive methods and real-time data to optimize vehicle positioning, reduce idle time, and balance system efficiency with responsiveness.

11 Future Research

The methods and insights presented in this thesis open several promising directions for future research. First, an important step forward in the domain of battery electric buses would be the development of a unified approach that simultaneously optimizes all three key planning problems: multi-period investment planning, charging infrastructure placement, and electric vehicle scheduling. By integrating these distinct elements into a single model, it would be possible to achieve more coordinated and efficient planning for BEB systems, ensuring that investment decisions, infrastructure deployment, and scheduling are optimized together.

Incorporating uncertainties into the planning of BEB systems is a crucial area for future research. Uncertainties related to factors such as battery performance, vehicle charging times, fuel prices, and passenger demand can significantly impact investment decisions, infrastructure deployment, and scheduling. Future models could integrate stochastic elements or robust optimization techniques to account for these uncertainties, ensuring that BEB systems remain resilient under various scenarios.

Another promising direction is the development of multi-objective solution methods. Given the trade-offs between charging infrastructure and vehicle fleet size, a more comprehensive analysis of these opposing objectives could lead to more balanced solutions. Multi-objective optimization approaches, which are gaining traction in operational research across various domains (Altekin & Bukchin, 2022; Cheaitou & Cariou, 2019; Fathollahi-Fard et al., 2023), could provide decision-makers with a set of optimal trade-offs and enable more informed, context-sensitive decisions.

In the domain of on-demand ridesharing, extending the rolling horizon approach and event-based methodologies with anticipatory rebalancing mechanisms for idle vehicles would be an exciting area for further research. Comparing the performance of these enhanced methods in cities with varying characteristics could offer deeper insights into their scalability and adaptability, as well as their impact on system efficiency and responsiveness in diverse urban settings.

A further extension would involve adapting the methods developed for urban areas to rural contexts. While the transportation needs of rural areas differ from those of cities, the application of on-demand and electric vehicle systems in such regions holds great promise. Research should focus on identifying key differences in requirements and tailoring the existing approaches to meet these distinct challenges, ensuring that rural areas can also benefit from optimized transportation planning.

Finally, an intriguing direction for future research would involve the integration of both urban and rural mobility domains, combining on-demand ridesharing systems with electric buses to create a seamless public transportation network. Investigating how these two types of transportation could complement each other, both within urban environments and in rural settings, could lead to more sustainable, flexible, and cost-effective transportation solutions across a wide range of contexts.

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