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Electrified Multimodal Urban Transport Planning and Operations under Uncertainty

Sara Momen



Electrified Multimodal Urban Transport Planning and Operations under Uncertainty

Electrified Multimodal Urban Transport Planning and Operations under Uncertainty

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for the purpose of obtaining the degree of doctor
at Delft University of Technology
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Looking back, I am glad for the resilience that carried me through and for the curiosity that keeps pulling me forward. If there is one thing I want to carry forward, it is this. Life is not a game of chess, where every outcome can be calculated in advance. We decide with the information we have and let uncertainty shape the rest, which is why the process deserves to be enjoyed rather than endured. And if we keep going, a path usually appears, often one we never saw coming.

و اگر بر تو ببندد همه ره‌ها و گذرها
ره پنهان بنماید که کس آن راه نداند

مولانا

*And if every road and passage is closed to you,
a hidden way will be revealed, one that no one
knows. — Rumi*

Sara Momen
Delft, September 2026

Summary

Cities worldwide are pursuing a transition from private, fossil-fuel reliant transport toward shared and electric alternatives. A combined electric public transport and shared e-micromobility system is an important backbone for sustainable urban transport that offers door-to-door trip options. In the implementation and operations of such systems, several challenges arise across decision-making levels from strategic to operational. These include charging infrastructure decisions for electrification, rebalancing operations planning for shared modes, and a passenger-centric approach for trip recommendation. A central difficulty is that electrified transport modes introduce new and interacting sources of uncertainty at each level. This dissertation develops a set of mathematical optimization models for electric urban multimodal transport, built on the principle that uncertainty modeling and passenger behavior must be embedded jointly into each decision layer. This joint embedding brings the resulting models closer to real-world conditions and yields more efficient decisions across strategic, tactical, and operational levels.

Electrifying an existing bus network with catenary-free electric buses, which operates on battery, introduces uncertainty in energy consumption, which depends on various factors such as driving style, weather, and passenger load. Charging infrastructure must nonetheless be designed before sufficient operational data exist. Mean energy estimates can lead to infeasible designs, while worst-case bounds inflate costs. In this setting, a robust optimization model that hedge against energy consumption uncertainty is needed to consider the sparse data into the model to protect both system performance and long-term investment costs. Our approach instead exploits the distributional characteristics of sparse field data to jointly optimize charging station placement, charger type selection, and onboard battery sizing. Evaluated on three lines of the Rotterdam bus network, our approach reduces total electrification costs by 28% relative to a worst-case design while maintaining service performance, and it extends battery longevity through optimal charge-discharge pattern.

The reach of electrified public transport can be extended by employing shared e-micromobility that covers the first and last mile of the trip. For shared e-micromobility systems, the recurring challenge is to address supply-demand mismatch efficiently. To this end, we develop the concept of *perceived usability*, which jointly considers vehicle availability, battery level, and passenger behavior in vehicle selection. We first investigate the behavioral factors that govern passenger selection of shared e-micromobility vehicles. Remaining driving range is a significant driver of selection, with individual heterogeneity in range anxiety. Building on this finding, we formulate a predictive rebalancing and recharging plan that redefines the rebalancing objective from conventional inventory balancing to the control of *perceived usability*. The model coordinates truck-based interventions with user-mediated drop-off incentives within a mixed-integer optimization

guided by Markovian state predictions of supply-demand uncertainty. The plan is reoptimized in a rolling horizon to capture the dynamic nature of the rebalancing problem. On real-world data from a major European shared e-scooter operator, our approach raises the average service level compared to no intervention and outperforms truck-only strategies, the current state of practice. User-mediated relocations also reduce truck-kilometers per unit of served demand and ensures the rebalancing plan is environmentally friendly.

Given the robust electric bus network and the rebalanced shared e-micromobility fleet, the final step of multimodal trip planning is to recommend door-to-door options under shared e-micromobility usability uncertainty. A shared e-micromobility offered at planning time may not be available at the passenger's arrival time, may lack sufficient battery, or may be perceived as unusable. Such failures are intrinsic to electric shared modes and erode system performance by leaving passengers stranded. To address this, we propose a welfare-maximizing trip recommendation combining electric bus with shared e-scooters, subject to passenger-specific battery sensitivity from a vehicle selection behavior model that is compared against the forecasted e-micromobility usability state. E-micromobility legs unlikely to be usable at execution time are filtered out from the admissible sets in the optimization model. Implemented in Rotterdam, the approach reduces the trip failure rate from 25% under myopic trip recommendation to below 5%, at the cost of three additional minutes of average walking time. In addition, behavioral acceptance of battery levels emerges as a structural determinant of trip execution success.

Together, the three mathematical optimization models form a decision-making architecture that spans strategic network design, tactical fleet management, and operational trip recommendation for reliable electrified multimodal urban transport under real-world uncertainties. For public transport authorities, the results demonstrate that integrating sparse operational data into strategic electrification decisions substantially reduces investment costs without compromising service reliability. For shared e-micromobility operators, they establish the value of a system-level perspective that embeds user behavior models into rebalancing and trip planning. Across both, quantifying uncertainty sources that define future system states proves essential to sustaining high service levels, whether a mode operates independently or as part of a multimodal trip.

Samenvatting

Wereldwijd maken steden de transitie van op fossiele brandstoffen gebaseerde transportmogelijkheden naar een gedeelde en elektrisch alternatieven. Een gecombineerd transportsysteem van elektrisch openbaar vervoer- en gedeeld e-micromobiliteit vormt een belangrijke ruggengraat voor duurzaam stedelijk vervoer dat deur-tot-deur reismogelijkheden biedt. Bij de implementatie en exploitatie van dergelijke systemen doen zich diverse uitdagingen voor op verschillende besluitvormingsniveaus, van strategisch tot operationeel niveau. Deze omvatten beslissingen over laadinfrastructuur voor elektrificatie, planning van herbalanceringsoperaties voor gedeelde modaliteiten, en een passagiersgerichte benadering voor reisaanbevelingen. Een overkoepelende uitdaging is dat geëlektrificeerde vervoerswijzen nieuwe en onderling samenhangende bronnen van onzekerheid introduceren op elk niveau. Dit proefschrift ontwikkelt een reeks wiskundige optimalisatiemodellen voor elektrisch stedelijk multimodaal vervoer, gebouwd op het principe dat onzekerheidsmodellering en passagiersgedrag gezamenlijk in elke beslissingslaag moeten worden ingebed. Deze gezamenlijke inbedding brengt de resulterende modellen dichter bij de praktijkomstandigheden en levert efficiëntere beslissingen op strategisch, tactisch en operationeel niveau.

Het elektrificeren van een bestaand busnetwerk met kettlijn-vrije elektrische bussen op batterij, introduceert onzekerheid in energieverbruik. Deze onzekerheid in energieverbruik is afhankelijk van diverse factoren zoals rij-stijl, weer en passagiersbezetting. De laadinfrastructuur moet desondanks worden ontworpen voordat er voldoende operationele data beschikbaar zijn. Gemiddelde energieschattingen kunnen leiden tot onhaalbare ontwerpen, terwijl worst-case-grenzen de kosten opdrijven. In deze context is een robuust optimalisatiemodel nodig dat beschermt tegen onzekerheid in het energieverbruik, waarbij de schaarse data in het model wordt meegenomen om zowel de systeemprestaties als de lange termijn investeringskosten te waarborgen. Onze aanpak benut de verdelingskenmerken van schaarse, empirische data om tegelijkertijd de plaatsing van laadstations, de selectie van het type lader en de dimensionering van de boordaccu te optimaliseren. Geëvalueerd op drie lijnen van het Rotterdamse busnetwerk, vermindert onze aanpak de totale elektrificatiekosten met 28% ten opzichte van een worst-case-ontwerp, met behoud van de dienstprestaties, en het verlengt de levensduur van de accu door een optimaal laad-ontlaadpatroon.

Het bereik van geëlektrificeerd openbaar vervoer kan worden uitgebreid door inzet van gedeelde e-micromobiliteit die het eerste en laatste stuk van de reis dekt. Voor gedeelde e-micromobiliteitssystemen is de terugkerende uitdaging om de mismatch tussen vraag en aanbod efficiënt aan te pakken. Hiertoe ontwikkelen wij het concept van *ervaren bruikbaarheid*, dat gezamenlijk voertuigbeschikbaarheid, accuniveau en passagiersgedrag bij voertuigselectie beschouwt. We onderzoeken eerst de gedragsfactoren

die de passagierskeuze van gedeelde e-micromobiliteitsvoertuigen bepalen. De resterende actieradius (resterend batterijniveau) is een significante drijfveer voor de keuze van het e-micromobiliteit, met individuele heterogeniteit in de zorg over het restante batterijniveau. Voortbouwend op deze bevinding, formuleren we een voorspellend herbalancerings- en herlaadplan dat de herbalanceringsdoelstelling herdefinieert van conventionele voorraadbalancerings, naar de beheersing van *ervaren bruikbaarheid*. Het model coördineert vrachtwagengebaseerde interventies met door gebruikers-gemedieerde afleverincentives binnen een mixed-integer-optimalisatie, gestuurd door Markoviaanse toestandsvoorspellingen van vraag-aanbodonzekerheid. Het plan wordt geheroptimaliseerd in een voortschrijdende horizon om het dynamische karakter van het herbalanceringsprobleem te vatten. Op basis van empirische data van een grote, Europese aanbieder van gedeelde e-scooters, verhoogt onze aanpak het gemiddelde serviceniveau ten opzichte van geen interventie. Verder leidt onze aanpak tot betere prestaties dan strategieën met alleen vrachtwagens, wat de huidige praktijk is. Door gebruikers-gemedieerde herplaatsingen, verminderen ook de vrachtwagenkilometers per eenheid bediende vraag en zorgen ervoor dat het herbalanceringsplan milieuvriendelijk is.

Gegeven het robuuste elektrische busnetwerk en de geherbalanceerde gedeelde e-micromobiliteitsvloot, is de laatste stap van multimodale reisplanning het aanbevelen van deur-tot-deur opties onder onzekerheid over de bruikbaarheid van gedeelde e-micromobiliteit. Een gedeeld e-micromobiliteitsvoertuig dat op het planningstijdstip wordt aangeboden, is mogelijk niet beschikbaar op het aankomsttijdstip van de passagier, heeft misschien onvoldoende accu, of wordt als onbruikbaar ervaren. Dergelijke mislukkingen zijn inherent aan elektrische gedeelde modaliteiten en ondermijnen de systeemprestaties doordat passagiers gestrand achterblijven. Om dit aan te pakken, stellen wij een welvaartsmaximaliserende reisaanbeveling voor die elektrische bus combineert met gedeelde e-scooters, rekening houdend met passagiersspecifieke accugevoeligheid uit een voertuigselectiegedragsmodel dat wordt vergeleken met de voorspelde bruikbaarheidstoestand van de e-micromobiliteit. E-micromobiliteitstrajecten die waarschijnlijk niet bruikbaar zijn op het uitvoeringsmoment, worden uit de toelaatbare verzamelingen in het optimalisatiemodel gefilterd. Toegepast in Rotterdam als case study, vermindert onze aanpak het percentage mislukte ritten van 25% bij kortzichtige reisaanbevelingen tot onder de 5%, ten koste van drie extra minuten gemiddelde looptijd. Daarnaast blijkt de gedragsmatige acceptatie van accuniveaus een structurele, bepalende factor te zijn in het slagen van de rit.

Samen vormen de drie wiskundige optimalisatiemodellen een besluitvormingsraamwerk dat strategisch netwerkontwerp, tactisch vlootbeheer en operationele reisaanbevelingen omvat voor betrouwbaar, geëlektrificeerd multimodaal stedelijk vervoer onder praktijkonzekerheden. Voor openbaarvervoersautoriteiten tonen de resultaten aan dat het integreren van schaarse operationele data in strategische elektrificatiebeslissingen de investeringskosten substantieel verlaagt zonder de betrouwbaarheid van de dienstverlening aan te tasten. Voor aanbieders van gedeelde e-micromobiliteit bevestigen zij de waarde van een systeemperspectief dat gebruikersgedragsmodellen inbedt in herbalancerings en reisplanning. Voor beide geldt dat het kwantificeren van onzekerheidsbronnen die

toekomstige systeemtoestanden bepalen essentieel is voor het handhaven van hoge serviceniveaus, ongeacht of een modaliteit zelfstandig opereert of als onderdeel van een multimodale reis.

Chapter 1

Introduction

1 1.1 Research Motivation

The transition toward zero-emission and shared urban mobility has become an important policy objective for cities worldwide (European Commission, 2021). A combined electric public transport and shared e-micromobility system is an important backbone for sustainable urban transport that offers door-to-door trip options. Achieving this transition requires more than deploying cleaner vehicles. It requires building networks where passengers can complete reliable door-to-door trips that match supply and demand realistically in a multimodal network. When such networks work reliably, they reduce emissions, alleviate congestion, and offer competitive alternatives to private car use. When they fail, passengers experience stranded buses, unavailable or uncharged e-micromobility vehicles, and failed trip connections. These failures erode the trust needed to sustain ridership.

Electrification of transport modes introduces new and interacting sources of uncertainty across decision-making levels. At the strategic level, cities must commit to costly charging infrastructure before sufficient operational data on energy consumption exist. This uncertainty arises because energy consumption depends on passenger load, congestion, and route topology (Chapter 2). At the tactical level, shared e-micromobility operators must continuously rebalance and recharge a fleet whose effective supply depends not only on vehicle location but also on battery state and user adoption behavior (Chapter 3). At the operational level, multimodal trip planners must recommend itineraries combining scheduled bus services with shared e-micromobility legs. However, vehicles that appear available at planning time may no longer be available, sufficiently charged, or acceptable at execution time (Chapter 4).

These uncertainties interact systematically. Infrastructure decisions determine bus network energy reliability. This reliability ensures the public transport backbone for multimodal trips. Fleet rebalancing plans shape the spatial distribution and battery composition of shared vehicles. This composition governs whether recommended e-micromobility legs can be executed at passenger's arrival time. Passenger behavior feeds back into both rebalancing and trip planning decisions. Specifically, the decision to select an e-micromobility vehicle based on battery level affects both operational levels. Despite this tight coupling, existing literature treats these problems largely separately.

This dissertation aims to enable reliable end-to-end multimodal trips while managing costs for infrastructure investors, operators, and passengers by developing a set of optimization models spanning the strategic, tactical, and operational decision levels. The unifying principle is that uncertainty modeling and passenger behavior must be embedded into each decision layer.

This chapter introduces the research by defining the scope and background and identifying key literature gaps. It then formulates the main research question and associated subquestions. It outlines the scientific and societal contributions and presents the dissertation structure.

1.2 Literature Review and Research Needs

This dissertation is positioned at the intersection of different levels of decision-making for a reliable electrified multimodal urban transportation, i.e., three evolving research domains: robust design of electric public transport infrastructure, operational control of shared electric micromobility, and reliable multimodal trip planning. This section sketches the research and application landscape in each domain and formulates the research needs that motivate the studies in this dissertation. A more comprehensive review of the relevant literature is provided in each subsequent chapter.

1.2.1 Robust design of strategic decisions in electric public transport networks

Electrifying public transit networks through battery electric buses (BEBs) requires joint decisions on charging station placement, charger type selection, and onboard battery sizing. These decisions commit substantial capital before operational experience accumulates, and their consequences persist over the infrastructure lifetime (Azadeh, Vester, and Maknoon, 2022). Such long-term commitments demand meticulous estimation of operational performance. However, BEB energy consumption varies considerably with traffic conditions, passenger load, and driving behavior. Accurate estimation requires costly field experiments that are rarely available at the design stage.

The literature addresses this energy consumption uncertainty through two main paradigms, each with critical limitations. Stochastic programming approaches (An, 2020; Zhou, Ong, et al., 2023) require predefined probability distributions that are unavailable when deployments are new and data is sparse. Robust optimization methods with budget-based uncertainty sets (Gairola and Nezamuddin, 2023; Iliopoulou and Kepaptsoglou, 2021) guarantee feasibility under worst-case realizations but can produce overly conservative designs that inflate capital costs.

Data-driven distributionally robust optimization (DRO) offers a middle ground by optimizing against the worst-case distribution within a data-driven ambiguity set (Mohajerin Esfahani and Kuhn, 2018), yet its application to BEB charging infrastructure design remains unexplored. As a result, cities planning new electrification deployments face a binary choice between ignoring energy uncertainty (risking operational infeasibility) and hedging against worst-case values (incurring excessive costs), with no principled mechanism to extract value from the sparse observations that early-stage deployments do provide. This methodological gap motivated the first sub-question of this thesis (Section 1.3).

1.2.2 Operational control of shared electric micromobility

Shared electric micromobility systems, particularly free-floating e-scooters, extend the reach of public transport in multimodal urban networks. Maintaining their effectiveness requires continuous intraday rebalancing to address spatial and temporal mismatches between vehicle supply and user demand. Traditional rebalancing approaches have

formulated this as a vehicle routing problem for repositioning fleet inventory. Central to these formulations is a binary representation of availability: a vehicle is either physically present at a location or absent. This abstraction, is increasingly challenged by two developments in electrified shared mobility.

First, electrification introduces battery charge as a critical state dimension that fundamentally alters the concept of availability. A physically present vehicle with insufficient charge does not constitute available supply. Battery depletion follows trip-dependent stochastic dynamics that interact with spatial demand patterns. Second, user selection behavior introduces a divergence between physical availability and perceived usability. Riders might avoid low-charge vehicles even when remaining range physically suffices for their intended trips. This behavioral mechanism means that rebalancing models operating on vehicle counts alone propagate an incomplete representation of system state.

Hybrid models that coordinate operator-based interventions (truck relocation, battery swapping) with user-mediated interventions (drop-off incentives) have emerged to simultaneously manage system performance and operational costs (Y. Li and Liu, 2021; Pfrommer et al., 2014). However, existing hybrid models treat user behavior as an exogenous response to incentives rather than as an endogenous mechanism governing how availability and battery states evolve under intervention. This formulation evaluates hybrid interventions against predicted availability that reflects physical inventory rather than realized usability, resulting in incomplete view of the system.

Addressing this limitation requires accurately identifying endogenous passenger behavior, and designing a tailored rebalancing and recharging plan. These consecutive needs form the basis for the second and third research sub-questions, respectively, detailed in Section 1.3.

1.2.3 Reliable multimodal trip planning

Literature in multimodal trip planning predominantly adopts the operator's perspective in designing trip recommendations by optimizing system-level objectives such as generalized cost across networks. Even though user welfare maximization has been growing in the literature, these approaches still face a critical research gap in handling uncertainty. Existing models address demand variability, travel time stochasticity, and public transport service disruptions (Ding et al., 2024; Mo et al., 2025). However, uncertainty in service reliability of shared modes remains unaddressed in user-facing trip planning. This research gap is critical because shared electric micromobility introduces systematic uncertainty that directly compromises user welfare. Unlike scheduled public transport where disruptions are exogenous events, shared vehicle availability is inherently stochastic. Vehicles may be relocated by prior users, carry insufficient battery charge, or be rejected by passengers based on subjective range-anxiety thresholds. These execution stage failures systematically reduce the reliability of recommended trips and diminish actual user welfare.

Current supply-side models predict e-micromobility availability and battery state for operator logistics planning (Emami and Ramezani, 2024; Zhou, Lin, et al., 2023). However, these uncertainty predictions are not integrated into user-facing trip recommendations. As

a result, passengers receive itineraries that may appear optimal under deterministic assumptions but fail at execution due to shared mode unreliability. Propagating these supply-side uncertainty considerations into trip planning could enable truly welfare-maximizing recommendations through more reliable itinerary choices. Developing an optimization model to achieve this integration is the focus of the fourth sub-question, defined in Section 1.3.

1.3 Research Questions

The primary objective of this dissertation is to develop a comprehensive model for reliable multimodal transportation planning and operations incorporating user, vehicle, and operator perspectives under consideration of real-world uncertainties. The overarching research question guiding this dissertation is:

How can electrified multimodal transport networks be designed and operated reliably by integrating user behavior, vehicle characteristics, and operator costs under uncertainty?

To address this question in different decision-making levels, this dissertation (i) develops a data-driven distributionally robust optimization model that leverages sparse energy consumption data to strategically design cost-efficient and operationally reliable charging infrastructure for battery electric buses (strategic level); (ii) identifies and quantifies the behavioral factors that govern passengers' decisions to select or avoid shared electric micromobility vehicles, with particular attention to the role of battery level and passengers' range anxiety; (iii) formulates a predict-then-optimize hybrid rebalancing model that connects uncertain vehicle *perceived usability*, jointly shaped by spatial availability, battery dynamics, and user selection behavior, to coordinated operator and user-mediated interventions; and in the most operational level of decision-making (tactical planning), (iv) integrates the supply-side service predictions and demand-side behavioral models into a multimodal trip planner that maximizes user welfare while preventing itinerary recommendations that are likely to fail at execution due to unusability of shared electric vehicles (operational level).

The research is structured around the following subquestions, each targeting a specific objective.

SQ1. *What is a cost-efficient and robust approach to electrifying an existing public transit network with sparse data, accounting for real-world uncertainties?*

This question targets the strategic decision of locations for charging stations and onboard battery size for catenary-free electric buses operating on a fixed-route network. The challenge arises from the novelty of the technology and lack of sufficient data on which to rely and optimize the system. Energy consumption of e-buses is uncertain as it depends on various factors such as passenger load, speed, and route topology. Due to the novelty of the implementation, sparse data can be obtained only through costly field experiments. We aim to integrate this sparse data into the strategic design of the charging

infrastructure network to hedge against the uncertainty while avoiding over-conservative and costly decisions.

SQ2. *What factors drive a passenger's decision to use a shared electric micromobility vehicle, and how do the vehicle's attributes shape that decision?*

This question examines the behavioral factors determining whether a rider selects a physically available e-micromobility. While existing literature has studied walking distance and pricing, vehicle characteristics such as battery level remain understudied. It aims to study the joint influence of battery level, walking distance, unlock and per-minute fees, vehicle type, rider experience, income, and range anxiety on vehicle selection probability. The calibrated choice models provide the passenger behavior inputs for further operational optimization models.

SQ3. *How should a shared e-micromobility operator manage its fleet to maintain service levels, given spatiotemporal mismatches between supply and demand and passengers' perceived usability of vehicles?*

This question addresses the tactical problem of intraday fleet management in free-floating e-micromobility systems. Demand varies stochastically across space and time, while battery depletion continuously reduces the effective supply of usable vehicles. Predicting future system states, including vehicle inventory and state of charge, enables the operator to make proactive rebalancing and charging decisions that maintain service levels and improve operational efficiency. A further component of this question is to quantify the impact of user-mediated interventions in rebalancing. In particular, we examine how user participation affects the performance and cost of truck-based rebalancing and the trade-offs users are willing to accept when contributing to operational objectives.

SQ4. *How can multimodal trip planners reliably integrate shared e-micromobility with public transport while accounting for uncertainty for shared vehicle usability as well as heterogeneous passenger behavior?*

This question targets the individual trip recommendation where a door-to-door itinerary combining electric bus transit with a shared e-micromobility leg is requested. There is a research need for considering service reliability of shared modes for trip planning, so that user welfare is maximized while feasibility is maintained at the time of execution. In particular, stochastic vehicle availability, battery state of charge, and passenger behavioral heterogeneity are required to be jointly embedded in a user-facing multimodal trip planner.

Figure 1.1 indicates the conceptual model and the role of each research question. The model demonstrates how SQ1 through SQ4 address specific real-world uncertainties across varying decision-making levels (rows). The horizontal span of the boxes visualizes the growing comprehensiveness of the models with regard to involved decision-makers.

Throughout this dissertation, mathematical optimization is the primary methodological approach due to its interpretability. The problems studied involve multiple interacting decision variables, constraints, and stakeholders whose relationships must be modeled explicitly. Mathematical optimization provides transparent formulations in which the structure of each problem can be interpreted and validated, unlike black-box methods where

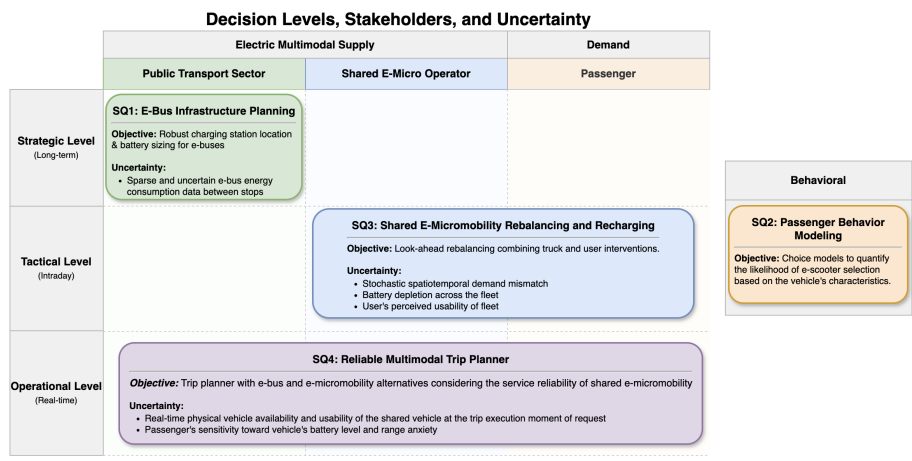


Figure 1.1 Conceptual model for reliable electrified multimodal network design.

the reasoning behind decisions remains opaque. Moreover, robust and distributionally robust optimization methods are well suited to the data-scarce conditions that characterize new technology deployment.

1.4 Contributions and Relevance

This dissertation makes several scientific contributions to the field of electric multimodal urban transport planning and operations. The central contribution is the development of a set of mathematical models that address strategic, tactical, and operational decision-making under multiple, interacting sources of uncertainty. The transition to zero-emission urban mobility demands coordinated decisions across municipalities, micromobility operators, public transport authorities, and passengers. The specific contributions, organized below, serve each of these stakeholders while advancing the methodological frontier.

Robust infrastructure design under data sparsity. We develop a data-driven distributionally robust optimization model that relies on sparse field observations to design robust charging infrastructure for battery electric buses, while controlling the risk of over-conservative solutions that inflate deployment costs (Chapter 2). For municipalities and transit authorities, this model provides a principled basis for electrification investments that avoids both under-designed networks and wasteful over-conservative designs, and can be adopted more broadly to guide long-term decisions in the implementation of emerging technologies.

Knowledge discovery from micromobility operational and behavioral data. We identify battery level as a substantial driver of vehicle selection in shared e-micromobility, showing that users systematically avoid low-charge vehicles even when the remaining range objectively suffices for their trip (Sub-chapter 3.1). We introduce the concept of

perceived usability, a service-level metric that integrates spatial availability, battery charge composition, and battery-dependent user selection behavior into a single state variable. We demonstrate that this comprehensive view of service quality, rather than conventional vehicle counts, is necessary to accurately estimate unmet demand and to guide fleet rebalancing and recharging decisions toward minimizing demand loss and operational costs (Sub-chapter 3.2). For shared micromobility operators, our approach enables a shift from reactive inventory management to predictive perceived usability control, bringing operational decisions closer to real-world service conditions. Embedding passenger behavior into rebalancing decisions also reveals that rebalancing plans can be tailored to behavioral profiles in addition to spatial and temporal patterns, meaning that a single rebalancing policy does not perform uniformly across user populations.

Integrating system operations with individual trip preferences. In a multimodal network of public transport and shared e-micromobility, we establish that reliable trip planning requires jointly accounting for stochastic vehicle availability, battery charge state, and passenger behavioral heterogeneity as distinct sources of service uncertainty. We show that reliability constraints specialize rather than eliminate e-micromobility, preserving it as a first- and last-mile connector under stricter service requirements, and that effective data sharing between operators is a prerequisite for efficient multimodal trip planning (Chapter 4). For multimodal trip planners, our approach prevents the recommendation of itineraries that are likely to fail at execution and shows that passenger-specific battery acceptance is a structural determinant of execution success. Predicting the shared e-micromobility state at the passenger's arrival time and integrating this information with trip planning platforms emerges as a prerequisite to reduce these failures in practice.

1.5 Thesis Outline

Figure 1.2 presents the structure of this dissertation. The thesis is organized into five chapters, grouped into three thematic blocks that correspond to the strategic, tactical, and operational decision levels introduced in the research needs. The arrows between blocks indicate how outputs from upstream chapters feed as inputs into downstream ones, reflecting the interconnected nature of the proposed model.

Chapter 2 addresses the first sub-question (SQ1). It develops a data-driven distributionally robust optimization model for charging infrastructure design to electrify an already existing bus network under sparse and uncertain energy consumption data. The output of this chapter is a robust e-bus network whose energy supply reliability is guaranteed. This robust backbone forms the fixed-schedule public transport layer on which the subsequent chapters build.

Chapter 3 addresses the tactical level under the theme of shared electric micromobility planning and comprises two interconnected parts. Sub-chapter 3.1 identifies the factors affecting users' decisions to select a shared electric micromobility vehicle, calibrating mixed multinomial logit and hybrid choice models from stated-preference survey data. This sub-chapter addresses the second sub-question (SQ2). Sub-chapter 3.2 formulates a rebalancing and recharging plan for a shared e-micromobility operator that incorporates

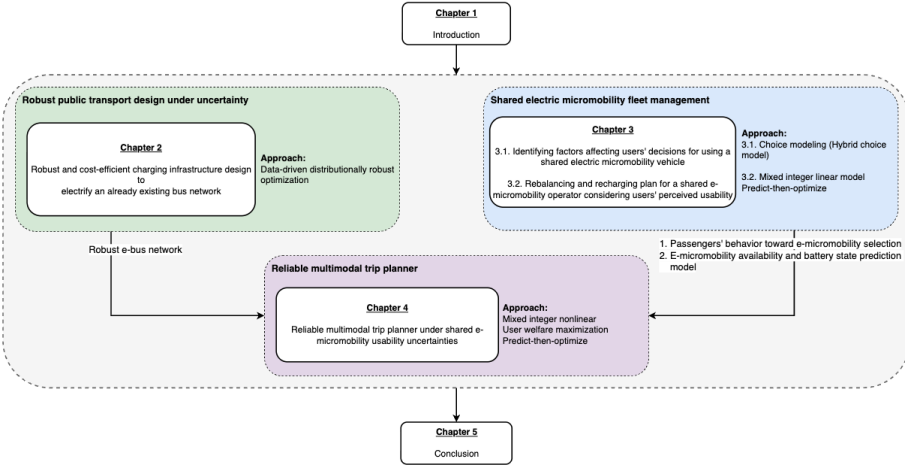


Figure 1.2 The outline of the dissertation

users' perceived usability into a predict-then-optimize mixed-integer linear programming model. This sub-chapter addresses the third sub-question (SQ3). The choice model from Sub-chapter 3.1 is embedded directly into the Markovian state-prediction model of Sub-chapter 3.2, ensuring that rebalancing decisions reflect realized usability rather than physical inventory alone. The calibrated passenger behavioral model toward e-micromobility selection, and the e-micromobility availability and battery state prediction model are the resulting inputs to Chapter 4.

Chapter 4 addresses the operational level under the theme of *reliable multimodal trip planning*. This chapter addresses the fourth sub-question (SQ4). It integrates the robust e-bus network from Chapter 2 with the behavioral and prediction models from Chapter 3 into a flow-based mixed-integer nonlinear optimization model that recommends welfare-maximizing multimodal itineraries subject to e-micromobility service reliability constraints. This chapter adopts a predict-then-optimize approach in which the supply-side predictions and demand-side behavioral models enter the trip planner as exogenous inputs, closing the loop from infrastructure design through fleet management to individual trip recommendation.

Chapter 5 concludes the dissertation by collecting the main findings across all chapters, discussing the theoretical and practical implications, and outlining directions for future research.

Chapter 2

Designing a Robust and Cost-Efficient Electrified Bus Network with Sparse Energy Consumption Data

As identified in Chapter 1, the success of electrified multimodal transport depends fundamentally on designing networks with a highly resilient energy supply. A major challenge in this phase is that strategic decisions, such as charging infrastructure locations and battery sizing, must be made before new technologies are deployed and operational data is available. To achieve this, this chapter develops a data-driven, distributionally robust optimization framework that guarantees a robust and cost-efficient design despite sparse and uncertain energy consumption data. By securing energy reliability at the strategic level, we lay the critical groundwork for electrified urban mobility. The resulting robust e-bus network serves as the core, fixed-schedule public transport layer that forms the backbone for the electric urban multimodal transport planning in the remainder of this research.

This chapter is based on the journal article:

1. Momen, S., Maknoon, Y., van Arem, B., & Azadeh, S. S. (2025). Designing a robust and cost-efficient electrified bus network with sparse energy consumption data. *Transportation Research Part C: Emerging Technologies*, 171, 105020.

Abstract

This paper addresses the challenges of charging infrastructure design (CID) for electrified public transport networks using Battery Electric Buses (BEBs) under conditions of sparse energy consumption data. Accurate energy consumption estimation is critical for cost-effective and reliable electrification but often requires costly field experiments, resulting in limited data. To address this issue, we propose two mathematical models designed to handle uncertainty and data sparsity in energy consumption. The first is a robust optimization model with box uncertainty, addressing variability in energy consumption. The second is a data-driven distributionally robust optimization model that leverages observed data to provide more flexible and informed solutions. To evaluate these models, we apply them to the Rotterdam bus network. Our analysis reveals three key insights: (1) Ignoring variations in energy consumption can result in operational unreliability, with up to 55% of scenarios leading to infeasible trips. (2) Designing infrastructure based on worst-case energy consumption increases costs by 67% compared to using average estimates. (3) The data-driven distributionally robust optimization model reduces costs by 28% compared to the box uncertainty model while maintaining reliability, especially in scenarios where extreme energy consumption values are rare and data exhibit skewness. In addition to cost savings, this approach provides robust protection against uncertainty, ensuring reliable operation under diverse conditions.

2.1 Introduction

Countries worldwide are increasingly striving to reduce their reliance on fossil fuel services. For instance, the Netherlands has made notable advancements, with The Hague taking a pioneering step by banning advertisements for fossil fuel-based services. In this paradigm, zero-emission urban mobility has emerged as a critical focus area. Battery Electric Buses (BEBs) are leading this change due to their independence from traditional infrastructure like cables and rails. This flexibility allows BEBs to integrate seamlessly into existing transport systems. They offer a scalable solution for cities to reduce their environmental impact. However, designing effective and reliable BEB networks poses challenges. A key issue is estimating the energy consumption and strategically placing charging stations to ensure continuous service.

Accurately estimating energy consumption is critical for the cost-efficient and reliable deployment of electrified transport networks. This estimation is challenging due to a wide range of influential factors, including traffic conditions, passenger load, weather, road characteristics, and driving behavior (Y. Chen et al., 2021). Inaccurate estimates of energy consumption impact electrification costs, battery lifetime, and service levels (Azadeh, Vester, & Maknoon, 2022).

In the literature, several methods have been proposed to estimate energy consumption. These methods can be categorized into two main groups. The first group comprises approaches developed based on physics-based and chemical process models to determine energy consumption (Hjelkrem et al., 2021; Scarinci et al., 2019; Teichert et al., 2019;

Zhou, Ong, et al., 2023). While advanced, these approaches are limited to laboratory settings and do not account for interactions between operational, topological, and environmental factors. The second group comprises data-driven methods, which leverage large datasets from real-world BEB operations to estimate energy consumption (Al-Ogaili et al., 2020; Gallet et al., 2018; Pamuła & Pamuła, 2020). These models excel at identifying interactions between various factors within existing systems. However, their reliance on extensive data streams restricts their applicability to well-established BEB networks. Additionally, since these models are trained on specific operational conditions, their predictions often lack generalizability to different contexts or new deployments. As a result, operators planning new BEB systems must rely on costly field tests to collect the necessary data, leading to significant uncertainty and variability in energy consumption estimates (Wagenknecht, 2017).

This study addresses the challenges of sparse energy consumption data in designing charging infrastructure for Battery Electric Buses (BEBs), a problem known as Charging Infrastructure Design (CID). By optimizing the placement and types of charging stations (e.g., fast-charging and standard stations) and determining onboard battery capacities, the proposed approach ensures reliable and cost-effective electrification. Incorporating data sparsity and operational uncertainty, our framework overcomes limitations of existing methods and enables robust, scalable infrastructure solutions for diverse deployment scenarios.

We first model the CID problem using average energy consumption estimates, acknowledging that neglecting energy consumption uncertainty can lead to designs that fail to ensure operational feasibility. To address this challenge in data-scarce environments, we propose two robust optimization models tailored to the CID problem. The first, a box uncertainty robust model with a budget (BoU-CID), uses an uncertainty box framework to account for variability by defining an average value and its maximum deviation. This approach is effective when only the range of uncertainty is known but can result in highly conservative designs. To balance cost-efficiency and reliability, the second model, a data-driven distributionally robust chance constraint approach (DRCC-CID), incorporates observed data characteristics into the robust optimization framework, producing more practical and adaptive solutions. Both models are evaluated under comprehensive scenarios to assess their performance in terms of cost-efficiency, design reliability, and computational time, demonstrating their potential for robust and scalable CID solutions.

We summarize the contributions of this paper as follows: We introduce two mathematical models for designing the charging infrastructure for BEBs under the constraints of uncertain and sparse energy consumption data and investigate the impact of different approaches to modeling uncertainty on the system's total cost. The scalability and performance of the proposed models are tested on a series of test instances as well as the Rotterdam bus network. The results demonstrate that incorporating sparse energy consumption data significantly reduces total electrification costs compared to the range-based approach, even under highly conservative design scenarios. Furthermore, we evaluate the long-term costs of BEB battery lifetimes by analyzing charge-discharge cycles until battery failure across different models. Our findings show that integrating sparse

data into robust design leads to a charge-discharge pattern that minimizes long-term battery-related costs. Lastly, we highlight the added value of data collection, quantifying how increasing the number of observations improves BEB charging infrastructure design in terms of computational efficiency and reliability.

The remainder of this paper is organized as follows. Relevant literature is discussed in Section 4.2. The elements of the CID problem and underlying assumptions as well as details of the mathematical models are provided in Section 4.4. In Section 3.2.8, computation results and the case study are discussed. Finally, our findings are summarized in Section 4.6.

2.2 Related Literature

Electrifying public transport systems with BEBs involves optimizing trade-offs between the strategic placement of charging stations, the selection of charger types (e.g., fast-feeding and standard charging station), and the determination of appropriate battery sizes. The introduction of fast charging technology enables buses to recharge rapidly at stops or terminals, achieving a full recharge in less than a minute Augé (2015). In this study, two types of charging stations are considered: fast-feeding and standard charging stations. Fast-feeding stations allow rapid recharging, capable of restoring a battery to 80% capacity within 15 to 20 seconds (Augé, 2015; Tomaszewska et al., 2019). In contrast, standard stations recharge batteries at a slower rate, with the amount of charge depending on dwell time and charger power. The efficiency of electrification deployment critically hinges on accurate energy consumption estimation.

The optimal solution balances these factors to ensure operational reliability, which can be expressed through specific bus schedules or generalized bus frequency, while considering costs of electrification. Finding a reliable, cost-efficient solution is heavily influenced by the availability and accuracy of data on energy consumption. In this section, we provide an overview of the state-of-the-art related to the planning problem. For a comprehensive review of optimization problems for electric buses, readers are referred to Zhou et al. (2024).

Studies on the design of BEB networks utilize three perspectives to model energy consumption: point estimation values, simulation-based approaches to identify variations, and random variable.

The first group focuses on the design problem using nominal energy consumption values. In Xylia et al. (2017) and Azadeh, Vester, and Maknoon (2022), the authors consider nominal energy consumption values. Xylia et al. (2017) studied the optimal placement of charging stations for a mixed fleet of biodiesel, electric, and biogas buses in Stockholm, providing an evaluation framework for deploying an alternative-fuel public transport network and performing sensitivity analysis to assess solution robustness. Azadeh, Vester, and Maknoon (2022) focused on battery lifetime as an additional component in the electrification process, formulating the problem as a bi-objective optimization with total ownership cost and battery lifetime as objectives. They considered

nominal energy consumption values and controlled robustness by imposing fixed upper and lower bounds on battery charge. Finally, He et al. (2022) studied the BEB deployment problem, incorporating detailed charging schedules. The authors proposed a two-phase optimization framework: the first phase uses conservative (worst-case) energy consumption values for system deployment and charging schedules, while the second phase employs a rolling horizon approach to adapt the bus schedule plan.

For BEBs, energy consumption is influenced by factors such as passenger load, travel time, weather conditions, and road characteristics. The first group of studies evaluates the robustness of solutions through post-analysis of energy consumption variability using scenarios. In contrast, the second group considers energy consumption variability a priori, employing simulation models. Sinhuber et al. (2012) considered factors such as vehicle speed and route stops, proposing a simulation model to understand energy consumption variation and inform battery size decisions. Rogge et al. (2015) further utilized this simulation model, proposing a hierarchical approach to determine fleet size, charging station placement, and battery capacity. In Sebastiani et al. (2016) and Teichert et al. (2019), the authors integrate simulation into a simulation-optimization framework. Sebastiani et al. (2016) simulate energy consumption variations based on bus speed and passenger load. This simulation is embedded in an optimization model to determine charging station placement and bus charging times. Teichert et al. (2019) study an existing system with a fixed bus schedule and characteristics. They assume uniform environmental conditions, with energy consumption influenced only by travel time variation. Their simulation model determines energy consumption variation. A numerical approach then minimizes ownership cost by optimizing battery size and the number and type of charging stations. Simulation models and expert judgments are commonly used to estimate system operations, but their predictions often deviate from empirical observations, failing to capture real-world variability in energy consumption. Recognizing these limitations, a second group of studies treats energy consumption as a random variable to explicitly incorporate uncertainty into the modeling process.

In the stochastic programming framework, random variables are assumed to follow known probability distributions, allowing uncertainty to be addressed using computationally intensive scenario-based methods. This approach is particularly effective when reliable probabilistic information is available. For example, An (2020) accounted for stochastic variations in electricity demand due to weather and traffic fluctuations, using stochastic integer programming to optimize charging station placement and fleet size. Similarly, Zhou, Ong, et al. (2023) modeled the state of charge as a stochastic variable influenced by travel time and battery degradation. By employing a two-stage stochastic programming approach, they optimized charging facility deployment and operational scheduling.

The second approach, robust optimization, addresses uncertainty by solving problems under the worst-case realization of random variables. This method has been widely applied to BEB-related challenges, with studies incorporating diverse sources of uncertainty into their formulations. For instance, Hu et al. (2022) accounts for travel time and passenger demand uncertainty to optimize charging station placement and bus schedules, while Gairola and Nezamuddin (2023) focuses on energy consumption variability with

similar objectives. Similarly, Bai et al. (2022) addresses fleet sizing and wireless bus design, incorporating uncertainties in energy consumption and charging supply, and Iliopoulou and Kepaptsoglou (2021) optimizes route planning and charging infrastructure under power supply and electricity demand uncertainty. Expanding on this, Avishan et al. (2023) integrates energy consumption and travel time uncertainty into electric bus scheduling, minimizing costs related to scheduling, fleet purchasing, energy procurement, and operations, while leveraging off-peak electricity tariffs.

While robust optimization is computationally efficient and well-suited to data-scarce environments, its reliance on worst-case scenarios often leads to overly conservative solutions that fail to capture the probabilistic nature of real-world uncertainty (Birge & Louveaux, 2011). To address these shortcomings, distributionally robust optimization (DRO) incorporates distributional information to balance robustness with performance, offering a more flexible approach to decision-making under uncertainty.

DRO extends beyond the limitations of both stochastic programming and robust optimization by considering the worst-case probability distribution within an ambiguity set defined by available data (Delage & Ye, 2010). Unlike stochastic programming, which relies on predefined probability distributions, and robust optimization, which assumes worst-case parameter realizations, DRO reduces conservatism while maintaining computational tractability. This makes it particularly effective for problems with limited or uncertain data (Delage & Ye, 2010; Mohajerin Esfahani & Kuhn, 2018).

A notable extension of DRO is the distributionally robust chance constraint (DRCC) approach, which applies the DRO framework to probabilistic constraints. DRCC ensures that constraints are satisfied with a specified probability across all distributions in the ambiguity set, effectively balancing reliability and flexibility. This feature is particularly advantageous in addressing the challenges of sparse and uncertain data, where traditional methods may either fail to generalize or result in overly conservative designs. In this study, we adopt the DRCC approach to incorporate empirical observations into the optimization process, enabling a robust and adaptive framework for handling energy consumption variability in charging infrastructure design.

Table 2.1 presents the most relevant studies focusing on the incorporation of uncertainty into the optimization of BEB networks. While robust optimization methods with budget parameters to control conservatism are widely used, they can be overly conservative. To address this, our study introduces a novel application of the data-driven DRO approach for designing BEB charging infrastructure. Furthermore, this study evaluates how these techniques impact system performance, focusing specifically on cost efficiency and the feasibility of the resulting solutions.

2.3 Model Formulation

We formulate the CID problem for the electrification of an existing bus network, addressing the challenges posed by sparse energy consumption data. The problem involves three core decisions: (1) selecting the type of charging station (e.g., fast-feeding or standard), (2)

Table 2.1 Relevant studies in BEB planning design under uncertainty

Authors	Decision level		Data feature	Modeling approach		
	Strategic	Tactical/operational		SP	Robust optimization	
					Uncertainty set with budget	Data-driven DRO
Z. Liu et al. (2018)	✓	✓	Range		✓	
An (2020)	✓		Scenario	✓		
Iliopoulou and Kepaptsoglou (2021)	✓		Range		✓	
Bai et al. (2022)	✓	✓	Range		✓	
Hu et al. (2022)	✓	✓	Range		✓	
Huang et al. (2023)		✓	Range		✓	
Zhou, Ong, et al. (2023)	✓		Scenario	✓		
Gairola and Nezamuddin (2023)	✓	✓	Range		✓	
Avishan et al. (2023)		✓	Range		✓	
This paper	✓		Range and sparse data		✓	

Legend– SP: Stochastic Programming; DRO: Distributionally Robust Optimization

identifying optimal charging station locations, and (3) determining onboard battery capacities.

This section begins by detailing the fundamental assumptions and components of the electrification problem. We then present the formulation of three models: the deterministic CID model, the BoU-CID, and the DRCC-CID. Each model adopts a unique approach to handling energy consumption data. In Section 2.3.1, the (deterministic) CID model based on expected energy consumption is presented. Next, Section 2.3.2 discusses the BoU-CID model which incorporates a range of uncertain values. Finally, Section 2.3.3, presents the DRCC-CID model, which directly integrates empirical observations into a robust optimization framework.

Cost structure. The system cost structure includes infrastructure costs for charging stations and onboard batteries. Energy consumption uncertainty affects charge-discharge patterns, impacting battery longevity and system costs in long term. Therefore, we perform analysis on battery lifetime under different approaches.

Network composition. The bus network consists of several lines, denoted by the set $k \in K$. Each line k requires a known number of buses. The BEB fleet size of bus line k is denoted by γ_k . All buses on line k start and end their trips at a terminal, denoted by o_k , which is equipped with charging stations. Bus lines can be either bidirectional or one-way, with terminals at both ends. Each line is represented by an ordered set of stops, S_k , and the set of all stops is $S = \cup_{k \in K} S_k$.

Charging infrastructure and battery specifications. As mentioned before, we consider two types of charging station: fast-feeding and standard stations, denoted by $t \in T$. Fast-feeding stations provide rapid charging, enabling batteries to recharge up to 80% in less than 20 seconds, making them ideal for intermediate stops where minimizing operational delays is critical. These systems are engineered to meet stringent safety standards, allowing safe operation even with passengers on board Augé (2015). Standard charging stations, in contrast, operate at a slower rate, with charging levels determined by the dwelling time and charger power. While these stations are better suited for end-of-line or depot locations, their slower charging rate can pose challenges for high-frequency operations. In this study, we assume that charging stations can be installed at any bus stop. However, logistical constraints, such as limited grid capacity or local policy restrictions, may limit the set of feasible locations in practice. These constraints can be incorporated into the model by excluding specific stops from the set of potential charging locations

Buses operating on the same line are assumed to have the same battery capacity. They must maintain a minimum energy level $\underline{b}$ and a maximum energy level $\bar{b}$ at all times. Additionally, BEBs are assumed to leave the terminal with maximum energy levels.

Energy consumption. We assume that energy consumption between consecutive stops is a random variable, with some observations available from field experiments. To address energy consumption uncertainty, we do not constrain the analysis to specific factors such as travel time or BEB speed. Instead, the model is designed to capture variability arising from unobserved factors, such as environmental conditions or operational inconsistencies, that influence energy consumption during a route. This flexibility ensures that the model remains applicable across diverse scenarios where detailed information on uncertainty drivers may be unavailable. Building on observed energy consumption data, we propose a set of robust and data-driven modeling approaches to systematically incorporate uncertainty into the charging infrastructure design process.

2.3.1 Formulation using mean energy consumption estimates

This model utilizes expected values to estimate uncertain energy consumption, serving as a baseline to gauge operational efficiencies. The notations used in the modeling formulation are summarized in Table 2.2. The objective function of all the models (2.1) aims to minimize the total cost, compromising the installation cost of type $t \in T$ of charging stations (denoted by α_t) and onboard battery costs per kWh (denoted by β). The BEB fleet size for each line $k \in K$ is given and denoted by γ_k . The binary variable x_{st} is set to 1 if a charging station type $t \in T$ is installed at stop s . Since different bus lines can share a single charging station, the index $k \in K$ is omitted for this variable. The battery capacity for each bus line is represented by the continuous variable z_k .

$$\min_{x,z} \sum_{s \in S} \sum_{t \in T} \alpha_t x_{st} + \sum_{k \in K} \beta \gamma_k z_k \quad (2.1)$$

Constraints for charging stations, energy flow, and battery energy levels are presented below. In the remainder of this section, we explain each family of constraints separately.

Table 2.2 List of notations used in modeling formulation

Notation	Description
Sets	
K	Set of bus lines, indexed by k
S	Set of all stops. S_k denotes the stops on bus line k . The terminal (depot) of bus line k is indexed as o_k
T	Type of charging stations, indexed by t
N	Sample size of observed energy consumption data, indexed by j
Parameters	
α_t	Installation cost of charging station type t (€)
β	Unit cost per kWh of BEB battery capacity (€ per kWh)
γ_k	BEB fleet size for bus line k
P_t	Power capacity of charging station type t
$\Delta_{k,s}$	Dwell time of the BEB at stop s on bus line k
$\bar{b}, \underline{b}$	Upper and lower bounds of allowable battery usage (%)
$\bar{\mu}_s^k, \hat{\mu}_s^k$	Average energy consumption and maximum deviation from the average between stops $s - 1$ and s on bus line k
μ_s^{kj}	j -th observed energy consumption sample between stops $s - 1$ and s on bus line k
Γ_s^k	Budget parameter controlling the conservatism level in the BoU-CID model
θ_s^k	Budget parameter controlling the conservatism level in the DRCC-CID model
ϵ	Risk parameter for the chance constraint in the DRCC-CID
Decision variables	
$e_{k,s}$	BEB energy level upon departure from stop s on bus line k
x_{st}	Binary variable equal to 1 if a charging station of type t is installed at stop s , and 0 otherwise
z_k	Continuous variable representing BEB battery capacity (kWh)

Charging station. In this problem, we assume that at most one type of charging station can be installed at each stop. This condition is enforced by Constraint 2.2.

$$\sum_{t \in T} x_{st} \leq 1, \quad \forall s \in S \quad (2.2)$$

$$x_{st} \in \{0, 1\}, \quad \forall s \in S, \forall t \in T \quad (2.3)$$

Energy flow. The variable $e_{k,s}$ represents the energy level of the BEB on line k as it departs stop s . Constraint (2.4) governs the energy flow between stops $s - 1$ and s . It ensures that the energy level at departure from stop s is the energy level at departure from stop $s - 1$ minus the expected energy consumption between these stops, denoted by $\bar{\mu}_s^k$, plus any energy gained at stop s . The power of the charging station type t is denoted by P_t , and $\Delta_{k,s}$ indicates the dwelling time at stop s for bus line k . For fast-feeding charging stations, the BEB departs with a fully charged battery regardless of the dwelling time, which is modeled as $P_{FF} = \bar{b}z_k$. BEBs must depart the terminal with maximum energy levels, given by $e_{k,o_k} = \bar{b}z_k$, $\forall k \in K$.

Using the energy flow Constraint (2.4), $e_{k,s}$ is computed cumulatively from the terminal, as defined in Constraint (2.5). This constraint represents the BEB energy level upon departure from stop s on line k . It is expressed as the maximum battery level at the terminal, $\bar{b}z_k$, minus the cumulative average energy consumption across all

preceding stops, $\sum_{i=o_k}^s \bar{\mu}_i^k$, plus the cumulative energy gained from charging at those stops, $\sum_{t \in T} \sum_{i=o_k}^s P_t \Delta_{ki} x_{it}$.

$$e_{ks} \leq e_{ks-1} - \bar{\mu}_s^k + \sum_{t \in T} P_t \Delta_{ks} x_{st}, \quad \forall k \in K, s \in S_k \quad (2.4)$$

$$e_{ks} = \bar{b}z_k - \sum_{i=o_k}^s \bar{\mu}_i^k + \sum_{t \in T} \sum_{i=o_k}^s P_t \Delta_{ki} x_{it}, \quad \forall k \in K, s \in S_k \quad (2.5)$$

Battery energy level. The BEB energy level at all stops must not exceed the maximum allowed, expressed as $e_{ks} \leq \bar{b}z_k$, $\forall k \in K, s \in S_k \setminus o_k$. When applied to Constraint 2.5, the term $\bar{b}z_k$ cancels out, simplifying the constraint. This ensures that the cumulative energy gained through charging up to stop s does not exceed the cumulative average energy consumption up to stop s , thereby preventing overcharging and adhering to the maximum allowed battery capacity, as shown in Constraint (2.6). Constraint (2.7) ensures that the energy level upon arrival at any stop s remains above the minimum required. The non-negativity of the battery capacity is shown in Constraint (2.8).

$$\sum_{t \in T} \sum_{i=o_k}^s P_t \Delta_{ki} x_{it} \leq \sum_{i=o_k}^s \bar{\mu}_i^k \quad \forall k \in K, s \in S_k \quad (2.6)$$

$$\bar{b}z_k - \sum_{i=o_k}^s \bar{\mu}_i^k + \sum_{t \in T} \sum_{i=o_k}^{s-1} P_t \Delta_{ki} x_{it} \geq \underline{b}z_k \quad \forall k \in K, s \in S_k \quad (2.7)$$

$$z_k \in \mathbb{R}^+, \quad \forall k \in K \quad (2.8)$$

The (deterministic) CID is formulated as follows.

$$\begin{aligned} CID = \min_{x, z} \quad & \sum_{s \in S} \sum_{t \in T} \alpha_t x_{st} + \sum_{k \in K} \beta \gamma_k z_k \\ \text{subject to:} \quad & (2.2, 2.3) \\ & (2.6 - 2.8) \end{aligned}$$

CID provides electrification solution by using the expected value of energy consumption. However, various contextual factors, such as weather, driving style, and passenger loads, cause deviations from this average consumption. If the true distribution of energy consumption is skewed, relying solely on average estimates may misrepresent the actual conditions and result in a charging infrastructure design that fails to provide feasible and reliable trips. This highlights the need for more comprehensive formulations that incorporate energy consumption uncertainty into the BEB CID. Consequently, two robust models are introduced and discussed below.

2.3.2 Formulation based on uncertainty range

In this approach, we consider energy consumption uncertainty as a range. This strategy is applicable when the range of energy consumption data is known to decision-makers.

For two subsequent stops $s - 1$ and s , the uncertainty box is defined by the expected energy consumption ($\bar{\mu}_s^k$) and its maximum deviation ($\hat{\mu}_s^k$). The deviation can be expressed as $\hat{\mu}_s^k = \bar{\mu}_s^k + \omega \bar{\mu}_s^k$. Therefore, the energy consumption belongs to the range of $[\bar{\mu}_s^k - \omega \bar{\mu}_s^k, \bar{\mu}_s^k + \omega \bar{\mu}_s^k]$, where $\omega \in [0, 1]$ indicating possible deviations up to the average energy consumption value Bertsimas and Sim (2003). Negative deviations are disregarded as they do not impact the bus system's service level. Consequently, the uncertainty range is defined as: $[\bar{\mu}_s^k, \bar{\mu}_s^k + \omega \bar{\mu}_s^k]$.

We standardized the random energy consumption parameter (μ_s^k) by defining $\mu_s^k = \frac{\mu_s^k - \bar{\mu}_s^k}{\hat{\mu}_s^k}$. Without constraints on μ_s^k , this approach can be overly conservative, allowing maximal deviations in energy consumption between all stops on the bus line. To mitigate this, we impose Γ_s^k as a budget to set an upper limit for energy consumption deviations up to stop s on bus line k . We define the box uncertainty set for μ_n^k as $\mathcal{C}_n^k$:

$$\mathcal{C}_n^k = \{\mu_i^k \in [0, 1] \mid \sum_{i=o_k}^s \mu_i^k \leq \Gamma_s^k, \quad \forall k \in K\}$$

The parameter Γ_s^k belongs to the interval $[0, |s|]$. This parameter indicates the cumulative allowed energy consumption deviation up to stop s . A value of $\Gamma_s^k = |s|$ means that the energy consumption is at its maximum level. The value of Γ_s^k depends on decision-maker opinion and indicates the robustness and level of conservatism of the solution. We will now consider the range of the energy consumption random parameter in (2.6) and (2.7) using the defined box uncertainty set $\mathcal{C}_n^k$ as shown below:

$$\sum_{t \in T} \sum_{i=o_k}^s P_t \Delta_{ki} x_{it} \leq \sum_{i=o_k}^s \bar{\mu}_i^k + \sum_{i=o_k}^s \hat{\mu}_{i i}^{kk}, \quad \forall k \in K, s \in S_k \quad (2.9)$$

$$\bar{b} z_k - \sum_{i=o_k}^s \bar{\mu}_i^k - \sum_{i=o_k}^s \hat{\mu}_{i i}^{kk} + \sum_{t \in T} \sum_{i=o_k}^{s-1} P_t \Delta_{ki} x_{it} \geq \underline{b} z_k \quad \forall k \in K, s \in S_k \quad (2.10)$$

The above constraints provide a formulation where the energy consumption is estimated using a box uncertainty set. This strategy aims to optimize BEB CID to be robust against maximum energy consumption deviation up to stop s , ($\sum_{i=o_k}^s \hat{\mu}_{i i}^{kk}$), within a predefined budget from the terminal up to stop s as Γ_s^k . This term in the above constraints is represented by the following optimization model:

$$\begin{aligned} & \max \sum_{i=o_k}^s \hat{\mu}_{i i}^{kk} \\ & \text{s.t.} \sum_{i=o_k}^s \mu_i^k \leq \Gamma_s^k, \quad \forall s \in S_k \\ & 0 \leq \mu_i^k \leq 1, \quad \forall s \in S_k \end{aligned} \quad (2.11)$$

The dual formulation can be written as:

$$\begin{aligned} \min_{u,v} \quad & \Gamma_s^k u^k + \sum_{i=o_k}^s v_i^k \\ \text{s.t.} \quad & u^k + v_s^k \geq \hat{\mu}_s^k, \quad \forall s \in S_k \\ & u^k, v_s^k \geq 0, \quad \forall s \in S_k \end{aligned} \quad (2.12)$$

Consequently, Constraints (2.9) and (2.10) are reformulated as (2.13) and (2.16).

$$\sum_{t \in T} \sum_{i=o_k}^s P_t \Delta_{ki} x_{it} \leq \sum_{i=o_k}^s \bar{\mu}_i^k + \Gamma_s^k u^k + \sum_{i=o_k}^s v_i^k, \quad \forall k \in K, s \in S_k \quad (2.13)$$

$$(\bar{b} - b)z_k + \sum_{t \in T} \sum_{i=o_k}^{s-1} P_t \Delta_{ki} x_{it} \geq \sum_{i=o_k}^s \bar{\mu}_i^k + \Gamma_s^k u^k + \sum_{i=o_k}^s v_i^k, \quad \forall k \in K, s \in S_k \quad (2.14)$$

$$u^k + v_s^k \geq \hat{\mu}_s^k, \quad \forall k \in K, s \in S_k \quad (2.15)$$

$$u^k, v_s^k \geq 0, \quad \forall s \in S_k \quad (2.16)$$

The deterministic equivalent counterpart of the box uncertainty robust model, i.e., BoU-CID, is as follows.

$$\begin{aligned} BoU - CID = \min_{x,z} \quad & \sum_{s \in S} \sum_{t \in T} \alpha_t x_{st} + \sum_{k \in K} \beta \gamma_k z_k \\ \text{subject to:} \quad & (2.2, 2.3, 2.8) \\ & (2.13 - 2.16) \end{aligned}$$

2.3.3 Empirical data-driven uncertainty modeling

In the previous section, we demonstrated the importance of accounting for values above the average consumption to ensure robustness of the design and developed a tractable formulation based on this concept. However, as discussed in Baron et al. (2011) and K. Liu et al. (2019), this model may be vulnerable to inaccuracies in estimating the worst-case scenarios. An exceptionally high but less probable worst-case realization of energy consumption at a stop can disproportionately influence the design of the entire network.

In this section, we introduce the third approach to handle the uncertainty in energy consumption, assuming access to a limited number of observational data points. The main idea is to construct a distributional set of energy consumption that integrates more data points beyond mere range information. By utilizing these observations to approximate the true probability distribution of energy consumption, this approach provides a solution robust against the worst probable distribution within a predefined budget. Consequently, it reduces reliance on extreme values and seeks to lower costs from overly conservative designs.

We consider N samples, each representing observations of energy consumption between consecutive bus stops on a specific bus line. The j -th energy consumption sample between stop $s - 1$ and s on bus line k is noted by μ_s^{kj} , where $\{j = 1, \dots, N\}$. The goal of this approach is to find a robust design that minimizes the electrification costs utilizing N energy consumption samples. It ensures that the cumulative energy consumption up to stop s on line k falls within a decision-dependent safety set with high probability $(1 - \epsilon)$ across all potential distribution (P), as shown in Constraints (2.17) and (2.18). In these constraints, the average energy consumption in **CID** is replaced by the observed values of energy consumption. The related risk parameter is shown by ϵ .

$$P \left[\sum_{t \in T} \sum_{i=o_k}^s P_t \Delta_{ki} x_{it} \leq \sum_{i=o_k}^s \mu_i^{kj}, \quad \forall k \in K, s \in S_k, j \in \{1, \dots, N\} \right] \geq 1 - \epsilon, \quad \forall P \in \mathcal{F}(\theta_s^k) \quad (2.17)$$

$$P \left[(\bar{b} - \underline{b})z_k + \sum_{t \in T} \sum_{i=o_k}^{s-1} P_t \Delta_{ki} x_{it} \geq \sum_{i=o_k}^s \mu_i^{kj}, \quad \forall k \in K, s \in S_k, j \in \{1, \dots, N\} \right] \geq 1 - \epsilon, \quad \forall P \in \mathcal{F}(\theta_s^k) \quad (2.18)$$

Given the N observations of energy consumption data, accurately estimating their true distribution, which is influenced by multiple factors, is complex. To address this, we define a distributional uncertainty set, or ambiguity set (denoted by $\mathcal{F}(\theta_s^k)$), that includes all possible distributions for energy consumption (P) within a specified distance (θ_s^k) from a reference distribution, denoted by $\hat{P}$. The reference distribution is modeled as a discrete uniform distribution calculated from the energy consumption observations, expressed as $\hat{P} = \frac{1}{N} \sum_{j=1}^N \delta_{\mu_s^{kj}}$, where δ represents the Dirac delta function for each energy consumption observation μ_s^{kj} . The ambiguity set is defined by $\mathcal{F}(\theta_s^k) = \{P : d_W(\hat{P}, P) \leq \theta_s^k\}$, with d_W being the Wasserstein metric measuring distributional distance. This metric effectively forms a ball of radius $\theta_s^k \geq 0$ centered on the empirical distribution $\hat{P}$.

The decision-dependent safety set, denoted as $\mathcal{S}(X)$, ensures that constraints (2.17) and (2.18) are met. This allows the model to probe the boundary of the safety set and identify the worst probable distribution of energy consumption influenced by the parameter θ_s^k . The parameter θ_s^k serves as a budget for displacement, dictating the extent to which observed energy data up to stop s on bus line k can shift toward the Boundary of its safety set. The decision maker determines the value of θ_s^k , which sets the size of the ambiguity set. A larger θ_s^k value provides more budget to transport an energy consumption sample to its worst value, leading to more conservative solutions. If $\theta_s^k = 0$, the model considers only the average value of the energy consumption data, i.e., **CID**.

We denote unsafe set by $\bar{\mathcal{S}}(X)$, representing the infeasible region of the model, which is the complement of $\mathcal{S}(X)$. To shift the observed data to the border of its safety set, the distance of the uncertain energy consumption data μ_s^{kj} , to the unsafe set is defined and

denoted by $\text{dist}(\mu_s^{kj}, \bar{\mathcal{S}}(X))$ as follows:

$$\begin{aligned} \text{dist}(\mu_s^{kj}, \bar{\mathcal{S}}(X)) = \max\{0, \min((\sum_{i=o_k}^s \mu_i^{kj} - \sum_{t \in T} \sum_{i=o_k}^s P_t \Delta_{ki} x_{it}), \\ ((\bar{b} - \underline{b})z_k + \sum_{t \in T} \sum_{i=o_k}^{s-1} P_t \Delta_{ki} x_{it} - \sum_{i=o_k}^s \mu_i^{kj})))\} \\ \forall j \in \{1, \dots, N\} \quad (2.19) \end{aligned}$$

For the energy consumption data μ_s^{kj} within the constraints (2.17) and (2.18), the distance to the unsafe set is calculated as the minimum distance to any of these constraints. This distance represents the required adjustment to move an observed energy consumption value towards its worst-case value. Energy consumption values that already fall outside the safety set are assigned a zero distance, as they are already in the unsafe set. The chance constraint ensures that the constraints are jointly feasible with a probability of at least $(1 - \epsilon)$ for data points within the safety set.

After calculating the distance of each observation μ_s^{kj} to the unsafe set, we sort these samples by increasing distance and reorder them using the index $\pi_j(X)$. The sorted energy consumption is then represented by $\mu_s^{k\pi_j(X)}$. This index arranges the observations based on their proximity to the unsafe set, contingent upon the decision variable X . The decision variable in the index represent the design with different robustness settings. The *displacement budget*, θ_s^k , is a key robustness setting that determines how many and which energy consumption data points are shifted towards the unsafe set to derive the worst-case energy consumption distribution as per constraint (2.20). The energy consumption data points are moved in the order specified by $\pi_j(X)$, within the limits of θ_s^k , to approximate the worst probable distribution of energy consumption. Detailed proofs are provided in Z. Chen et al. (2022).

$$\sum_{j=1}^{\epsilon N} \text{dist}(\mu_s^{k\pi_j(X)}, \bar{\mathcal{S}}(X)) \geq \theta_s^k N \quad (2.20)$$

Constraint (2.20) ensures that the distances of observations from the unsafe set are adjusted according to the robustness parameter, θ_s^k . Specifically, this equation selects the first ϵN energy consumption samples nearest to the unsafe set and moves them towards the Boundary, determining the worst energy consumption distribution.

The calculation of distances to the unsafe set involves Constraints (2.19) and (2.20). To eliminate the partial sum operator and the permutation index $\pi_j(X)$, Constraint (2.20) is replaced by equations (2.21) and (2.22), without approximation, but at the cost of

introducing additional variables $q^k \geq 0$ and $r_s^{kj} \geq 0$. These variables are dual variables.

$$\epsilon N q^k - \sum_{i=o_k}^s \sum_{j \in \{1, \dots, N\}} r_i^{kj} \geq \theta_s^k N \quad \forall k \in K, s \in S_k \quad (2.21)$$

$$\text{dist}(\mu_s^{kj}, \bar{\mathcal{S}}(X)) \geq q^k - \sum_{i=o_k}^n r_i^{kj} \quad \forall k \in K, s \in S_k, j \in \{1, \dots, N\} \quad (2.22)$$

The final step in the DRCC-CID formulation is the linearization of the distance function (2.22). Following Z. Chen et al. (2022), we introduce a binary variable y_s^{kj} , where $y_s^{kj} = 1$ indicates that the sample μ_s^{kj} does not satisfy the chance constraint, and vice versa.

$$M(1 - \sum_{i=o_k}^s y_i^{kj}) \geq q^k - \sum_{i=o_k}^s r_i^{kj} \quad \forall k \in K, s \in S_k, j \in \{1, \dots, N\} \quad (2.23)$$

$$- \sum_{t \in T} \sum_{i=o_k}^s P_t \Delta_{ki} x_{it} + \sum_{i=o_k}^s \mu_i^{kj} + M \sum_{i=o_k}^s y_i^{kj} \geq q^k - \sum_{i=o_k}^s r_i^{kj} \quad \forall k \in K, s \in S_k, j \in \{1, \dots, N\} \quad (2.24)$$

$$(\bar{b} - \underline{b})z_k + \sum_{t \in T} \sum_{i=o_k}^{s-1} P_t \Delta_{ki} x_{it} - \sum_{i=o_k}^s \mu_i^{kj} + M \sum_{i=o_k}^s y_i^{kj} \geq q^k - \sum_{i=o_k}^s r_i^{kj} \quad \forall k \in K, s \in S_k, j \in \{1, \dots, N\} \quad (2.25)$$

$$y_s^{kj} \in \{0, 1\}^N, r_s^{kj}, q^k \geq 0, \quad \forall k \in K, s \in S_k \quad (2.26)$$

Constraints (2.21) and (2.23–2.26) limit the distance of observations to the unsafe set, ensuring that the probability of not satisfying the chance constraint is smaller than ϵ . Constraints (2.23–2.25) include a sufficiently large constant $M \in \mathbb{R}^+$, ensuring that the value of $\text{dist}(\mu_s^{kj}, \bar{\mathcal{S}}(X))$ is always non-negative.

The DRCC Constraints (2.17) and (2.18) can now be replaced by their equivalents (2.21) and (2.23–2.26). The *DRCC – CID* model, is ultimately reformulated as an MILP and presented below:

$$\begin{aligned} DRCC - CID = \min_{y, r, q, x, z} & \sum_{s \in S} \sum_{t \in T} \alpha_t x_{st} + \sum_{k \in K} \beta \gamma_k z_k \\ \text{subject to: } & (2.2, 2.3, 2.8), \\ & (2.21) \text{ and } (2.23 - 2.26) \end{aligned}$$

2.4 Computational Results

In this section, we outline the data structure required to implement the proposed models (Section 2.4.1) and evaluate their applicability and scalability. The performance of the CID,

BoU-CID, and DRCC-CID models is first tested on a series of hypothetical grid networks (Section 2.4.2) to assess scalability and subsequently applied to the Rotterdam bus network (Section 2.4.3) to demonstrate their practical effectiveness. To compare the feasibility of the design solutions generated by the CID, BoU-CID, and DRCC-CID approaches, a Monte Carlo simulation procedure is detailed in Section 2.4.4. The impact of sample size on the performance of the DRCC-CID model is analyzed in Section 2.4.4, while Section 2.4.5 presents sensitivity analyses on economic factors, including charging station costs and BEB fleet size. The models are implemented using Python 3.9.13, with the Gurobi 9.5.2 optimizer serving as the MIP solver. All computational experiments were conducted on an Apple M1 with 16 GB of RAM.

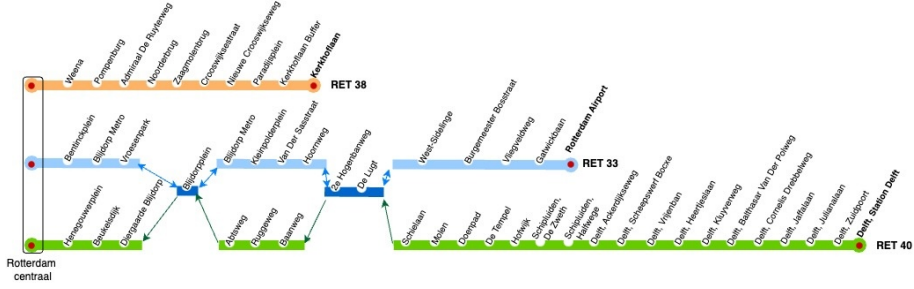
2.4.1 Data structure

This section details the specifications of the datasets used in our study, including both case study and synthetic data. These data sets are used to evaluate the effectiveness of the proposed approach.

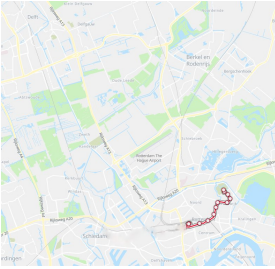
Hypothetical grid network structure. To test the scalability of the proposed models, a 10×10 grid network is generated to represent various bus network structures. This grid comprises 100 nodes located at intersections, serving as both bus stops and potential charging station locations. We simulate different scenarios with varying numbers of bus lines ($k \in \{5, 25, 45\}$), and bus stops per line ($s_k \in \{25, 45\}$). In each scenario, number of bus stops per line are predefined, and their locations are randomly generated on the grid, resulting in interconnected routes with varying inter-stop distances. All synthetic grid-based bus lines share common start and end depots. Energy consumption data is simulated based on the distance between stops, as detailed in a subsequent section. A schematic view of the simulated bus lines with different scales is provided in Appendix 2.4. The model's performance in finding exact optimal solutions is evaluated across these scenarios.

Selected bus lines in Rotterdam bus network. In this case study, we select three distinct bus lines within the Rotterdam bus network to investigate the deployment of charging infrastructure for BEBs. Our objective is to examine how different modeling approaches impact bus lines with varying spatial characteristics. Specifically, we analyze bus lines 33, 38, and 40, which include both short-distance and intercity routes. All lines begin at the common terminal, *Rotterdam Centraal Station*, and may share stops with one another. Each line is serviced by a fleet of 10 buses. A schematic representation of the studied network is shown in Figure 2.1.

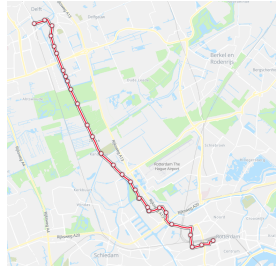
Bus line 38 is an intra-city route with 11 closely spaced stops. In contrast, Bus line 40 is an intercity route connecting Rotterdam and Delft, with 28 widely spaced stops. Bus line 33 serves a peripheral area with 15 stops. Both bus lines 33 and 38 are circular routes that start and end at *Rotterdam Centraal Station*, while bus line 40 operates as a one-way route with distinct terminals at each end. Additionally, bus lines 33 and 40 share three stops; however, bus line 33 serves these stops in both directions, unlike bus line 40.



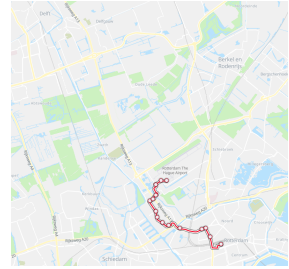
(a) Graphical depiction of Rotterdam bus network for bus lines 33, 38, and 40



(b) Part of bus line 38



(c) Bus line 40



(d) Bus line 33

Figure 2.1 Rotterdam bus lines depicted on the map

Charging station parameters and BEB specification. The specifications of the two types of charging stations, fast-feeding and standard stations, and BEB batteries are summarized in Table 2.3. We assume that all buses within a given line have homogeneous battery capacities, although different bus lines may have varying capacities. In our model, buses are assumed to charge en route at bus stops, as in Augé (2015) and Bai et al. (2022).

The electrification of bus networks involves two primary cost components: initial investment and long-term operational expenses related to battery life. After the design phase, we evaluate the long-term cost based on battery life, specifically the number of cycles until BEB battery failure, N_{cycle} , which depends heavily on the charge-discharge patterns defined by each modeling approach. Following Zang et al. (2022), the Depth of Discharge at stop s on line k (DOD_s^k) and the charge received at each stop s ($charge_s^k$) are defined as follows:

$$DOD_s^k = \frac{(z_k - y_s^k)}{z_k}, \quad y_s^k \in [0, \bar{b}z_k] \quad (2.27)$$

$$charge_s^k = \frac{z_k - Y_s^k}{z_k}, \quad Y_s^k \in [0, \bar{b}z_k] \quad (2.28)$$

where y_s^k is the BEB remaining energy upon arrival at stop s and Y_s^k is the battery level upon departure from stop s . The difference $(Y_s^k - y_s^k)$ indicates the charge received at stop s . Therefore, N_{cycle} for each bus line k can be deduced as follows, with constants

$g_1 = 1331$ and $g_2 = 1.825$ for typical Li-ion batteries Dallinger (2013).

$$N_{cycle}^k = g_1 \cdot \sum_s ((DOD_s^k)^{-g_2} + (charge_s^k)^{-g_2}) \quad (2.29)$$

The cost-efficiency of each model is evaluated by computing the *battery cost per cycle* for each bus line as:

$$\text{Cost per cycle} = \frac{\beta \times z_k}{N_{cycle}} \quad (2.30)$$

Table 2.3 List of parameters used in the models

Parameter description	Notation	Value	Reference
Infrastructure related			
Charging type	T	{ <i>Standard, Fast-feeding</i> }	-
Cost of installing charging stations	α_{SS}	20,000 €	Assumption (sensitivity analysis)
	α_{FF}	80,000 €	Assumption (sensitivity analysis)
Unit cost of battery	β	1750 €/kWh	Lajunen (2014), Z. Liu et al. (2018)
Maximum Power of chargers	P_S	100 kW	Pihlatie and Paakkinen (2017)
	P_{FF}	600 kW	Pihlatie and Paakkinen (2017)
Lower percentage of battery usage limit	$\underline{b}$	20%	Azadeh, Vester, and Maknoon (2022)
Upper percentage of battery usage limit	$\bar{b}$	80%	Z. Liu et al. (2018)
BEB dwell time at stops	Δ	N(20,4) Seconds	Augé (2015), Azadeh, Vester, and Maknoon (2022)

Energy consumption synthetic data generation. Various methods have been proposed for estimating energy consumption in BEBs, accounting for key determinants such as aerodynamic design, rolling resistance between tires and road surfaces, gravitational forces, and other influencing factors Fiori et al. (2021) and Fontana (2013). While these methods provide detailed insights into energy consumption fluctuations, they often rely on specific parameter estimation. By treating energy consumption as an exogenous input to the model, we reduce dependency on detailed parameter estimation. In this study, we address energy consumption uncertainty without focusing on specific underlying factors, the average energy consumption ($\bar{\mu}$) is simulated based on the distance between two consecutive stops, with a consumption rate of 1.3 kWh per km Bai et al. (2022). Google Maps is used to calculate the distances between each pair of stops for the Rotterdam bus lines. For the BoU-CID robust model, the maximum deviation from the mean energy consumption ($\hat{\mu} = \bar{\mu} + \omega \bar{\mu}$) is randomly generated where $\omega \in [0, 1]$, similar to Bertsimas and Sim (2003). This selection indicates that the energy consumption between these locations can deviate up to their average energy consumption value.

In the DRCC-CID the base scenario involves generating 100 energy consumption samples from a uniform distribution within the range $[\bar{\mu}, \hat{\mu}]$ for each pair of stops. Other

parameters are set as follows: the risk tolerance ϵ is set to 0.1 to satisfy the chance constraints, and M is fixed at 25 after systematic evaluation.

Budget parameters for robust models. It is important to note that the budget parameters in the BoU-CID and DRCC-CID robust models differ in their definitions. Although both parameters represent the conservatism level in the solution, their interpretations differ between the models. In the BoU-CID model, the budget parameter (Γ) represents the maximum allowable deviation from the average energy consumption value. In contrast, the budget parameter in the DRCC-CID model (θ) serves as a displacement budget, governing the extent to which the observed energy data can shift toward the safety set boundary. This approach constructs the worst-case distribution of energy consumption, rather than emphasizing the worst individual value.

In this study, two conservatism levels are selected for the robust models to represent low- and high- conservatism solutions, with $\Gamma = \{0.2, 0.8\}$ and $\theta = \{0.2, 0.8\}$. A sensitivity analysis examining the impact of other values for the budget parameters on the robust model solutions for the Rotterdam bus network, is presented Appendix 2.11 and 2.12.

2.4.2 Hypothetical grid network

To evaluate the performance of CID, BoU-CID, and DRCC-CID models on large-scale networks, the models are applied to the grid-based bus network structure described in 2.4.1. Input parameters, including charging station installation costs, battery capacity, and BEB fleet size (10 BEBs per line), remain consistent with earlier definitions to assess model scalability. The charging infrastructure design problems are solved using the Gurobi optimizer.

For the deterministic solution, which uses average energy consumption in the modeling, all tested network scenarios were solved to optimality in under 10 seconds. With energy consumption uncertainty included in the BoU-CID model, all scenarios were also solved to optimally. The runtime for the largest network (45 bus lines, each with 45 stops) increased to approximately 16 minutes. This highlights the efficiency of robust solutions in finding optimal solutions within reasonable computational time.

Table 2.4 summarizes the results for DRCC-CID across different network sizes and uncertainty levels, with 100 simulated energy consumption samples between consecutive stops. For low conservatism ($\theta = 0.2$), DRCC-CID found optimal solutions for all scenarios except for the network with 5 bus lines and 45 stops, indicating that scalability is more affected by the number of stops per line than by the number of lines. This is due to the increase in the number of data in dense bus lines.

For high conservatism ($\theta = 0.8$), increasing network size leads to a decline in solution quality and a significant increase in computation times. Nevertheless, DRCC-CID remains capable of finding feasible solutions for large networks, though identifying the optimal solution takes longer (than the 2-hour time limit) due to the increased number of constraints and variables. However, these decisions are strategic and typically finalized before system operation begins, making computational times less critical.

Table 2.4 Scalability test scenarios of the DRCC-CID model on grid-based bus networks

Uncertainty level (θ)	Grid-based bus network size		Electrification costs (10^6€)		Final upper bound (10^6)	Final lower bound (10^6)	Final gap (%)	CPU time (s)
	Number of bus lines	Number of bus stops	Charging in-stallment	BEB bat-tery				
0.2	5	25	1.76	2.74	4.504	4.504	0	422
		45	1.92	2.85	4.774	4.542	5.29	7200
	25	25	4.72	10.06	14.788	14.788	0	3595
		45	4.24	10.65	14.899	14.899	0	6224
	45	25	5.46	17.34	22.808	22.808	0	1048
		45	4.96	18.63	23.597	23.597	0	3695
0.8	5	25	1.76	2.77	4.539	4.460	1.75	7200
		45	2.48	4.68	7.166	5.751	24.6	7200
	25	25	4.64	10.68	15.325	14.183	3.8	7200
		45	4	15.03	19.030	14.183	25.5	7200
	45	25	5.92	17.72	23.597	22.433	5.1	7200
		45	4.34	26.12	30.469	21.115	44.3	7200

Electrification costs rise with network size and conservatism. The costs of BEB batteries account for over 60% of the total electrification costs across all scenarios. To provide a tangible perspective on the charging infrastructure design and cost structure of CID, BoU-CID, and DRCC-CID models, the next section compares their solutions using three bus lines from the Rotterdam bus network.

2.4.3 Deterministic and robust solutions on Rotterdam bus lines

This section provides an in-depth examination of the CID, BoU-CID, and DRCC-CID solutions for the Rotterdam bus network including a detailed analysis of initial investment, charging infrastructure design and a review on long-term battery lifetime costs in Tables (2.5), (2.6), and (2.7). All three models found optimal solutions for Rotterdam bus line instances.

The total electrification costs of the CID, BoU-CID, and DRCC-CID models for different budget parameters are shown in Table 2.5. The first row of the table presents the deterministic CID model results, serving as a benchmark for the BoU-CID and DRCC-CID solutions listed below. Column 2 shows uncertainty levels, and Column 3 lists the total costs for each model. Column 4 shows the cost difference of solutions compared to the benchmark. Columns 5 and 6 present the percentage of the total electrification cost attributed to charging station installation and BEB battery capacity, respectively. The results show that modeling uncertainty using worst-case values (BoU-CID) leads to designs that are 67% more expensive than the CID model under high conservatism, with

increases observed in both charging station installation and battery capacity costs. In contrast, the DRCC-CID model incorporates additional data points into robust modeling, effectively managing cost increases while ensuring a robust design. Even under the more conservative setting, DRCC-CID incurs substantially lower costs compared to BoU-CID. The cost breakdown shows that DRCC-CID primarily addresses uncertainty by optimizing BEB battery capacity, reducing the need for costly charging station installations, and minimizing overall system costs.

Table 2.5 Electrification costs breakdown of models

Model	Uncertainty level	Total costs (€)	Relative difference (%)	Cost type percentage	
				CS installment	BEB bat- tery
CID	-	8.413×10^5	benchmark	41%	59%
BoU-CID	low: ($\Gamma = 0.2$)	1.18×10^6	24%	43%	57%
	high: ($\Gamma = 0.8$)	1.40×10^6	67%	48%	52%
DRCC-CID	low: ($\theta = 0.2$)	9.81×10^5	17%	27%	73%
	high: ($\theta = 0.8$)	9.98×10^5	19%	26%	74%

Table 2.6 highlights the charging infrastructure solutions for each model. Columns 3 and 4 display the charging station installation costs and the bus line number, respectively. Column 5 shows the Relative difference in battery capacity between the robust and deterministic solutions. The final two columns present the number and types of installed charging stations for each bus line. Detailed information on the decision variables, including battery capacity values and charging station locations, as well as CPU time performance, can be found in Appendix A.2.

The deterministic CID solution installs five charging stations across the bus network. When accounting for worst-case energy consumption uncertainty in the BoU-CID solution, the required number of charging stations increases to seven or nine, depending on the allocated uncertainty budget. This reflects the trade-off between infrastructure expansion and uncertainty consideration. Increased charging station installations or the use of more powerful station types reduce battery capacity requirements, as charging becomes more frequent and efficient. For example, in the less conservative BoU-CID solution for bus line 40, battery capacity decreased compared to the CID solution due to the installation of additional charging stations, including fast-feeding types. However, allocating larger budgets to address uncertainty fluctuations results in simultaneous increases across all cost components, significantly driving up overall costs.

DRCC-CID shows greater design stability compared to those relying solely on worst-case scenarios. In BoU-CID, charging station locations vary with the conservatism level, resulting in changing layouts and increased planning complexity. Conversely, DRCC-CID achieves a consistent and robust design for charging station locations and

types, regardless of the conservatism degree. Additionally, DRCC-CID effectively manages larger uncertainty budgets by strategically increasing battery capacity in a controlled and cost-efficient manner. The charging infrastructure design and battery

2

Table 2.6 Charging infrastructure solution of the models

Model	Uncertainty level	Charging station cost (€)	Bus line number	Relative difference in battery capacity	Number of Charging stations	
					Dedicated	Shared
CID	-	340000	38	Benchmark	1FF	
			33		1FF	1FF
			40		1SS, 1FF	
BoU-CID	Low: ($\Gamma = 0.2$)	440000	38	+38%	1FF	
			33	+44%	1SS, 1FF	1SS, 1FF
			40	-7%	2FF	
	High: ($\Gamma = 0.8$)	660000	38	+35%	2FF	
			33	+79%	1SS, 2FF	2FF
			40	+42%	2FF	
DRCC-CID	Low: ($\theta = 0.2$)	260000	38	+80%	1FF	
			33	+20%	1SS	1FF
			40	+31%	1FF	
	High: ($\theta = 0.8$)	260000	38	+85%	1FF	
			33	+27%	1SS	1FF
			40	+31%	1FF	

Legend: **FF**: fast-feeding charging station; **SS**: Standard charging station

capacity significantly impact the BEB battery lifetime that is shown in Table 2.7. The first three columns follow the same definitions as in the previous table. The fourth column indicates the optimal BEB battery capacity of each bus line. The fifth column presents the number of cycles to BEB battery failure, N_{cycle} , calculated using Equation 2.29. The cost per cycle is derived from Equation 2.30, and the sixth column highlights the difference in cost per cycle between the robust designs and the deterministic solution. Finally, the last column shows the average relative cost per cycle across the entire network. The results show that, although BoU-CID achieves lower costs per cycle for certain bus lines compared to the deterministic solution, it increases average costs across the entire network. In contrast, DRCC-CID consistently delivers lower costs per cycle for all bus lines, resulting in over 48% cost savings per BEB battery cycle. This highlights the superior cost-efficiency of the DRCC-CID model in managing long-term battery lifetime expenses.

Table 2.7 Battery lifetime of each model

Model	Uncertainty level	Bus line number	Battery capacity (kWh)	N_{cycle}	Relative cost per cycle	Average cost difference for network
CID	-	38	7.5	489940.95	bench.	
		33	9.26	444205.1		
		40	11.87	481227.57		
BoU-CID	low: ($\Gamma = 0.2$)	38	10.81	538176.8	19.8%	
		33	12.75	620035.04	8.8%	
		40	11.09	525469.46	-14.44%	
	high: ($\Gamma = 0.8$)	38	13.42	597594.36	62.74%	+4.48%
		33	12.49	741116.75	-10.76%	
		40	16.82	704672.65	-26.24%	
DRCC-CID	low: ($\theta = 0.2$)	38	9.01	1104716.88	-51.7%	
		33	16.63	1506432.1	-41.6%	
		40	15.54	1406003.3	-55.19%	
	high: ($\theta = 0.8$)	38	9.51	1104716.88	-49.01%	-49.5%
		33	17.13	1506432.1	-39.84%	
		40	15.54	1406003.3	-55.19%	

2.4.4 Monte Carlo simulation: feasibility analysis of the results of the three models

Comparing the optimal solution costs and performance of robust and deterministic models can be misleading since each model is optimized for a different dataset. Specifically, the deterministic CID model relies on nominal realizations of energy consumption data, the BoU-CID model addresses worst-case scenarios, and the DRCC-CID model integrates sparse data into robust modeling. To ensure a fair comparison, we adopt the approach of Avishan et al. (2023), employing a Monte Carlo simulation experiment to evaluate the optimality and feasibility of the models on equal terms. In this method, energy consumption data are randomly sampled from various distributions. A charging infrastructure design is deemed infeasible for a given scenario if the battery level upon arrival at a stop falls below the minimum allowed limit, indicating that the design cannot support the trip under the realized conditions. This process is repeated for each design solution, and the number of infeasible scenarios is recorded based on the sampled energy data. The entire procedure is repeated 100 times, and the feasibility rates for each bus line and the average feasibility rate across the network are reported. The pseudo-code for the simulation algorithm is presented in Appendix A.3.

Modified in-sampling performance of the models. We evaluate the effectiveness of the robust approach in addressing uncertainty by employing the Monte Carlo simulation

method described earlier. Uncertainty parameters are sampled from four different distributions: uniform ($\mathcal{U}$) and triangular ($\mathcal{T}$), as well as asymmetric right-triangular and left-triangular distributions. The robust models are tested under 20% and 80% conservatism levels, with results summarized in Table 2.8. The modified in-sample testing refers to the calibration process in which the data is known to decision makers but does not adhere to the typical budget constraint. This modification is intended to highlight the inefficiency of robust modeling when the data is known, but the budget is limiting. The first and second columns of the table specify the simulation number and the sampling distribution for the uncertainty parameters, respectively. The third and fourth columns detail the model name and budget parameter settings. Column 5 reports the total electrification costs associated with each sampling distribution. Columns 6 to 8 present the feasibility percentages of the obtained designs over 100 simulation runs, and the final column provides the average feasibility performance across the entire bus network.

The four sampling distributions are designed to evaluate model performance under varying data characteristics. The first distribution is a uniform distribution centered on the mean energy consumption, with a range extending to the maximum deviation. The second is a symmetric triangular distribution. The third and fourth are asymmetric right- and left-triangular distributions, representing scenarios where the maximum deviation from the mean has the least and highest probability of occurrence, respectively. This selection of distributions enables us to assess the impact of incorporating sample data into robust modeling, especially in cases where the range or average values may poorly represent the actual data.

The results demonstrate that while the deterministic CID model performs well when energy consumption data is centered around the average (instances 1 and 2) or skewed towards lower values (instance 3), it fails to maintain feasibility in more extreme scenarios, such as instance 4, where higher-than-average values dominate, leading to a 55% infeasibility rate. As expected, BoU-CID ensures full feasibility across almost all scenarios, particularly under higher uncertainty budgets. However, the DRCC-CID model strikes a balance by significantly improving feasibility over CID, especially when average values poorly represent the data distribution, while consistently achieving lower costs than BoU-CID. This highlights DRCC-CID's ability to provide robust and cost-efficient solutions under diverse uncertainty conditions.

Table 2.8 Modified in-sample simulation results for CID, BoU-CID, and DRCC-CID

nr.	Sampling dis- tribution	Uncertainty level of solved problem		Total cost (€)	Bus line number			Average feasibil- ity of the bus network
					38	33	40	
1	$\mathcal{U}[0, \hat{\mu}]$	model						
		CID	-	8.1×10^5	56%	97%	67%	73%
		BoU-CID	low: ($\Gamma = 0.2$)	8.76×10^5	100%	60%	100%	87%
			high: ($\Gamma = 0.8$)	1.31×10^6	Fully feasible			
		DRCC-CID	low: ($\theta = 0.2$)	8.1×10^5	51%	93%	92%	79%
			high: ($\theta = 0.8$)	8.31×10^5	96%	93%	97%	95%
2	$\mathcal{T}[0, \hat{\mu}, \frac{\hat{\mu}}{2}]$	CID	-	7.56×10^5	52%	68%	70%	63%
		BoU-CID	low: ($\Gamma = 0.2$)	9.58×10^5	Fully feasible			
			high: ($\Gamma = 0.8$)	1.32×10^6	Fully feasible			
		DRCC-CID	low: ($\theta = 0.2$)	8.72×10^5	43%	92%	92%	76%
			high: ($\theta = 0.8$)	8.75×10^5	96%	93%	97%	93%
3	$\mathcal{T}[0, \hat{\mu}, 0]$	CID	-	6.32×10^5	68%	71%	76%	72%
		BoU-CID	low: ($\Gamma = 0.2$)	7.51×10^5	100%	98%	100%	99%
			high: ($\Gamma = 0.8$)	1.24×10^6	Fully feasible			
		DRCC-CID	low: ($\theta = 0.2$)	6.43×10^5	74%	99%	91%	88%
			high: ($\theta = 0.8$)	6.63×10^5	99%	99%	95%	98%
4	$\mathcal{T}[0, \hat{\mu}, \hat{\mu}]$	CID	-	8.94×10^5	40%	20%	75%	45%
		BoU-CID	low: ($\Gamma = 0.2$)	1.29×10^6	95%	98%	98%	97%
			high: ($\Gamma = 0.8$)	1.38×10^6	Fully feasible			
		DRCC-CID	low: ($\theta = 0.2$)	9.19×10^5	36%	80%	91%	69%
			high: ($\theta = 0.8$)	9.97×10^5	65%	92%	89%	82%

Out-of-sampling performance of the models. This section explores the performance of the models under unobserved conditions by altering the probability distributions used for sampling. In this modified simulation experiment, the sampling distributions for testing differ from the distribution utilized in designing the models, differing in their supports and distributional characteristics. Table 2.9 summarizes the findings, with the second column indicating the distribution used to achieve the design decisions of the model and the third column is the sampling distribution used for testing the performance of the model in previously unconsidered scenarios. The sixth column shows the relative difference in total electrification costs for robust models compared to the CID solution. The remaining columns show the feasibility performance of each bus line and the average feasibility performance across entire bus network.

The first and second simulation numbers examine cases where the test energy consumption values can exceed the design data by 20% in the range. Simulations 3 and 4 explore scenarios where the test and design distributions differ in their characteristics: a symmetric triangular design distribution is compared against a left-triangular distribution and a symmetric triangular distribution with a shifted mode. These test distributions assign the highest and lowest probabilities, respectively, to maximum deviations from the average energy consumption.

The results reveal that relying solely on average energy consumption for the design of the charging infrastructure, as in the CID model, leads to high infeasibility in all scenarios, with average feasibility rates ranging from 0% to 17%. The CID model is particularly inadequate in the third simulation, where the probability of worst-case values is high, leading to complete infeasibility. By accounting for uncertainty, BoU-CID ensures full feasibility under high conservatism (80%). However, under low conservatism (20%), feasibility drops to 41% in the second simulation, where both the range and data characteristics deviate from the design. The DRCC-CID model consistently outperforms the deterministic CID model in all simulations, demonstrating improved feasibility under uncertainty. When test data differ only in range but retain similar distributional properties (simulation numbers 1 and 2), DRCC-CID maintains a reasonable level of feasibility while avoiding the excessive costs associated with BoU-CID. However, in Simulation 3, where test data are centered around worst-case values, the feasibility of DRCC-CID decreases. Although BoU-CID ensures full feasibility in such extreme scenarios, it does so at significantly higher costs due to its focus on the worst case.

Table 2.9 Out-of-sample simulation results for CID, BoU-CID, and DRCC-CID

nr.	Design distrib- ution	Out-of-sampling distribution	Level of uncertainty		Relative differ- ence in total cost	Bus line feasibility			Average feasi- bility of the net- work
						model	38	33	
1	$\mathcal{U}[0, \hat{\mu}]$	$\mathcal{U}[0, 1.2\hat{\mu}]$	CID	-	bench.	12%	17%	14%	14%
			BoU-CID	low: ($\Gamma = 0.2$)	+8%	68%	59%	40%	56%
				high: ($\Gamma = 0.8$)	+62%	Fully feasible			
			DRCC-CID	low: ($\theta = 0.2$)	+0.2%	14%	48%	49%	37%
				high: ($\theta = 0.8$)	+3%	53%	50%	65%	56%
			2	$\mathcal{T}[0, \hat{\mu}, \hat{\mu}]$	$\mathcal{T}[0, 1.2\hat{\mu}, 1.2\hat{\mu}]$	CID	-	bench.	2%
BoU-CID	low: ($\Gamma = 0.2$)	+44%				49%	40%	35%	41%
	high: ($\Gamma = 0.8$)	+54%				Fully feasible			
DRCC-CID	low: ($\theta = 0.2$)	+3%				4%	20%	20%	15%
	high: ($\theta = 0.8$)	+12%				39%	54%	48%	47%
3	$\mathcal{T}[0, \hat{\mu}, \frac{\hat{\mu}}{2}]$	$\mathcal{T}[\bar{\mu}, \hat{\mu}, \hat{\mu}]$				CID	-	bench.	1%
			BoU-CID	low: ($\Gamma = 0.2$)	+27%	49%	58%	32%	46%
				high: ($\Gamma = 0.8$)	+75%	Fully feasible			
			DRCC-CID	low: ($\theta = 0.2$)	+15%	4%	20%	20%	15%
				high: ($\theta = 0.8$)	+16%	17%	20%	13%	17%
			4	$\mathcal{T}[0, \hat{\mu}, \frac{\hat{\mu}}{2}]$	$\mathcal{T}[0, \hat{\mu}, 0.8\frac{\hat{\mu}}{2}]$	CID	-	bench.	14%
BoU-CID	low: ($\Gamma = 0.2$)	+27%				96%	89%	82%	89%
	high: ($\Gamma = 0.8$)	+75%				Fully feasible			
DRCC-CID	low: ($\theta = 0.2$)	+15%				37%	41%	43%	40%
	high: ($\theta = 0.8$)	+16%				63%	71%	81%	71%

The DRCC-CID model effectively integrates empirical data into the robust optimization framework, excelling when worst-case scenarios are less frequent, and data are skewed away from extremes, as demonstrated in simulation number 4. DRCC-CID minimizes unnecessary costs and avoids overcompensation for unlikely extremes, striking an optimal balance between feasibility and cost-efficiency. This data-driven approach ensures robust performance and resource efficiency in practical applications, making it a compelling and cost-efficient alternative to worst-case-focused models like BoU-CID.

Effect of data quantity on data-driven distributionally robust optimization solutions

The DRCC-CID model is designed to perform effectively with sparse sample data. In this section, we evaluate the impact of sample size on the DRCC-CID performance, focusing on the feasibility of the design and computational time. In the previous section, Table 2.9, the out-of-sample performance was evaluated using a baseline of 100 energy consumption data points between consecutive stops. Here, we extend the analysis by solving the DRCC-CID model with varying sample sizes of 100, 300, and 500 data points. This analysis uses the first simulation scenario from Table 2.9 as the design and test distributions. Detailed results for this and the third simulation scenario are provided in A.4. The findings for the first simulation scenario are summarized in Figure 2.2, illustrating the impact of sample size on design feasibility and computational efficiency. Results are presented for two budget parameters: 20% (2.2(a)) and 80% (2.2(b)).

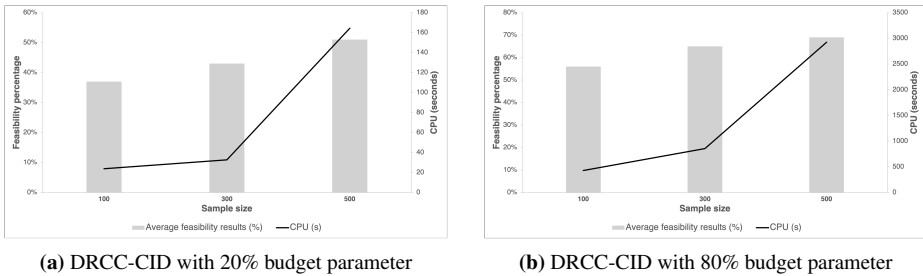


Figure 2.2 Impact of sample size on feasibility and computational time of the DRCC-CID model

For a 20% budget parameter, Figure 2.2(a), increasing the sample size from 100 to 500 data points improves feasibility from 37% to 51%, while CPU time increases significantly from 24 seconds to nearly 15 minutes. Similarly, for an 80% budget parameter, Figure 2.2(b), the feasibility improves from 56% to 69% as the sample size increases from 100 to 500 data points, but the computational time rises steeply from 7 minutes to 48 minutes. These results indicate that while increasing sample size enhances feasibility, the improvement is relatively modest compared to the computational time.

A sensitivity analysis of the budget parameters reveals that the feasibility of the design is more strongly influenced by the parameters of the robust model, i.e. budget parameter, than by the sample size. This underscores the effectiveness of the DRCC-CID model in

maintaining performance even with sparse data, making it a practical and computationally efficient choice in settings with limited data or resource constraints.

2.4.5 Sensitivity analysis in charging infrastructure design

In this section, we examine the sensitivity of the models to key economic factors, including charging station installation costs and BEB fleet size. Although the BEB fleet size is treated as a known parameter in our study, we investigate how variations in fleet size influence the cost structure of the models, offering valuable insights into their adaptability and robustness under different economic scenarios.

Economic factor sensitivity

This section investigates the sensitivity of the models to charging station installation costs and their influence on total onboard battery capacities. The analysis is conducted by fixing the budget parameters for both robust modeling approaches at 20% and 80%, representing low and high conservatism levels, respectively.

For the analysis, we assume that the installation cost of standard chargers ranges from $\alpha_{SS} = [10000, 60000]$ euros, and for fast-feeding chargers, $\alpha_{FF} = [60000, 160000]$ euros. The maximum cost values are based on Lajunen (2014). Figure 2.3 illustrates the impact of variations in charging station costs on total battery capacity of BoU-CID and DRCC-CID models, in the first and second rows respectively.

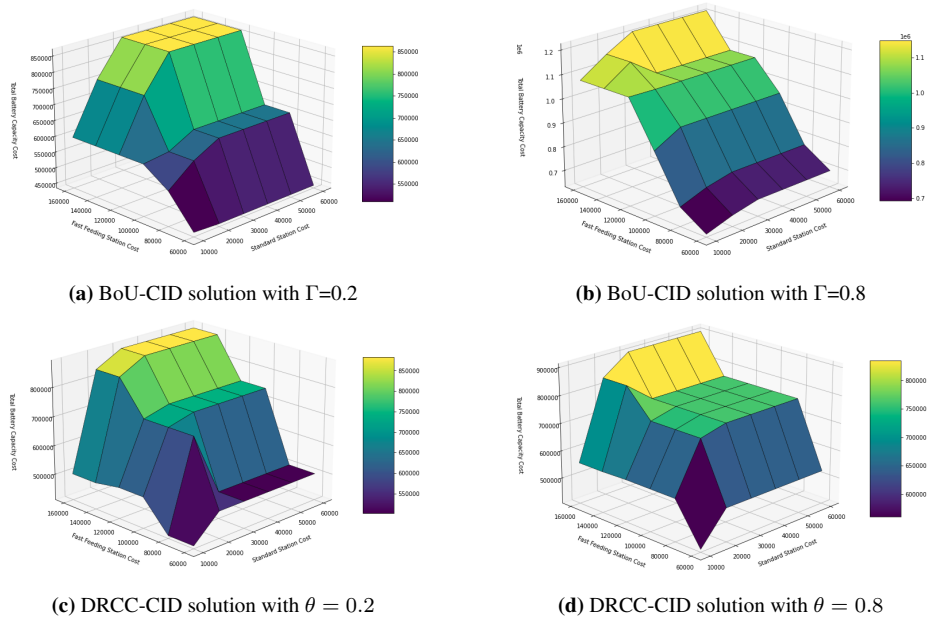


Figure 2.3 The impact of charging station costs on total battery capacity of robust models

At a low conservatism level, the BoU-CID Figure 2.3(a) increases total battery capacity more significantly than DRCC-CID 2.3(c). However, the BoU-CID stabilizes total battery capacity at the highest charging station costs, indicating a preference for installing charging stations rather than addressing uncertainty through further capacity increases. In contrast, the DRCC-CID continues to rely more heavily on capacity adjustments, showing less stability at higher charging station costs.

At high conservatism levels, both robust models prioritize installing more fast-feeding charging stations and show indifference to increases in standard charging station costs. The BoU-CID solution in Figure 2.3(b) consistently increases total battery capacity while installing more stations. In comparison, the DRCC-CID solution Figure 2.3(d), demonstrates greater stability in total battery capacity, emphasizing cost-efficient solutions rather than excessive capacity increases.

Fleet size sensitivity

This section evaluates the impact of BEB fleet size on charging infrastructure design and the cost structure of the solution. Testing different fleet sizes is essential to understanding how operational decisions, such as increasing fleet size for improved reliability or contingency planning, affect the overall electrification strategy. While the base scenario, assuming 10 BEBs per bus line, aligns with the case study assumptions, scenarios with 5 and 15 BEBs per line allow us to explore the trade-offs between fleet size and other factors, such as charging station installations and battery capacity.

The results, summarized in Table 2.10, are organized as follows: the first and second columns specify the model name and the corresponding uncertainty level, respectively. Column 3 presents the fleet sizes analyzed (5, 10, and 15 BEBs per bus line), while Column 4 details the relative differences in charging station installation costs and battery capacity compared to the benchmark. Finally, the last columns provide the cost composition, showing the percentage contributions of charging station installations and battery capacity to the total electrification costs for each solution.

In the deterministic CID model, a reduction in fleet size to 5 results in no charging station installations and an 18% increase in battery capacity compared to the base solution. Conversely, for a fleet size of 15, the model opts to install charging stations and reduce battery capacity, effectively balancing total electrification costs. A similar pattern of adjusting charging station installations and battery capacity with fleet size is observed in the robust models.

However, an exception occurs in the BoU-CID model under a 20% conservatism level. For a fleet size of 15, the model retains a similar charging station installation design as for a fleet size of 10, while increasing battery capacity significantly to hedge against uncertainty. In contrast, DRCC-CID demonstrates a more balanced approach across both 20% and 80% budget parameters. For a fleet size of 5, DRCC-CID reduces charging station installation costs by 30-39% and increases battery capacity by only 22-24%, minimizing total costs. For a fleet size of 15, it increases charging station costs moderately

Table 2.10 Impact of BEB fleet size on charging station installation and battery capacity costs

Model	Uncertainty level	BEB fleet size	Relative difference		Cost type percentage	
			CS installation costs (€)	Battery capacity (kWh)	CS installation (€)	Battery capacity (€)
CID	-	10	benchmark			
		5	-	+18%	0%	100%
		15	+17%	-58%	64%	36%
BoU-CID	low: ($\Gamma = 0.2$)	10	benchmark			
		5	-69%	+67%	29%	71%
		15	+0.09%	+177%	42%	58%
	high: ($\Gamma = 0.8$)	10	benchmark			
		5	-50%	+58%	37%	63%
		15	+18%	-56%	47%	53%
DRCC-CID	low: ($\theta = 0.2$)	10	benchmark			
		5	-39%	+22%	27%	73%
		15	+5%	-30%	39%	61%
	high: ($\theta = 0.8$)	10	benchmark			
		5	-30%	+24%	25%	75%
		15	+7%	-26%	39%	61%

by 5-7% and reduces battery capacity by 26-30%, achieving a more cost-efficient and balanced design compared to BoU-CID.

A consistent trend emerges across all models. With larger BEB fleet sizes, the models focus on installing additional charging stations to accommodate increased demand, thereby reducing reliance on onboard battery capacity. For smaller fleet sizes, charging station installations are minimized, and the models compensate by increasing battery capacity to ensure feasibility. It is important to note that fleet size decisions are closely linked to bus scheduling considerations, which are beyond the scope of this study.

2.5 Conclusion

In this study, we investigate the value of energy consumption data collection and its impact on the cost efficiency of robust Battery Electric Bus (BEB) charging infrastructure design. To address the challenges posed by sparse and uncertain energy consumption data, we implement two robust modeling approaches. The first approach, range-bound scenario planning, uses a box uncertainty set with a budget parameter to manage conservatism, relying on the range characteristics of the random parameter. The second approach, a data-driven distributionally robust optimization, directly incorporates sparse sample data

into the robust optimization process. Our analysis evaluates the effectiveness of these uncertainty modeling techniques, with a focus on cost efficiency and solution feasibility.

We validate these approaches using hypothetical grid networks and a real-world case study of the Rotterdam bus network. Both robust models are capable of delivering optimal solutions within acceptable computation times, even for large-scale bus networks. However, the results show that relying solely on the range of uncertain energy consumption values can lead to significantly inflated electrification costs. Conversely, the data-driven distributionally robust optimization consistently demonstrates superior cost-efficiency and high feasibility, particularly when worst-case scenarios are infrequent, and data are skewed away from extreme values. Sensitivity analyses on sample size and computation time reveal that the data-driven distributionally robust optimization model maintains robust performance even with limited data, making it a practical and computationally efficient option in resource-constrained settings.

This study highlights the substantial influence of uncertainty modeling approaches on BEB infrastructure design and electrification costs. Future research should explore additional dimensions of uncertainty, such as supply-side factors, and extend to tactical and operational decision-making, including the integration of bus schedules with BEB fleet sizing. While this study assumes a complete transition to BEBs, future work could examine the implications of partial electrification and the associated infrastructure adjustments. Addressing these aspects will further enhance the robustness and efficiency of BEB infrastructure design, contributing to more sustainable and reliable urban transit systems.

Appendix A

A.1 Hypothetical grid network

Figure 2.4 presents a schematic view of generated bus networks over a 10×10 grid. Each node on the grid represents a potential bus stop or charging station location. The scenarios depict varying densities and distances between stops, reflecting diverse network configurations. Figure 2.4(a) illustrates a sparse network with 5 bus lines, each containing 5 stops, characterized by widely spaced stops. Figure 2.4(b) represents a more dense network with more closely spaced stops. Finally, Figure 2.4(c) shows the largest network, consisting of 45 bus lines, each with 45 stops, representing a highly dense and interconnected bus network.

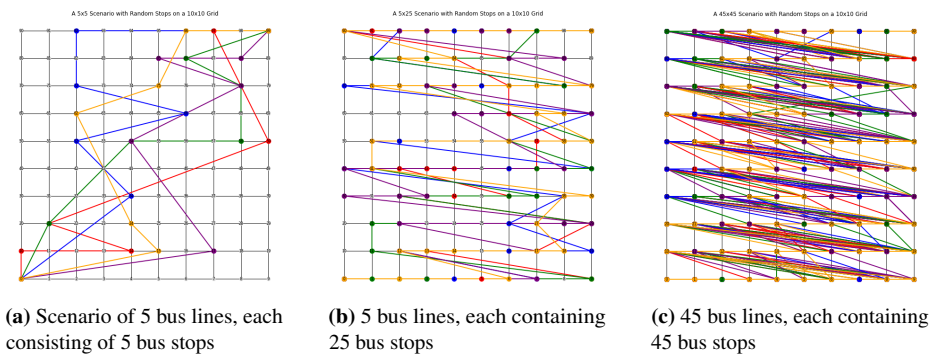


Figure 2.4 Diverse network configuration scenarios in hypothetical grid network with varying level of inter-connectivity

A.2 Performance of BoU-CID and DRCC-CID models under varying conservatism levels

Table 2.11 BoU-CID solution sensitivity in terms of budget parameter (Γ)

(Γ)	Electrification cost			Battery capacity (kWh)			CPU(s)	Network configuration	
	OFV (€)	CS installation	Relative difference	Line 33	Line 38	Line 40		SS	FF
0	8.413×10^5	340000	benchmark.	9.26	7.5	11.87	9.41	{Delft, Balthasar Van Polweg}	{Paradijsplein, Schipluiden-De Lugt, 2e Hogenbanweg}
0.2	1.18×10^6	440000	+24%	12.75	10.81	11.09	14	{Blijdorppelein, Kleinpolderpelein}	{Kerkhoflaan Buffer, Hofwijk, return-West-Sidelinge, Delft, Vrijenban, 2e Hogenbanweg}
0.4	1.18×10^6	500000	+41%	16.61	8.98	13.59	16	{Blijdorppelein}	{Zaagmolenbrug, return-Nieuwe Crooswijkseweg, Hofwijk, return-West-Sidelinge, Delft, Vrijenban, 2e Hogenbanweg}
0.6	1.29×10^6	500000	+55%	19.11	11.31	15.29	22	{Blijdorppelein}	{Zaagmolenbrug, return-Nieuwe Crooswijkseweg, Hofwijk, return-West-Sidelinge, Delft, Vrijenban, 2e Hogenbanweg}
0.8	1.40×10^6	660000	+67%	12.5	13.42	16.82	25	{return-Gatwickbaan}	{return-Vliegvelddweg, return-Van Der Sasstraat, Blijdorppelein, De Lugt, Delft, Heertjeslaan, return-Nieuwe Crooswijkseweg, Schipluiden-De Zweth, Crooswijksestraat}
1	1.50×10^6	660000	+79%	14.72	15.09	18.49	38	{return-Vliegvelddweg}	{return-Van Der Sasstraat, Blijdorppelein, De Lugt, Delft, Heertjeslaan, return-Nieuwe Crooswijkseweg, Schipluiden-De Zweth, Crooswijksestraat, return-Gatwickbaan}

OFV: Objective function value or total costs; **CS installation:** Charging station installation; **SS:** standard charging station; **FF:** fast-feeding charging station; Network configuration contains stop names (shown in Figure 2.1(a)) that specific charging station types is installed

Table 2.12 DRCC-CID solution sensitivity in terms of budget parameter (θ)

θ	Electrification cost			Battery capacity (kWh)			CPU(s)	Network configuration	
	OFV (€)	CS instal- lation	Relative difference	Line 33	Line 38	Line 40		SS	FF
0	8.413×10^5	340000	benchmark.	9.26	7.5	11.87	9.41	{Delft, Balthasar Van Polweg}	{Paradijsplein, Schipluiden-Halfwege, return-De Lugt, 2e Hogenbanweg}
0.2	9.81×10^5	260000	17%	16.61	9.01	15.54	31	{return-Gatwickbaan}	{Delft, Akerdijkseweg, De Lugt, 2e Hogenbanweg, Paradijsplein}
0.4	9.95×10^5	260000	18%	16.55	9.75	15.7	96	{return-Gatwickbaan}	{Delft, Akerdijkseweg, De Lugt, 2e Hogenbanweg, Paradijsplein}
0.6	9.98×10^5	260000	19%	17.14	9.49	15.54	135	{return-Gatwickbaan}	{Delft, Akerdijkseweg, De Lugt, 2e Hogenbanweg, Paradijsplein}
0.8	9.98×10^5	260000	19%	17.12	9.51	15.54	330	{return-Gatwickbaan}	{Delft, Akerdijkseweg, De Lugt, 2e Hogenbanweg, Paradijsplein}
1	1.005×10^6	260000	20%	17.02	10.05	15.54	393	{return-Gatwickbaan}	{Delft, Akerdijkseweg, De Lugt, 2e Hogenbanweg, Paradijsplein}
2.5	1.005×10^6	260000	20%	17.02	10.05	15.54	1296	{return-Gatwickbaan}	{Delft, Akerdijkseweg, De Lugt, 2e Hogenbanweg, Paradijsplein}

OFV: Objective function value or total costs; CS installation: Charging station installation; SS: standard charging station; FF: fast-feeding charging station; Network configuration contains stop names (shown in Figure 2.1(a)) that specific charging station types is installed

A.3 Simulation pseudo-code

Algorithm 1 Simulation Pseudo-Code for Feasibility of CID Problem

1: **Input:** Charging station locations and types (x_{st}), battery capacity (z_k), number of simulation scenarios (N'), energy consumption distribution
2: **Output:** Feasibility results and violations per scenario for each bus line
3: **for** each bus line k **do**
4: Initialize feasibility: feasible $\leftarrow$ True
5: **for** scenario $s = 1$ to N' **do**
6: Calculate initial battery capacity at depot: $B_k \leftarrow \bar{b}z_k$
7: Set initial battery level: $b_k \leftarrow B_k$
8: Generate random energy consumption between consecutive stops i and j for line k (EC_{ij})
9: **for** each consecutive stops i and j on bus line k **do**
10: **if** Charging station type t is installed at i : $x_{it} = 1$ **then**
11: Calculate charging received: Charging received $\leftarrow P_t \Delta_{ks}$
12: Update battery level: $b_k \leftarrow \min(B_k, b_k + \text{Charging received})$
13: **end if**
14: Update battery level after consumption: $b_k \leftarrow b_k - EC_{ij}$
15: **if** $b_k < \underline{b}z_k$ **then**
16: Set feasible $\leftarrow$ False and record violation
17: **break**
18: **end if**
19: **end for**
20: **end for**
21: **end for**
22: Compute feasibility rate of bus line k : $\frac{\text{Number of Feasible Simulations}}{N'} \times 100\% = 0$

A.4 DRCC performance sample size analysis

Table 2.13 Impact of Sample Size on the Feasibility of DRCC-CID Solutions

nr.	Design distribution	Out-of-sampling distribution	Uncertainty level of DRCC-CID	Data sample size	Bus line feasibility			Average feasibility of the network	CPU (s)
					38	33	40		
1	$\mathcal{U}[0, \hat{\mu}]$	$\mathcal{U}[0, 1.2 \times \hat{\mu}]$	low: $(\theta = 0.2)$	100	14%	48%	49%	37%	24
				300	39%	48%	43%	43%	164
				500	47%	48%	58%	51%	853
			high: $(\theta = 0.8)$	100	53%	50%	65%	56%	428
				300	56%	64%	75%	65%	799
				500	57%	77%	73%	69%	2923
2	$\mathcal{T}[0, \hat{\mu}, \frac{\hat{\mu}}{2}]$	$\mathcal{T}[0, \hat{\mu}, \hat{\mu}]$	low: $(\theta = 0.2)$	100	4%	20%	20%	15%	19
				300	4%	6%	4%	5%	193
				500	17%	12%	17%	15%	118
			high: $(\theta = 0.8)$	100	17%	20%	13%	17%	101
				300	8%	10%	19%	12%	799
				500	11%	29%	46%	29%	5231

Chapter 3

Shared Electric Micromobility: User Behavior and Hybrid Predictive Rebalancing and Recharging

This chapter shifts from the strategic to the tactical level, focusing on the shared e-micromobility layer that complements the fixed-schedule public transport in a multimodal urban transportation. The chapter comprises two interconnected parts that address SQ2 and SQ3. Sub-chapter 3.1 identifies the behavioral factors that determine whether a passenger selects a shared electric micromobility vehicle, calibrating mixed multinomial logit and hybrid choice models from stated-preference survey data collected in Rotterdam, the Netherlands. This behavioral analysis sheds light on quantifying perceived usability. Sub-chapter 3.2 then embeds the calibrated choice model directly into a Markovian state-prediction and rolling-horizon optimization framework for hybrid rebalancing that coordinates operator-based truck relocation and battery swapping with user-mediated drop-off incentives. By linking passenger behavior to fleet management, this chapter supplies both the behavioral model and the availability predictions that feed into the multimodal trip planner of Chapter 4.

This chapter is based on the journal article:

1. Momen, S., Maknoon, Y., van Arem, B., & Azadeh, S. S. (2026). Hybrid Predictive Rebalancing Control of Perceived Usability in Shared E-Scooter Systems. *Transportation Research Part C: Emerging Technologies*, major revision.

3.1 Passenger Behavior toward E-micromobility Vehicle Selection

As discussed in the literature review, most existing rebalancing approaches treat vehicle availability as a binary indicator and do not account for the role of vehicle characteristics such as battery level, pricing in determining whether a physically present vehicle is actually perceived as usable. To address this gap and answer the second sub-question (SQ2) which is “What factors drive a passenger’s decision to use a shared electric micromobility vehicle, and how do the vehicle’s attributes shape that decision?”, a research effort was carried out in the form of a master thesis project, co-supervised by the author of this dissertation. This section summarizes the research process, the methodological approach, and the main findings that are subsequently used in the mathematical models of the remaining chapters. The results of this study have been published in:

Burghardt, S. P., Momen, S., Maknoon, Y., Azadeh, S. S., & Kavta, K. (2025). Behavioral impact of range anxiety and unlock fees on shared electric-moped usage. *Transportation Research Part D: Transport and Environment*, 145, 104772.

3.1.1 Research Need

Uncovering the behavioral drivers of e-micromobility usage is vital for optimizing user-based rebalancing and understanding the dynamic evolution of the system. As demonstrated in the development of the hybrid rebalancing model, accurately predicting future system states requires knowing which vehicles users are willing to ride, not just which ones are physically available. We examine passengers’ behavior constructs such as range anxiety which means the fear of battery depletion before reaching a destination. While extensively studied in privately owned electric vehicles, this phenomenon has remained largely unexplored within shared micromobility. While extensively studied in privately owned electric vehicles, this phenomenon has remained largely unexplored within shared micromobility. Consequently, the research question was designed to identify the primary determinants of e-moped choice, focusing on the impact of remaining driving range under critical battery conditions, the influence of new pricing structures, and the broader implications for user-driven relocation strategies.

3.1.2 Methodological Approach

A stated-preference (SP) survey approach was adopted, as it allows the simulation of decision-making under controlled conditions, including critical range situations that are difficult to observe from revealed-preference data alone. The survey was designed with a fixed trip context (a 5-km urban errand) and varied five vehicle attributes: walking distance to the vehicle (1–10 minutes), unlock fee (€0.50–€2.00), per-minute ride fee (€0.27–€0.36) aligned with practice pricing, remaining driving range (5–14 km), and vehicle type (25 km/h or 45 km/h). The range levels were deliberately chosen to confront respondents with critical range situations, where the lowest level equals the trip distance. Designed choice set presented two unlabeled e-moped alternatives, followed by a labeled

stage with an opt-out option. In addition, two latent attitudinal constructs, i.e., attitude toward e-moped sharing and perceived range anxiety, were measured using Likert-scale indicators, along with socio-demographic characteristics. Data was collected in Rotterdam, the Netherlands between May and July 2024 through social media, mailing lists, and flyer handouts at micromobility hubs. A total of 133 eligible respondents (aged above 18, valid driving license) completed the survey, yielding 532 usable choice observations. The sample included approximately equal shares of users and non-users.

To model user's behavior, three discrete choice models were estimated sequentially. A multinomial logit (MNL) model providing baseline estimates, a mixed multinomial logit (MMNL) model capturing preference heterogeneity through random parameters, and a hybrid choice model (HCM) integrating latent variables and socio-demographics alongside the labeled experiment with opt-out. The HCM constitutes the final specification and is the model whose parameters are adopted in the remainder of this dissertation. The utility specification and the full set of estimated coefficients are presented in Equation 4.1 and Appendix B.1, respectively.

$$\begin{aligned}
 V_i^p = & ASC_{es} + \beta_w walk + \beta_{UNF} \rho_0 + \beta_{RF} \rho_1 + \beta_p p + \beta_{type} Type \\
 & + \beta_{exp} Use + \beta_{bike} Bike + \beta_{income} Income + \beta_{live.alone} Alone \\
 & + \beta_{live.shared} Shared + \beta_{perception} Att + \beta_{range.anx} Anx + \beta_{interaction} Inter
 \end{aligned}
 \tag{3.1}$$

The utility specification includes monetary and access costs, battery-related attributes, and user-specific characteristics. Battery preferences are captured through the coefficient β_p , which measures the marginal utility of additional battery range. Observed heterogeneity is represented through indicators of vehicle type, prior e-scooter experience, bike ownership, income status, and residential characteristics, while latent attributes, including perceived reliability and range anxiety, enter through additional interaction terms. A complete description of all coefficients and estimation details is provided in B.1.

3.1.3 Main Results

Across all three model specifications, the estimated parameters are consistent in sign and significance, confirming the robustness of the findings. Walking distance, unlock fee, and per-minute ride fee all carry negative coefficients, indicating that higher costs and longer access times reduce vehicle attractiveness. These results are in line with previous studies on shared micromobility preferences (Hoobroeckx et al., 2023).

The central finding concerns the role of remaining driving range. The HCM estimates a mean coefficient of 0.271 per kilometer of remaining range, with a standard deviation of 0.079 (log-normal distribution, 95% interval: 0.149–0.454). This substantial heterogeneity implies that some riders strongly avoid low-range vehicles while others are relatively indifferent, meaning that identical fleet conditions can produce markedly different effective service levels across users. This result justifies the use of perceived usability rather than physical inventory as the basis for rebalancing decisions in Sub-chapter 3.2. Interestingly, while the latent variable for perceived range anxiety carries a negative coefficient, it does

not reach conventional significance. This suggests that range anxiety does not operate as a standalone attitudinal driver of mode choice but rather manifests indirectly through the significant heterogeneity in the battery range coefficient.

The willingness-to-pay analysis derived from the HCM reveals that, on average, a ride fee reduction of approximately €0.015/min can compensate for one additional minute of walking time, though this value ranges from €0.007 to €0.028 across individuals. Similarly, users can be incentivized to accept lower-range vehicles through fee reductions, a finding with direct implications for the user-mediated incentive mechanism in the rebalancing framework.

3

3.1.4 Application in the Rebalancing and Trip Planning Models

The estimated choice model parameters are adopted in two ways in the subsequent chapters. In Sub-chapter 3.2, the vehicle selection probabilities parameterized by battery state are embedded directly into the Markovian state-prediction model (Section 3.2.6), where they govern how demand draws from each battery class and shape the expected demand loss that the rebalancing optimization seeks to minimize. The same behavioral structure governs user participation in incentive-based rebalancing, where riders trade off monetary incentives against additional walking distance when selecting drop-off locations. In Chapter 4, the same parameters enter the service reliability filter of the multimodal trip planner, determining the probability that a recommended e-micromobility leg is acceptable to a given passenger. A detailed description of how the choice model is integrated into both frameworks is provided in the respective sections.

3.2 Hybrid Predictive Rebalancing Control of Perceived Usability in Shared E-Scooter Systems

Abstract

Vehicle availability in shared electric micromobility systems is commonly assessed through fleet counts, yet realized service quality often diverges from physical inventories. This divergence arises because a vehicle contributes to service only if it is at the right location, sufficiently charged for the intended trip, and acceptable to users; we refer to this conjunction as the *perceived usability* of the vehicle, explicitly distinguishing it from mere physical *availability*. Consequently, to maintain realized service levels in geo-fenced shared e-micromobility systems, operators must pivot from maintaining fleet sizes to actively optimizing perceived usability.

This paper presents a Direct Look-ahead Hybrid Rebalancing scenario (*DL-HR*) that controls perceived usability by jointly coordinating truck-based relocation and battery swapping with user-mediated drop-off incentives. The framework embeds a Markovian state-prediction model that propagates zone-level usability under stochastic demand and battery-dependent user choice, and evaluates rebalancing actions by their impact on expected demand loss over a forward-looking horizon. We solve the resulting mixed integer program to proven optimality during each rebalancing period. By embedding this within a rolling horizon framework, the model continuously reoptimizes its strategy by ingesting periodic battery level updates from the operator. This explicitly captures the discrete and delayed impacts of both operator and user interventions as new information becomes available.

Using data from a European e-scooter sharing operator, we show that explicitly accounting for user behavior within look-ahead rebalancing improves spatial supply–demand alignment relative to truck-only practices. Specifically, the *DL-HR* scenario increases the average daily service level by 5.8 percentage points over a truck based strategy that already incorporates battery swapping. This higher performance is achieved while simultaneously reducing the average truck kilometers traveled per served trip. Furthermore, shifting from a traditional availability only approach to the usability perspective delivers its most pronounced operational gains during critical peak hour operations.

3.2.1 Introduction

Shared electric micromobility services, including e-scooters and e-bikes, have expanded rapidly as flexible first- and last-mile travel options in urban networks. By allowing users to pick up and park vehicles throughout a service area, these systems introduce a high degree of spatial and temporal flexibility in vehicle use. At the same time, this flexibility complicates operational control, as vehicles tend to accumulate in low-demand locations while shortages arise elsewhere (Ataç et al., 2021). Such imbalances directly affect whether trip requests can be served when and where they occur. Operators therefore rely on rebalancing plans, the continuous redistribution of vehicles across the service area, to align

supply with uncertain, time-varying demand and sustain service quality throughout the operating day.

How rebalancing plan is optimized depends on how supply management is viewed. Existing approaches predominantly adopt an *availability* perspective, in which supply is the count of vehicles physically present in each area. In battery dependent e-micromobility systems, however, this view can offer incomplete perspective as riders may systematically avoid low-charge e-scooters even when the remaining range is adequate (Burghardt et al., 2025). Hence, vehicles that are available are not necessarily selected. Building on this, we propose a *usability* perspective, in which supply is the count of vehicles users will perceive usable given their battery state. As a result, areas with identical vehicle counts can experience markedly different service levels depending on battery state distributions and user choices.

Because usability determines realized service, understanding how it evolves over time is central to system management. Vehicle usability evolves through the interaction of operational processes and user behavior. Operator activities, such as vehicle relocation and battery replenishment using staff and trucks, reshape the spatial distribution and energy availability of the fleet. At the same time, user decisions determine where vehicles become available after trips, with drop-off locations influenced by incentives and individual preferences. These operational and behavioral processes jointly shape which vehicles are usable at different locations and times, and their effects accumulate as the system evolves throughout the day.

Managing usability over time is complicated by uncertainty in trip demand and by the delayed effects of rebalancing operational interventions. Pickups and drop-offs fluctuate across space and time, and actions intended to improve usability often influence future conditions rather than immediately correcting current imbalances. As a result, decisions aimed at improving service must be evaluated based on their expected impact on downstream outcomes, such as unmet demand, rather than on instantaneous vehicle counts. This temporal separation between actions and outcomes under uncertainty is a central challenge in managing shared e-micromobility systems.

Existing look-ahead approaches forecast service loss by propagating current system conditions forward in time Raviv and Kolka (2013) and Zhou, Lin, et al. (2023). The accuracy of these forecasts depends critically on which aspects of the system are represented in the prediction. In shared e-micromobility systems, future service availability depends not only on where vehicles are located, but on which vehicles users are willing and able to ride, a choice strongly conditioned by battery level and perceived usability (Burghardt et al., 2025). When battery condition and user selection behavior are not embedded in predictive models, forecasts of availability and unmet demand become systematically biased, limiting the ability of look-ahead methods to inform effective operational decisions.

To address this gap, we develop a unified, direct look-ahead hybrid rebalancing framework that explicitly represents perceived usability as the basis for operational decision making. The framework coordinates operator-based actions, including e-scooter

relocation and on-street battery swapping, with user-mediated drop-off incentives to jointly influence spatial availability and battery distribution. A Markovian predictive look-ahead layer captures the evolution of system conditions under stochastic demand, battery depletion, and user response, and evaluates candidate actions by their expected impact on future unmet demand over a finite planning horizon. Decisions are updated within a rolling-horizon scheme as new information becomes available, ensuring consistency with intraday operational decision cycles.

This paper advances the operation of shared e-micromobility systems in three ways. First, it reframes rebalancing around perceived usability—an outcome shaped jointly by spatial availability, battery condition, and user behavior—rather than around vehicle counts alone. Second, it develops a behaviorally embedded, direct look-ahead framework that anticipates future service loss by accounting for demand uncertainty, battery dynamics, and user selection behavior, and uses these predictions to coordinate operator- and user-based interventions. Third, it implements the proposed framework within a rolling horizon decision process validated by extensive operational data from a European electric scooter system. We demonstrate that the *DL-HR* approach enhances service levels and spatial supply and demand alignment. Specifically, it outperforms truck based rebalancing and traditional availability metrics while maintaining control over operating costs..

The remainder of this paper is organized as follows. Section 3.2.2 reviews the related literature. Section 3.2.5 introduces the problem setting and system components. Section 3.2.6 presents the architecture of the proposed framework, including the user-choice model and the Markovian state prediction mechanism. Section 3.2.7 details the mathematical formulation of the hybrid rebalancing problem. Computational results are reported in Section 3.2.8, followed by concluding remarks in Section 4.6.

3.2.2 Related Literature

This section reviews rebalancing approaches in shared micromobility systems through the lens of system-state representation and control under uncertainty, with particular emphasis on how vehicle availability, battery dynamics, and user behavior are modeled to inform predictive and hybrid rebalancing decisions.

3.2.3 Dynamic Rebalancing, Battery Swapping, and System State Prediction

In shared micromobility systems, rebalancing seeks to control vehicle availability and battery conditions as user trips continuously reshape system state. Unlike static rebalancing, which sets inventory levels over a fixed horizon and does not account for within-day dynamics (Kaspi et al., 2017; Y. Liu et al., 2018; Osorio & Ouyang, 2025), intraday control requires anticipating how demand uncertainty, battery depletion, and relocation actions jointly influence the evolution of future service conditions.

Many operational approaches proceed without explicit state prediction, relying instead on threshold-based rules for vehicle counts or battery swapping, or on enforcing target

fill levels at the area level. For example, Chu et al. (2023) propose an operator-based rebalancing policy with fixed battery thresholds for swapping, while Lee et al. (2024) develop a joint repositioning and battery-swapping model in which operator staff redistribute scooters and batteries toward prescribed target inventories. Other approaches address uncertainty through scenario-based stochastic programming or robust optimization without propagating system state forward in time (Fu et al., 2022). While these methods offer tractable control rules, they evaluate actions primarily against current conditions rather than anticipated future service loss.

3

Predictive approaches address this limitation by explicitly linking present decisions to expected future demand (Powell, 2019). In the bike sharing literature, (Raviv & Kolka, 2013) introduce demand loss as the expected number of rejected requests over a future horizon due to insufficient supply, computed from a Markovian model of station-level inventory evolution, a concept later used to guide static repositioning plan (Raviv et al., 2013). This framework is extended to carsharing systems by Repoux et al. (2019), who employ a Markovian state prediction model to support operator-based relocation. Boyacı et al. (2017) develop an integrated optimization–simulation framework that jointly relocates vehicles and personnel, capturing the coupling between vehicle availability, charging, and staff logistics, and Stokkink and Geroliminis (2021) shift part of the relocation effort onto users through predictive incentives that anticipate future imbalance. Closest to our setting, Zhou, Lin, et al. (2023) adapt predictive guidance to a shared e-scooter system with discretized battery states, supporting repositioning and battery swapping.

Across these predictive frameworks, system state is primarily represented through vehicle availability and coarse battery categories, implicitly assuming that all available vehicles are equally usable. Recent empirical evidence, however, shows that user behavior interacts strongly with battery status: riders may systematically avoid low-charge scooters even when remaining range is sufficient, inducing perceived usability to diverge from objective vehicle availability Burghardt et al. (2025). As a result, future service conditions depend not only on where scooters are located and how charged they are, but also on which vehicles users are willing to select. Predictive rebalancing models that omit these behavioral filters therefore propagate an incomplete system state, limiting their ability to accurately forecast unmet demand and guide effective intraday control in battery-dependent micromobility systems.

3.2.4 Hybrid Rebalancing and Users' Behavioral Responses

Rebalancing in shared micromobility systems is implemented through two distinct classes of interventions that act on the same evolving system state. Operator-based interventions rely on dedicated staff and trucks to relocate vehicles and replenish batteries, enabling direct but capacity-limited adjustments to spatial availability and energy distribution. User-mediated interventions act indirectly by shaping riders' pick-up and drop-off choices through incentives, thereby influencing where vehicles re-enter the system following trips. Because these intervention channels operate through different mechanisms and on different

time scales, hybrid rebalancing frameworks have emerged to coordinate their use within a single operational setting.

Early hybrid formulations treat operator-based and user-mediated actions primarily as substitutable control levers, balancing truck deployment costs against incentive expenditures. For example, Pfrommer et al. (2014) combine truck-based redistribution with real-time pricing incentives in a bike-sharing system and show that user participation can partially offset staff costs. Subsequent studies incorporate similar incentive mechanisms into static or dynamic rebalancing plans under budget constraints (Haider et al., 2018; Y. Li & Liu, 2021; Pfrommer et al., 2014; Singla et al., 2015). In these models user participation is typically represented through homogeneous or reduced-form sensitivity assumptions. This approach allows incentives to be optimized without explicitly embedding user behavior into system-state transitions.

More recent work acknowledges the limitations of such abstractions, particularly in battery-dependent micromobility systems. Emami and Ramezani (2024) propose a hybrid framework that combines truck-based repositioning with user incentives while tracking vehicle charge levels; however, user responses are still modeled through parametric utility functions applied independently at the vehicle level (R. Zhang et al., 2023). Related studies analyze user parking or drop-off choices using discrete choice models without coupling these behaviors to rebalancing operations or predictive control (S. Zhang et al., 2026). As a result, user behavior is incorporated as an external response to incentives rather than as a mechanism governing how availability and battery states evolve under intervention.

Empirical evidence indicates that this separation is consequential. In battery-dependent systems, user selection behavior directly determines which vehicles are used, how batteries are depleted, and where charged scooters reappear after trips. For instance Xie et al. (2024) shows that behavior critically affect battery allocation and service quality in station-based e-bike battery swapping, while Burghardt et al. (2025) demonstrate that range anxiety, walking distance, and pricing jointly shape vehicle choice in shared e-moped and e-scooter systems. These behavioral filters therefore play a central role in shaping system-state transitions following both operator- and user-mediated interventions.

Existing hybrid rebalancing models consequently coordinate trucks and incentives without a state representation in which user behavior, battery dynamics, and operator actions jointly define transition dynamics. When user choice is excluded from state evolution, predicted availability reflects physical inventory rather than realized usability, and hybrid interventions are evaluated against systematically distorted forecasts. This fundamentally limits the effectiveness of hybrid rebalancing in settings where perceived usability, rather than vehicle counts alone, governs service performance.

3.2.5 Problem Description

We consider a geo-fenced e-scooter sharing system operating over an urban area partitioned into a finite set of geo-fenced zones. Each zone is associated with a prescribed parking capacity imposed by the operator to regulate sidewalk use and street occupancy (Figure (3.1)). These zones constitute the spatial units through which both user access and operator

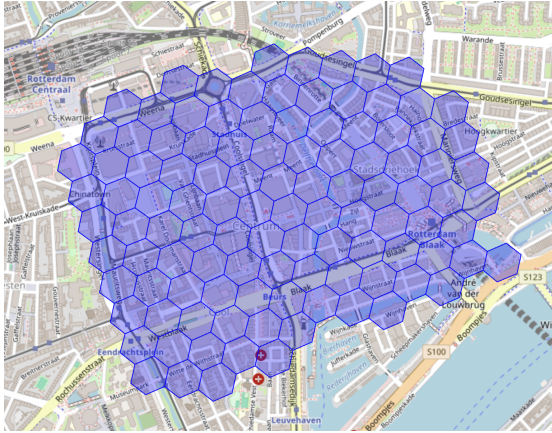


Figure 3.1 Geo-fenced areas in the Beurs area (Rotterdam).

rebalancing actions are defined. All trips originate and terminate within zone boundaries, and zone-level inventories are directly observable to users through the mobile application. As trips occur and batteries are depleted through riding, the spatial distribution and usability of e-scooters evolve endogenously over time, giving rise to persistent imbalances in which demand pressure and excess inventory are unevenly distributed across zones. E-scooters are categorized into three operational battery states defined by their suitability for serving trips: inactive, low-power, and high-power e-scooters. Inactive e-scooters have a battery level below a threshold at which the operator withdraws the vehicle from service. Low-power e-scooters carry enough charge to cover the average distance trip observed in the system but can induce range anxiety, leading users to avoid them. High-power e-scooters have sufficient charge to serve any trip without range concerns. Low-power and high-power scooters are visible to users and eligible for rental, while inactive e-scooters are unavailable for service and must undergo battery replacement before re-entering operation. This classification induces discrete feasibility constraints on both user access and operator interventions, and it governs which vehicles can be relocated, swapped, or selected at each decision epoch.

The system state at a given time is defined by the joint distribution of e-scooters across geo-fenced zones and battery states. Specifically, the state records the number of e-scooters in each battery category present in each zone at the current time step. This representation jointly captures spatial availability, battery composition, and user-visible supply, thereby defining the set of scooters perceived as usable by riders. Rebalancing actions are designed to influence the evolution of this state so as to preserve future usability under stochastic demand conditions.

State dynamics are driven in part by exogenous user demand. Trip requests arise stochastically across time and space, and realized trips induce battery depletion and spatial transfers of e-scooters between zones. These demand-driven transitions continuously reshape the system state throughout the operating day, even in the absence of rebalancing

actions. As a result, effective intraday control requires anticipating how current relocation, charging, and incentive decisions interact with uncertain future demand and battery consumption to determine downstream system states and service outcomes.

The operator influences system-state evolution through two classes of control actions: operator-based interventions and user-mediated interventions. Operator-based actions are carried out by a fleet of identical trucks operating from a central depot and subject to capacity constraints on both transported e-scooters and spare batteries. These actions allow e-scooters to be relocated between zones and enable on-street battery swapping for inactive and low-power vehicles using onboard fully charged batteries. Depleted batteries are removed from service and returned to the depot, where they are recharged and reintroduced as spare high-power batteries. The depot is assumed to hold a sufficient supply of fully charged batteries throughout the operating day, so that recharging capacity at the depot is not a binding constraint on field battery swapping.

User-mediated interventions influence system evolution by shaping post-trip vehicle availability. For trips completed using high-power e-scooters, the operator may offer location-dependent incentives that encourage riders to park in nearby underutilized zones. Incentive offers depend on trip characteristics, including ride duration and intended destination, and user participation is governed by a discrete choice model capturing willingness to deviate from the original drop-off location in exchange for a per-minute ride fee exemption. Through this mechanism, user behavior enters the control problem as an endogenous channel affecting how e-scooters re-enter the system following trips.

Time is discretized into uniform planning periods. Rebalancing actions are selected over a finite and fixed planning horizon comprising multiple periods, during which operator-based and user-mediated interventions are jointly coordinated. Although actions are implemented over this planning horizon, their performance is evaluated over a longer look-ahead horizon that captures delayed effects arising from demand uncertainty, battery depletion, and downstream state transitions.

Rebalancing decisions are updated within a rolling-horizon control framework. Specifically, the system operates on a two hour rebalancing planning horizon but receives new information regarding demand, battery levels, and vehicle locations on an hourly basis. At the start of each hourly interval, the model observes the real time system state and generates predictions for the entire look ahead horizon to propagate state evolution under uncertainty. The control actions are subsequently reoptimized based on these forecasts. This yields a closed loop policy that continuously adapts interventions to match the newly updated system state.

The scope of the rebalancing problem is defined by several structural assumptions. Each geo-fenced zone may be served at most once within a planning horizon, either through a truck visit or through participation in user-mediated rebalancing. Since truck and user-mediated actions realize their inventory effects at different times, permitting both actions in the same zone within the same horizon would make it difficult to trace the post-decision state and evaluate the corresponding demand loss. The restriction binds within each planning horizon and is mitigated across the operating day by the

rolling-horizon implementation, which re-observes the state and allows a zone to be reconsidered for a different intervention type in a subsequent epoch. Battery swapping is performed only at geo-fenced areas; no new e-scooters are sourced from the depot. Trucks may return to the depot to replenish spare batteries when onboard supplies are depleted, at which point all carried low-power and inactive e-scooters are upgraded to the high-power state. These assumptions bound the action space and are relaxed dynamically through the rolling-horizon implementation (D. Zhang et al., 2017; Zhou, Lin, et al., 2023).

3

3.2.6 Direct Look-ahead Hybrid Rebalancing (DL-HR) Architecture

This section specifies the architecture of the Direct Look-ahead Hybrid Rebalancing (DL-HR) framework, which integrates user behavior, battery dynamics, and operator interventions within a unified predictive control structure. The framework is organized around the propagation and control of the system state, defined by the joint distribution of e-scooters across geo-fenced zones and battery states, and evaluates rebalancing actions by their anticipated impact on future usability under demand uncertainty.

The DL-HR architecture comprises four interdependent components. A user choice model captures how battery level and vehicle attributes govern e-scooter selection and participation in user-mediated rebalancing (Section 3.2.6). A Markovian state prediction module propagates zone-level usability forward in time under stochastic demand and battery depletion and estimates the resulting expected service loss over a finite look-ahead horizon (Section 3.2.6). Operator- and user-based rebalancing actions induce discrete decision-dependent transitions in the system state, which are embedded within the prediction module to assess the downstream impact of candidate interventions (Section 3.2.6). These components are coordinated within a rolling horizon scheme that enables sequential re-optimization as new information on the system state becomes available (Section 3.2.6).

User choice model

User choice constitutes a core mechanism through which perceived usability evolves in shared e-scooter systems. Vehicle selection determines not only whether demand is served, but also which battery states are depleted and how scooters re-enter the system following trips. To capture these effects within the rebalancing framework, user behavior is modeled explicitly and embedded as a behavioral component of system-state transitions for future usability prediction.

We adopt the discrete choice model estimated by Burghardt et al. (2025), which specifies the probability that an e-scooter is selected as a function of vehicle attributes, including battery level, access distance, and pricing. Battery states are indexed by $p \in P = \{n, l, h\}$, corresponding to inactive, low-power, and high-power e-scooters. Only low-power and high-power e-scooters are available for selection. The systematic utility associated with selecting an e-scooter of battery state p in area i is denoted by V_i^p and is specified in Equation (3.2). Battery level enters the utility function directly and

governs relative selection probabilities across available vehicles.

$$V_i^p = ASC_{es} + \beta_w walk + \beta_{\rho_0} \rho_0 + \beta_{\rho_1} \rho_1 + \beta_p p + \beta_{type} Type + \beta_{soc}^\top \mathbf{X}_{soc} + \beta_{lat}^\top \mathbf{X}_{lat} \quad (3.2)$$

The utility specification combines vehicle and access attributes (battery level p , vehicle type, walking access time $walk$), trip pricing (unlock fee ρ_0 and per-minute ride fee ρ_1), and user-specific characteristics grouped into a socio-demographic vector $\mathbf{X}_{soc}$ and a latent attitudinal vector $\mathbf{X}_{lat}$. The corresponding coefficient vectors β_{soc} and β_{lat} are estimated jointly with the remaining parameters. Battery preferences enter through β_p , which measures the marginal utility of additional battery range, and price sensitivity enters through β_{ρ_1} . User behavior is represented by a homogenous specification in which the coefficients are evaluated at population means. Consequently, selection among available battery states depends only on the alternative-varying attributes, i.e., battery level (p) and per-minute fee (ρ_1). A complete description of all coefficients and estimation details is provided in Appendix B.1.

The choice set comprises three alternatives: a low-power e-scooter, a high-power e-scooter, and opting out from the system. It is defined independently of realized availability, which enters the framework through the state-prediction model by scaling pickup rates with the corresponding selection probabilities. Choice probabilities are given by multinomial logit formulation in Equation (4.2), where Pr_i^a denotes the probability that alternative $a \in \{l, h, \text{opt-out}\}$ is chosen in area i .

$$Pr_i^a = \frac{e^{V_i^a}}{\sum_{a=\{l, h, \text{opt-out}\}} e^{V_i^a}} \quad (3.3)$$

These choice probabilities induce pickup rates for each battery state and parameterize the Markovian state prediction model, for future usability prediction, described in Section 3.2.6. The same behavioral structure governs user participation in incentive-based rebalancing, in which riders trade off monetary incentives against additional walking distance when selecting drop-off locations recommended by the system.

Direct look-ahead prediction of future system state and expected demand loss

Rebalancing decisions are evaluated by their impact on future service performance rather than on instantaneous inventory levels. To support such evaluation, a direct look-ahead prediction model propagates the system state forward in time under stochastic demand, battery depletion, and battery-dependent user choice. The resulting state forecasts characterize the future availability of usable e-scooters and provide the basis for quantifying expected demand loss over a finite look-ahead horizon.

Time is discretized into uniform steps of length τ , indexed by $t \in \{0, 1, \dots, T\}$. All states, transitions, and decisions are defined on this discrete time step. The system state of areas i at time t is defined as $\mathcal{X}_i^t = (X_i^{tn}, X_i^{tl}, X_i^{th})$, where X_i^{tn} , X_i^{tl} , and X_i^{th} denote the predicted numbers of inactive, low-power, and high-power e-scooters, respectively.

Table 3.1 State transitions in the Markovian model of e-scooter availability and battery usability for geo-fenced area i .

Event	Current state	Next state	Transition rate
1- A low-power e-scooter leaves the area	$(X_i^{tn}, X_i^{tl}, X_i^{th})$	$(X_i^{tn}, X_i^{tl} - 1, X_i^{th})$	$\mu_i^{t,l} = Pr_i^l \mu_i^t$
2- A high-power e-scooter leaves the area	$(X_i^{tn}, X_i^{tl}, X_i^{th})$	$(X_i^{tn}, X_i^{tl}, X_i^{th} - 1)$	$\mu_i^{t,h} = Pr_i^h \mu_i^t$
3- A low-power e-scooter arrives at the area without power decline	$(X_i^{tn}, X_i^{tl}, X_i^{th})$	$(X_i^{tn}, X_i^{tl} + 1, X_i^{th})$	$(1 - \phi_i^{t,(ln)}) \lambda_i^{t,l}$
4- A high-power e-scooter arrives at the area without power decline	$(X_i^{tn}, X_i^{tl}, X_i^{th})$	$(X_i^{tn}, X_i^{tl}, X_i^{th} + 1)$	$(1 - \phi_i^{t,(hl)}) \lambda_i^{t,h}$
5- A low-power e-scooter arrives at the area and becomes inactive	$(X_i^{tn}, X_i^{tl}, X_i^{th})$	$(X_i^{tn} + 1, X_i^{tl}, X_i^{th})$	$\phi_i^{t,(ln)} \lambda_i^{t,l}$
6- A high-power e-scooter arrives at the area and becomes low-power	$(X_i^{tn}, X_i^{tl}, X_i^{th})$	$(X_i^{tn}, X_i^{tl} + 1, X_i^{th})$	$\phi_i^{t,(hl)} \lambda_i^{t,h}$

Each area is subject to parking capacity constraint C_i , requiring $X_i^{tn} + X_i^{tl} + X_i^{th} \leq C_i$ at all times. This state representation jointly captures spatial availability, battery composition, and the subset of vehicles perceived as usable by riders.

User pickups and drop-offs induce stochastic transitions of the system state. Pickup requests in area i arise according to a time-heterogeneous Poisson process with rates μ_i^t , while e-scooter arrival (drop-offs) follow a time-heterogeneous Poisson process with rates $\lambda_i^{t,h}$ and $\lambda_i^{t,l}$ for high-power and low-power e-scooters, respectively. Because users do not select vehicles uniformly, pickup demand is partitioned across battery states using the choice probabilities derived in Section 3.2.6. Specifically, $\mu_i^{t,h} = Pr_i^h \mu_i^t$ and $\mu_i^{t,l} = Pr_i^l \mu_i^t$ so that state transitions reflect realized usability rather than physical availability alone. The expected numbers of pickup and drop-off arrivals per slot (i.e., Poisson counts over the interval τ), calibrated from historical data at interval length resolution.

Battery depletion occurs through riding activities and induces probabilistic transitions between battery states upon trip completion. Natural discharge during parking is negligible. Let $\phi_i^{t,(hl)}$ and $\phi_i^{t,(ln)}$ denote the probabilities that a high-power e-scooter becomes low-power and that a low-power e-scooter becomes inactive, respectively, following a trip. We assume that direct transitions from high-power to inactive will not happen after one trip. Also, 15% of the battery power can be ridden for over 10 kilometers and such distances do not exist in the historical data. Under these dynamics, the evolution of $\mathcal{X}_i^t$ is modeled as a Markov chain governed by the six transition events summarized in Table (3.1).

Given these transition dynamics, the distribution of future system states is propagated over a finite look-ahead horizon of t_f discrete steps, and the corresponding expected

demand loss (EDL) is evaluated. EDL is defined as the expected number of pickup or drop-off requests that cannot be served over the look-ahead horizon due to either the absence of usable e-scooters or insufficient parking capacity (count of demand loss). While EDL could be evaluated by Monte Carlo simulation, this approach is computationally costly and subject to sampling noise. We propagate the transient state distribution as a discrete-time Markov chain over slots of length τ , treating arrival and departure rates as piecewise constant within each time step and updating the state probabilities for each time step, following (Raviv & Kolka, 2013; Zhou, Lin, et al., 2023). Because each area's inventory is capacity-bounded, the local state space is finite and the distribution is carried exactly at the vector level, independently across areas. Let $\pi_{\mathcal{X}_i^0 \mathcal{X}_i'^t}$ denote the probability of being in state $\mathcal{X}_i'^t$ at time t given the initial state $\mathcal{X}_i^0$. The EDL function for area i is given by

$$\begin{aligned} \mathcal{F}(\mathcal{X}_i^0, t=0, t_f) &= \sum_{t=0}^{t_f} \sum_{\mathcal{X}_i'^t \in \mathcal{S}_{\text{empty}}} \pi_{\mathcal{X}_i^0 \mathcal{X}_i'^t} (\mu_i^{t,h} + \mu_i^{t,l}) \\ &+ \sum_{t=0}^{t_f} \sum_{\mathcal{X}_i'^t \in \mathcal{S}_{\text{full}}} \pi_{\mathcal{X}_i^0 \mathcal{X}_i'^t} (\lambda_i^{t,h} + \lambda_i^{t,l}) \end{aligned} \quad (3.4)$$

where $\mathcal{S}_{\text{empty}}$ denotes states with no usable e-scooters ($X_i^{tl} = X_i^{th} = 0$) and $\mathcal{S}_{\text{full}}$ denotes states in which area capacity is fully occupied. This formulation defines the predictive performance metric used to evaluate and compare rebalancing actions within the DL-HR framework. We pre-calculate the EDL and adopt it as input parameter for the optimization model. Later, an approximation method is used to embed EDL in the optimization model when the state itself becomes a decision variable. The approximation is introduced in Section 3.2.7.

Effect of rebalancing actions on future system state and expected demand loss predictions

Rebalancing actions affect expected demand loss by inducing discrete, decision-dependent adjustments to the system state that alter its subsequent stochastic evolution. Within the DL-HR framework, these effects are evaluated by embedding rebalancing actions directly into look-ahead state prediction and recomputing expected demand loss over the remaining horizon.

Let $E\mathcal{X}_i^t$ denote the expected future state trajectory of area i at time t obtained from the Markovian state prediction model in the absence of rebalancing interventions. This baseline forecast defines the reference trajectory against which candidate actions are evaluated. When a rebalancing action modifies the state of area i at time t , the expected state trajectory is adjusted and the state prediction is recomputed forward from the updated state for the remainder of the look-ahead horizon.

Truck-based rebalancing actions induce localized state adjustments at the time of execution. Let $S_i^t = (s_i^{tn}, s_i^{tl}, s_i^{th})$ denote the post-decision state of area i following a

truck visit at time t , whose components give the post-decision numbers of inactive, low-power, and high-power e-scooters. It is given by $S_i^t = E\mathcal{X}_i^t + A_i^t$, where $E\mathcal{X}_i^t$ is the pre-decision expected state and A_i^t represents the net effect of scooter relocation and battery swapping actions applied in area i at time step t only. Expected demand loss accrued prior to time t follows the baseline forecast, while expected demand loss over the remaining horizon is recomputed using S_i^t as the new initial condition. This mechanism quantifies the marginal impact of truck-based interventions on future service performance.

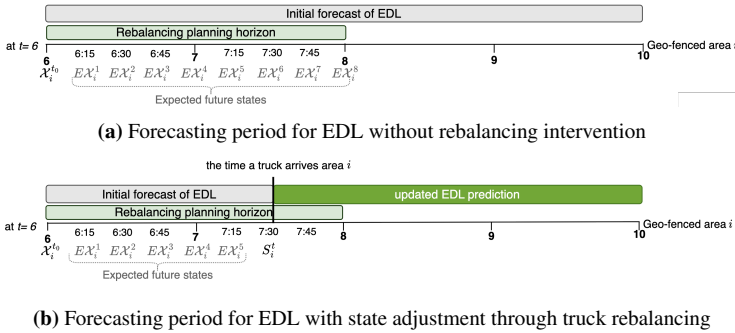


Figure 3.2 EDL prediction for geo-fenced area i in an illustrative rebalancing planning horizon example.

User-mediated rebalancing actions differ from truck-based actions in both spatial scope and temporal realization. A user-based intervention simultaneously affects the original drop-off zone and a system-selected target zone, and the corresponding state adjustments occur at trip completion rather than at the time the incentive is offered. Let rt_{oi} denote the ride time from origin zone o to target zone i , expressed in discrete time steps.

When a user accepts a drop-off incentive, the induced state deviations are realized at time $t+rt_{oi}$ for the target zone and at time $t+rt_{od}$ for the original destination zone.

These delayed and coupled state adjustments are incorporated into the look-ahead prediction by modifying the expected state trajectory at the corresponding future times and recomputing expected demand loss from those points onward. As a result, incentive offers must be issued anticipatively: to affect availability at a future time τ , incentives must be offered sufficiently in advance to account for ride duration. Figures 3.2(a), 3.2(b), and 3.3 illustrate the resulting updates to expected demand loss trajectories under truck-based and user-based rebalancing actions.

DL-HR plan in a rolling horizon approach

Direct look-ahead predictions are conditioned on the currently observed system state and on stochastic models of demand, battery depletion, and user behavior. As realized trips, battery transitions, and user responses unfold, deviations from predicted state trajectories inevitably arise. To ensure consistency between prediction and control, the DL-HR

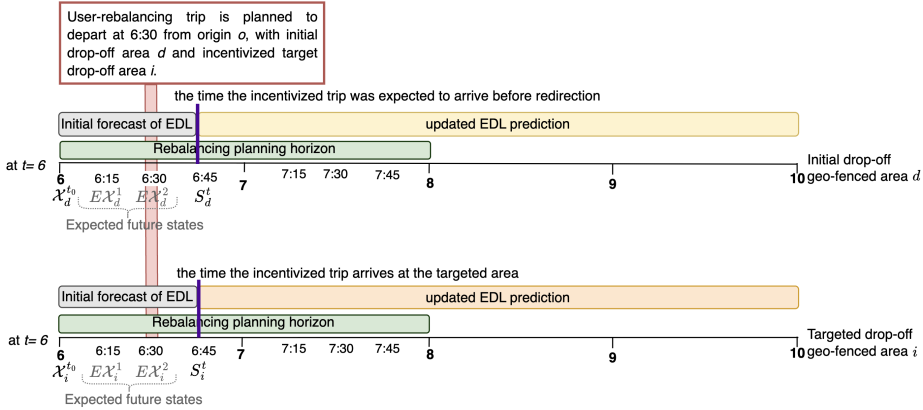


Figure 3.3 Update of EDL predictions for the initial and target drop-off areas induced by a user-based rebalancing action in an illustrative rebalancing planning horizon.

framework is implemented within a rolling-horizon control scheme that repeatedly updates rebalancing decisions as new information becomes available.

Under this scheme, rebalancing actions are optimized over a finite planning horizon and evaluated against a longer look-ahead horizon. At the beginning of each replanning epoch, the current system state, defined by the spatial distribution of e-scooters and their battery states, is observed and used to reinitialize the Markovian state prediction model. Based on the updated forecasts of future usability and expected demand loss, a new hybrid rebalancing plan is computed that jointly coordinates truck-based interventions and user-mediated incentives.

Only actions scheduled for implementation prior to the next replanning epoch are executed. The remaining portion of the plan is discarded and recomputed at the subsequent update, yielding a receding-horizon control structure that closes the loop between prediction and intervention. Forecast errors induced by stochastic demand, delayed user responses, and battery-dependent vehicle selection are thereby corrected through successive re-optimization.

These components form the decision making architecture from inputs to decisions. The discrete choice model of Section 3.2.6 converts e-scooter attributes into battery-state pickup probabilities, which parameterize the Markovian state prediction; propagating this chain over the look-ahead horizon yields the expected demand loss for each area. EDL therefore serves as the interface between the prediction layer (choice model and Markovian forecast) and the optimization layer (linearized EDL and MILP); the rolling-horizon execution of this pipeline is depicted in Figure 3.4.

Figure 3.4 illustrates this sequential decision process. Each rebalancing plan spans a planning horizon t_R and is evaluated over a look-ahead horizon t_f , but is revised whenever new system-state information becomes available. This rolling-horizon implementation relaxes the modeling assumption that each geo-fenced zone may be served at most once

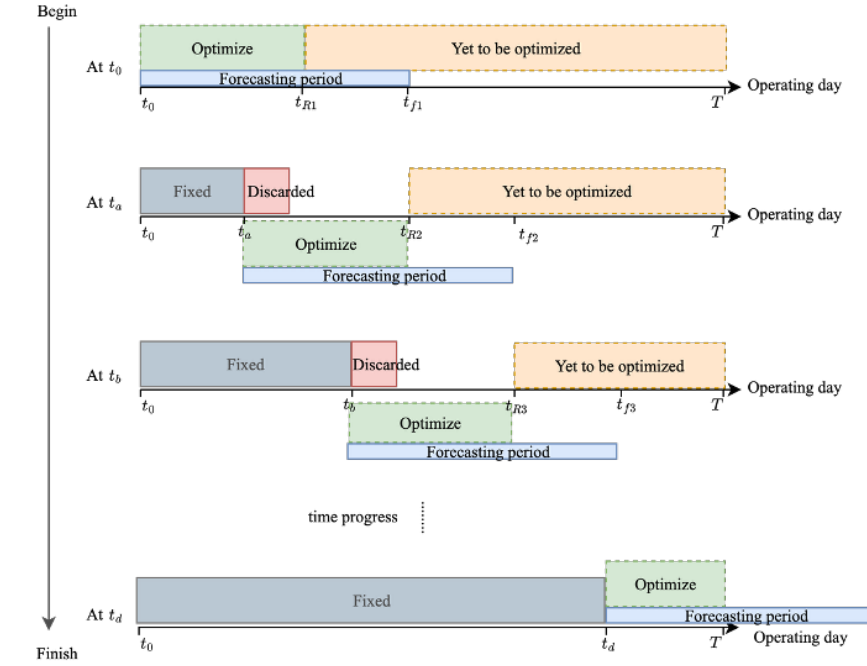


Figure 3.4 Rolling-horizon decision structure of the DL-HR framework. Rebalancing actions are optimized over a planning horizon and evaluated using direct look-ahead predictions of expected demand loss over a longer horizon; when new system-state information arrives, future actions are discarded and the problem is re-optimized.

within a planning horizon: zones affected by earlier truck visits or user incentives may be reconsidered in subsequent replanning steps as the discarded portion of the plan is replaced.

By embedding direct look-ahead prediction within a rolling-horizon control structure, the DL-HR framework enforces continuous alignment between predicted and realized system states, enabling coordinated management of operator-based and user-mediated rebalancing actions under uncertainty and delayed behavioral effects.

3.2.7 Dynamic Look-ahead Hybrid Rebalancing Optimization Model

This section formulates the Direct Look-ahead Hybrid Rebalancing (DL-HR) problem as a time-dependent optimization model that jointly coordinates operator-based and user-mediated interventions to mitigate future demand loss. The formulation of the Markovian state prediction is developed in Section 3.2.6 and incorporated directly into the

objective function, so that rebalancing decisions are evaluated by their anticipated impact on system usability over a finite look-ahead horizon rather than by instantaneous inventory conditions.

Rebalancing decisions are optimized over a planning horizon $[t_0, t_R]$, where $t_0 = 0$ and t_R denote the first and last decision epoch. Their downstream consequences are evaluated over a longer look-ahead horizon $[t_0, t_f]$ through EDL. Both horizons originate at t_0 , but the look-ahead horizon extends beyond the planning window to capture delayed effects arising from demand uncertainty, battery depletion, and user response. T is the final planning period in a working day. Time is discretized into periods of equal length τ , and the planning horizon consists of a fixed number of such periods.

The system comprises a set N of geo-fenced areas and a fleet V of identical rebalancing trucks. Each truck departs from a central depot (indexed by 0) at the beginning of the planning horizon and returns to the depot by the end of the operating day. Let $N_0 = N \cup \{0\}$ denote the set of all nodes. Each truck $v \in V$ is equipped with two resource compartments $m \in M = \{\text{es}, \text{bat}\}$ for transporting e-scooters and spare batteries, with corresponding capacities C_v^m . Each geo-fenced area $i \in N$ has a parking capacity C_i . The initial system state at time t_0 is given by $\mathcal{X}_i^{t_0} = (X_i^{ton}, X_i^{tol}, X_i^{toh})$, representing the numbers of inactive, low-power, and high-power e-scooters in area i . Truck travel times between areas i and j are denoted by tt_{ij} and expressed in discrete time steps.

In addition to truck-based interventions, the formulation incorporates user-mediated rebalancing through incentive offers that redirect trips from their original drop-off areas to nearby system recommended locations. For each geo-fenced area i , the set of neighboring areas eligible for incentive-based drop-off redirection is denoted as N_i and defined as

$$N_i = \{j | j \in N \wedge w_{ij} \leq \bar{w}\} \quad (3.5)$$

where w_{ij} denotes the walking distance between the centroids of areas i and j , and $\bar{w}$ is the maximum acceptable walking distance. Let rt_{ij} denote the riding time between areas i and j . An incentive issued at time t affects the system state at time $t + rt_{oi}$ for the targeted drop-off area i , reflecting the delayed realization of user-based inventory adjustments.

The decision variables of the DL-HR model therefore include truck routing and on-site operations (loading, unloading, and battery swapping), as well as the selection and timing of user incentives that redirect trips across geo-fenced areas. Tables (3.2), (3.3), and (3.4) summarize the sets, parameters, and decision variables used in the formulation. We next present the objective function, followed by constraints governing feasible truck operations, user-based rebalancing, and inventory evolution.

Objective function. The objective minimizes the total system cost associated with a rebalancing plan by jointly accounting for operational expenditures and monetized expected demand loss. Expected demand loss is evaluated using the direct look-ahead prediction model and reflects the anticipated impact of rebalancing actions on future system usability over the look-ahead horizon. The objective is composed of four components: truck routing cost (3.6), truck operation cost (3.7), baseline demand loss in areas that

Table 3.2 Sets

Set	Description
N	Geo-fenced areas, indexed by $\{i, j, o, d\}$ to represent generic, origin, and destination areas
N_0	All geo-fenced areas and the depot (node 0), $N \cup \{0\} \in N_0$
N_i	Set of neighboring areas to area i that are within walking distance of area i ($N_i \subset N$).
V	Rebalancing trucks, $v \in V$.
P	Battery level classes: inactive (n), low-power (l), high-power (h) ($p \in P = \{n, l, h\}$).
M	Resource types in truck inventory, $m = \{es, bat\} \in M$.

receive no rebalancing service, (3.8), and intervention-dependent demand loss in areas affected by truck-based or user-mediated actions (equations (3.9) and (3.10)). . The first component captures truck deployment and routing costs. Equation (3.6)) includes a fixed cost c_v incurred when truck v is dispatched from the depot at the beginning of the planning horizon, as well as distance-based routing cost c_{ij} for truck movements between areas. The binary variable y_{ijv}^t equals 1 if truck v travel from area i to area j at time t , and 0 otherwise.

$$\sum_{v \in V} \left(\sum_{j \in N} c_v y_{0jv}^{t_0} + \sum_{t=0}^T \sum_{i \in N_0} \sum_{j \in N_0} c_{ij} y_{ijv}^t \right) \quad (3.6)$$

The second component accounts for operational costs associated with truck-based rebalancing activities. Equation (3.7) captures the cost of loading and unloading e-scooters and performing on-site battery swapping. Variables s_{iv}^{+tp} and s_{iv}^{-tp} denote the number of p -power level e-scooters loaded into and unloaded from area i by truck v at time t , respectively. The number of batteries swapped to a high-power state is captured by b_{iv}^{tp} . Parameters θ_1 and θ_2 represent unit costs for relocation and battery swapping, respectively.

$$\sum_{t=1}^T \sum_{v \in V} \sum_{i \in N} \sum_{p \in P} (\theta_1 (s_{iv}^{+tp} + s_{iv}^{-tp}) + \theta_2 b_{iv}^{tp}) \quad (3.7)$$

Expected demand loss is monetized using γ , the average revenue per rental. For geo-fenced areas that receive no rebalancing service during the planning horizon, expected demand loss follows the baseline forecast evaluated over the entire look-ahead horizon $[t_0, t_f]$. Equation (3.8) captures this cost, where r_i is a binary variable equal to 1 if i is not served by any rebalancing action.

$$\sum_{i \in N} \gamma \cdot \mathcal{F}_i(\mathcal{X}_i^0, t_0, t_f) \cdot r_i \quad (3.8)$$

Table 3.3 Parameters

Symbol	Description
Time	
τ	Length of one planning period (15 min).
t_0	Start of the planning horizon.
T	The final planning period in an operating day.
tt_{ij}	Truck travel time (in periods) from area i to area j .
rt_{ij}	E-scooter riding time (in periods) on the shortest path between areas i and j .
Cost	
c_v	Fixed cost of deploying a truck.
c_{ij}	Truck routing cost per km travelling from area i to j .
θ_1, θ_2	Unit costs for loading/unloading and battery swapping by truck.
ρ_0 and ρ_1	User unlock fee and per-minute ride fee.
γ	Expected revenue per rental: $\gamma = \rho_0 + \rho_1 \cdot (\text{average ride time})$.
B	Budget for user incentives.
Prediction model	
$\mathcal{X}_i^t$	Inventory state at area i and time t : $(X_i^{tn}, X_i^{tl}, X_i^{th})$.
$E\mathcal{X}_i^{t,t'}$	Expected inventory at time t' given the state at t : $(EX_i^{tn}, EX_i^{tl}, EX_i^{th})$.
$\mathcal{F}(\mathcal{X}_i^t, t, t')$	Expected near-future demand loss at area i from t to t' , given the state at t .
Other	
C_i, C_v^m	Capacity of area i and capacity of truck compartment $m \in \{\text{es}, \text{bat}\}$.
ω_{od}^{th}	Number of high-power e-scooters flowing from origin o to destination d at time t .

Once an intervention is applied, the EDL of the affected zones is decomposed into two parts: the demand loss accrued before the realization time of the intervention, evaluated on the baseline state $\mathcal{X}_i^{t_0}$ (Equation 3.9), and the demand loss accrued afterward, evaluated on the post-decision state S_i^t (Equation 3.10). Equations (3.9a)–(3.9b) account for expected demand loss accrued up to the realization time of truck-based and user-based rebalancing actions, respectively. For user-based actions, this realization time differs across the two affected zones, since the inventory effect at the origin zone d is realized at $t + rt_{od}$ and the effect at the target zone i at $t + rt_{oi}$, capturing the cross-zone, delayed nature of incentivized redirection. The binary variable x_{oi}^{dt} equals 1 if, at time t , an incentive is offered to redirect a trip originating in area o with initial destination d to a target drop-off area i .

$$\sum_{t=0}^T \sum_{i \in N} \left(\sum_{v \in V} \sum_{j \in N_0} \gamma \cdot \mathcal{F}_i(\mathcal{X}_i^{t_0}, 0, t) \cdot y_{ijv}^t \right) \quad (3.9a)$$

$$+ \sum_{o \in N} \sum_{d \in N_i} \gamma (\mathcal{F}_d(\mathcal{X}_d^{t_0}, 0, t + rt_{od}) + \mathcal{F}_i(\mathcal{X}_i^{t_0}, 0, t + rt_{oi})) x_{oi}^{dt} \quad (3.9b)$$

Table 3.4 Decision variables

Variable	Description
r_i	Binary. Equals 1 if area i receives no rebalancing during the planning horizon.
s_i^{tp}	Auxiliary integer. Number of e-scooters of power class p at area i at time t .
Truck based	
y_{ijv}^t	Binary. Equals 1 if truck v departs area i for area j at time t .
s_{iv}^{+tp}	Integer. Number of p -power level e-scooters loaded into area i from truck v at time t .
s_{iv}^{-tp}	Integer. Number of p -power level e-scooters unloaded from area i onto truck v at time t .
b_{iv}^{tp}	Integer. Number of p -power level e-scooters whose batteries are swapped to high power by truck v at area i and time t .
q_{ijv}^{tpm}	Integer. Inventory of resource $m \in \{\text{es, bat}\}$ with power p carried on truck v when departing i for j at time t .
$O_{iv}^{+tp}, O_{iv}^{-tp}, O_{iv}'^{tp}$	Auxiliary binary variables indicating whether loading, unloading, or battery swapping operations are performed at area i , time t by truck v of p -power level.
User based	
x_{oi}^{dt}	Binary. Equals 1 if at time t an incentive is offered to redirect a trip from origin o to area i with initial drop-off d ; 0 otherwise.
z_{oi}^{dt}	Integer. Number of incentivized trips from origin o to area i at time t (initial drop-off d).

Equations (3.10a) and (3.10b) compute expected demand loss over the remaining look-ahead horizon using the updated post-intervention states S_i^t and S_d^t . These inventory updates enter the post-decision states S_d^t and S_i^t through the geo-fenced inventory state Constraints (3.38)- (3.40).

$$\sum_{t=0}^T \sum_{i \in N} \left(\sum_{v \in V} \sum_{j \in N_0} \gamma \cdot \mathcal{F}_i(S_i^t, t, t_f) \cdot y_{ijv}^t \right) \quad (3.10a)$$

$$+ \sum_{o \in N} \sum_{d \in N_i} \gamma (\mathcal{F}_d(S_d^t, t + rt_{od}, t_f) + \mathcal{F}_i(S_i^t, t + rt_{oi}, t_f)) x_{oi}^{dt} \quad (3.10b)$$

Since the post-intervention inventory state S_i^t are decision-dependent, the resulting objective is nonlinear. Section 3.2.7 presents a linearization strategy that yields an equivalent mixed-integer linear formulation.

Next, we introduce the constraints that ensure feasible truck operations, inventory consistency across geo-fenced areas, and temporal coherence for both truck-based and user-mediated rebalancing actions.

1- Rebalancing type for geo-fenced areas. Within a given planning horizon, each geo-fenced area is assigned exactly one rebalancing status. It is either (i) served by a truck-based intervention, (ii) involved in user-mediated rebalancing as a source or target of

redirected drop-offs, or (iii) not served by any rebalancing action. This exclusivity is imposed to prevent overlapping intervention modes within a single planning horizon and to preserve consistency with the rolling-horizon implementation.

Constraint (3.11) enforce this assignment. The binary variable r_i equals 1 if area i receives no rebalancing service during the planning horizon. the remaining terms indicate whether area i is affected by at least one truck visit or by at least one user-based redirection, either as a target drop-off area or as an original destination whose drop-offs are redirected elsewhere. This single-intervention rule prevents overlapping interventions on the same zone within a planning horizon; within each optimization it binds in full, while across successive re-optimization epochs of the rolling horizon a zone served in one epoch becomes eligible again in the next, so that over the operating day it may be served multiple times. Binary domain restrictions are specified in Constraint (3.12).

$$\sum_{t=0}^T (\sum_{v \in V} \sum_{j \in N_0} y_{ijv}^t + \sum_{o \in N} \sum_{d \in N_i} x_{oi}^{dt} + \sum_{k \in N} \sum_{l \in N_i} x_{kl}^{it}) + r_i = 1 \quad \forall i \in N \quad (3.11)$$

$$\begin{aligned} r_i, x_{oi}^{dt} &\in \{0, 1\} & \forall o, i \in N, d \in N_i, t \in \{0, \dots, T\} \\ y_{ijv}^t &\in \{0, 1\} & \forall i, j \in N_0, v \in V, t \in \{0, \dots, T\} \end{aligned} \quad (3.12)$$

2- Truck routing. Truck movements are represented on a time-expanded network over the planning horizon. Each truck departs from the depot at the beginning of the horizon, traverses geo-fenced areas subject to travel-time constraints, and returns to the depot by the end of the planning horizon. Constraint (3.13) requires each truck to initiate its route at the depot at time $t = 0$. Flow conservation on the time-expanded network is enforced by Constraint (3.14), which ensures that a truck arriving at an area must also depart from that area after accounting for travel time. Since flow conservation is enforced over $N_0 = N \cup \{0\}$, a truck may return to the depot mid horizon to replenish spare batteries, and a truck that is not needed can remain at the depot via the self-arc $y_{00v}^{t_0} = 1$ without incurring the fixed dispatch cost c_v , which is charged only on arcs to non-depot areas. Travel times between areas i and j are denoted by tt_{ij} and expressed in discrete time steps. Waiting at an area is permitted through self-arcs with $tt_{ii}=1$. Constraint (3.15) requires each truck to return to the depot by the end of the planning horizon.

$$\sum_{j \in N_0} y_{0jv}^{t_0} = 1 \quad \forall v \in V \quad (3.13)$$

$$\sum_{j \in N_0} y_{jiv}^{t-tt_{ji}} = \sum_{k \in N_0} y_{ikv}^t \quad \forall i \in N_0, t = \{1, \dots, T-1\}, v \in V \quad (3.14)$$

$$\sum_{i \in N_0} y_{i0v}^{T-tt_{i0}} = 1 \quad \forall t = \{1, \dots, T-1\}, v \in V \quad (3.15)$$

3- Truck operations. When a truck visits a geo-fenced area, it may perform e-scooter repositioning and battery swapping operations that modify the local inventory state. These actions are governed by auxiliary binary variables O_{iv}^{+tp} , O_{iv}^{-tp} , and $O_{iv}'^{tp}$, which indicate

whether truck v performs loading, unloading, or battery swapping, respectively, for e-scooters of power class p in area i at time t .

Operational actions are permitted only when a truck is physically present. Constraint (3.16) requires that any truck visits to an area be associated with at least one operational action, thereby excluding idle visits. Constraints (3.17)–(3.19) link each operation type to the corresponding truck-routing decisions, ensuring that loading, unloading, and battery swapping can occur only if the truck is routed to the area at the relevant time.

The magnitudes of truck operations are represented by integer variables. The variables s_{iv}^{+tp} and s_{iv}^{-tp} denote the numbers of p -power level e-scooters loaded into and unloaded from area i by truck v at time t , respectively, while b_{iv}^{tp} denotes the number of batteries swapped to high power state. Constraints (3.20)–(3.22) bind these quantities to their corresponding binary activation variables and restrict them by the capacities of both the truck and the area. Feasibility with respect to the truck's onboard inventory is enforced through the inventory balance constraints introduced later in this section.

Additional constraints ensure operational consistency. Constraint (3.23) prohibits loading and unloading operations at the depot. Constraint (3.24) excludes battery swapping for high-power e-scooters. Constraint (3.25) prevents unloading and swapping of e-scooters of the same power class at the same area and time. Whereas Constraints (3.23) and (3.25) impose operational consistency, Constraint (3.24) additionally serves as a valid inequality that tightens the linear relaxation by eliminating an action that incurs a swap cost without altering the post-decision state. Finally, Constraint (3.26) enforces non-negativity of the truck-operation variables.

$$\sum_{p \in P} (O_{iv}^{'tp} + O_{iv}^{+tp} + O_{iv}^{-tp}) \geq \sum_{j \in N_0} y_{ijv}^t \quad \forall t = \{1, \dots, T\}, v \in V \quad (3.16)$$

$$\sum_{p \in \{n, l\}} O_{iv}^{'tp} \leq \sum_{j \in N_0} y_{ijv}^t \quad \forall i \in N, t = \{1, \dots, T-1\}, v \in V \quad (3.17)$$

$$\sum_{p \in P} O_{iv}^{+tp} \leq \sum_{j \in N_0} y_{ijv}^t \quad \forall i \in N, t = \{1, \dots, T-1\} \quad (3.18)$$

$$\sum_{p \in P} O_{iv}^{-tp} \leq \sum_{j \in N_0} y_{ijv}^t \quad \forall i \in N, t = \{1, \dots, T-1\} \quad (3.19)$$

$$b_{iv}^{tp} \leq \min(C_i, C_v^{bat}) O_{iv}^{'tp} \quad \forall i \in N, t = \{1, \dots, T-1\}, v \in V, p \in \{n, l\} \quad (3.20)$$

$$s_{iv}^{+tp} \leq \min(C_i, C_v^{es}) O_{iv}^{+tp} \quad \forall i \in N, t = \{1, \dots, T-1\}, p \in P \quad (3.21)$$

$$s_{iv}^{-tp} \leq \min(C_i, C_v^{es}) O_{iv}^{-tp} \quad \forall i \in N, t = \{1, \dots, T-1\}, p \in P \quad (3.22)$$

$$\sum_{p \in P} (s_{0v}^{+tp} + s_{0v}^{-tp}) = 0 \quad \forall t = \{1, \dots, T\}, v \in V \quad (3.23)$$

$$\sum_{t=1}^T \sum_{i \in N} b_{iv}^{tp} = 0 \quad \forall v \in V, p \in \{h\} \quad (3.24)$$

$$O_{iv}^{'tp} + O_{iv}^{-tp} \leq 1 \quad \forall i \in N, t = \{1, \dots, T-1\}, p \in \{n, l\} \quad (3.25)$$

$$s_{iv}^{+tp}, s_{iv}^{-tp}, b_{iv}^{tp} \geq 0 \quad \forall i \in N, t = \{1, \dots, T-1\}, p \in P \quad (3.26)$$

4- Truck's inventory. Truck inventory dynamics are represented on the routing arcs of the time-expanded network to ensure consistency between routing decisions, operational actions, and onboard resource availability. For any truck v traversing arc (i, j) at time t , the variable q_{ijv}^{tpm} denotes the quantity of resource $m \in \{es, bat\}$ with power class p carried onboard during the traversal.

Onboard inventory is subject to capacity and conservation constraints. Constraint (3.27) limits the total quantity of e-scooters and batteries transported on each arc by the corresponding truck capacity. Inventory evolution across successive arcs is governed by update constraints that account for operational actions performed at visited areas. Constraint (3.28) updates the number of e-scooters onboard after a visit to a non-depot area by incorporating loading and unloading operations executed at the location. Constraint (3.29) updates the inventory of high-power batteries to reflect battery swapping activities. Only high-power batteries are explicitly tracked in the truck inventory state, as low-power and inactive batteries collected in the field are returned to the depot for recharging and do not constrain subsequent operations. Finally, Constraint (3.30) enforces non-negativity and domain restrictions for all onboard inventory variables.

$$\sum_{p \in P} q_{ijv}^{tpm} \leq C_v^m y_{ijv}^t \quad \forall i, j \in N_0, t = \{1, \dots, T-1\}, v \in V, m \in \{es, bat\} \quad (3.27)$$

$$\sum_{j \in N} q_{jiv}^{t-tt_{ji}pm} = \sum_{k \in N} q_{ikv}^{tpm} - s_{iv}^{-tp} + s_{iv}^{+tp} \quad \forall i \in N, t = \{1, \dots, T-1\}, v \in V, p \in P, m = \{es\} \quad (3.28)$$

$$\sum_{j \in N} q_{jiv}^{t-tt_{ji}hm} = \sum_{k \in N} q_{ikv}^{thm} + \sum_{p \in \{n, l\}} b_{iv}^{tp} \quad \forall i \in N, t = \{1, \dots, T-1\}, v \in V, m = \{bat\} \quad (3.29)$$

$$q_{ijv}^{tpm} \geq 0 \quad \forall i \in N_0, t = \{1, \dots, T-1\}, p \in P, m \in \{es, bat\} \quad (3.30)$$

Depot visits induce centralized inventory transformations that capture recharging and replenishment processes not available in the field. Upon arrival at the depot, all inactive and low-power e-scooters collected by a truck are assumed to be fully recharged and converted to the high-power state. This abstraction is enforced by Constraint (3.31), which maps returned scooters into high-power inventory.

Flow conservation of high-power e-scooters at the depot is enforced by Constraint (3.32), which accounts for both recharged vehicles and those already onboard prior to arrival. In addition, Constraint (3.33) reset the onboard battery inventory at the depot by requiring each truck to depart with a full complement of high-power batteries.

This ensures the feasibility of subsequent battery swapping operations during field rebalancing.

$$\sum_{j \in N_0} q_{j0v}^{t-tt_{j0}pm} = b_{0v}^{tp} \quad \forall t = \{1, \dots, T-1\}, v \in V, p \in \{n, l\}, m = \{es\} \quad (3.31)$$

$$\sum_{j \in N_0} q_{j0v}^{tpm} + \sum_{p \in \{n, l\}} b_{0v}^{tp} = \sum_{k \in N_0} q_{0kv}^{t-tt_{i0}pm} \quad \forall t = \{1, \dots, T-1\}, v \in V, p \in \{h\}, m = \{es\} \quad (3.32)$$

$$q_{0jv}^{tpm} = C_v^m y_{0jv}^t \quad \forall j \in N_0, t = \{1, \dots, T-1\}, v \in V, p \in \{h\}, m \in \{bat\} \quad (3.33)$$

5- User-based rebalancing. User-mediated rebalancing actions redirect trips from their original drop-off areas to alternative nearby areas through monetary incentives, which are per-minute ride-fee discounts. These actions affect system inventory only upon trip completion and must therefore respect both temporal feasibility and budget limitations.

Constraint (3.34) prohibits offering incentives for trips whose completion occurs beyond the planning horizon, ensuring that all inventory effects induced by user-based rebalancing are realized within the horizon under consideration. The variable z_{oi}^{dt} denotes the number of trips originating in area o with original destination d that are redirected to target area i at time t . Constraint (3.35) links z_{oi}^{dt} to the binary incentive-offer decision variable x_{oi}^{dt} , implying that redirected trips can occur only if an incentive is offered.

The number of redirected trips is bounded by both demand and vehicle availability. The high-power origin-destination flow, ω_{od}^{th} , is a point estimate of the high-power trip volume on origin-destination pair at time t , computed from historical data. Constraint (3.36) restricts z_{oi}^{dt} by the historical high-power origin-destination flow, ω_{od}^{th} , and by the expected number of high-power e-scooters available at the origin area, EX_o^{th} , reflecting that only high-power vehicles are eligible for incentive-based redirection. The high-power flows are treated as a simplifying exogenous cap. Total expenditure on user incentives is limited by the remaining budget B till the current rebalancing period through Constraint (3.37), where the cost of each incentivized trip equals the per-minute fee ρ_1 multiplied by the riding time rt_{oi} .

$$x_{oi}^{dt} = 0 \quad \forall o, i \in N, d \in N_i, t = \{0, \dots, T\}, t + rt_{oi} > T \quad (3.34)$$

$$z_{oi}^{dt} \geq x_{oi}^{dt} \quad \forall o, i \in N, d \in N_i, t = \{0, \dots, T\} \quad (3.35)$$

$$z_{oi}^{dt} \leq \min(EX_o^{th}, \omega_{od}^{th}) x_{oi}^{dt} \quad \forall o, i \in N, d \in N_i, t = \{0, \dots, T\} \quad (3.36)$$

$$\sum_{t=0}^T \sum_{o, i \in N} \sum_{d \in N_i} \rho_1 rt_{oi} z_{oi}^{dt} \leq B - \sum_{t'=0}^t \sum_{o, i \in N} \sum_{d \in N_i} \rho_1 rt_{oi} z_{oi}^{dt'} \quad (3.37)$$

6- Geo-fenced inventory state. The following constraints track the evolution of e-scooter inventories within each geo-fenced area over the planning horizon. Inventory

dynamics are disaggregated by battery state and reflect the combined effects of truck-based operations and user-mediated rebalancing.

The inventory of inactive e-scooters changes only through truck operations. Constraint (3.38) updates inactive inventory by accounting for unloading and battery swapping actions. Low-power inventory evolves through loading, unloading, and battery swapping, as captured by Constraints (3.39).

$$s_i^{tn} = EX_i^{tn} - \sum_{v \in V} (s_{iv}^{-tn} + b_{iv}^{tn}) \quad \forall i \in N, t = \{1, \dots, T-1\} \quad (3.38)$$

$$s_i^{tl} = EX_i^{tl} + \sum_{v \in V} (s_{iv}^{+tl} - s_{iv}^{-tl} - b_{iv}^{tl}) \quad \forall i \in N, t = \{1, \dots, T-1\} \quad (3.39)$$

High-power e-scooter inventory is affected by both truck operations and user-based rebalancing actions. Constraint (3.40) updates high-power inventory by incorporating loading, unloading, and battery swapping operations, as well as delayed arrivals and departures induced by redirected user trips. The temporal offsets account for riding times between origin and drop-off areas.

$$s_i^{th} = EX_i^{th} + \sum_{v \in V} (s_{iv}^{+th} - s_{iv}^{-th} + \sum_{p \in \{n,l\}} b_{iv}^{tp}) + \sum_{\substack{o \in N \\ d \in N_i}} z_{oi}^{d(t-rt_{oi})} - \sum_{\substack{k \in N \\ j \in N_i}} z_{kj}^{i(t-rt_{ki})} \\ \forall i \in N, t = \{1, \dots, T-1\} : (t - rt_{oi}) \geq t_0, (t - rt_{ki}) \geq t_0 \quad (3.40)$$

Finally, Constraint (3.41) enforces the parking capacity of geo-fenced areas, and Constraint (3.42) ensures non-negativity of all area-level inventories.

$$\sum_{p \in P} s_i^{tp} \leq C_i \quad \forall i \in N, t = \{1, \dots, T\} \quad (3.41)$$

$$\sum_{p \in P} s_i^{tp} \geq 0 \quad \forall i \in N, t = \{1, \dots, T-1\} \quad (3.42)$$

Model transformation

The optimization model introduced in Section 3.2.7 is nonlinear due to the interaction between rebalancing decisions and the expected demand loss (EDL) evaluated over the look-ahead horizon. In particular, the objective terms in Equation (3.10) involve products between decision variables and state-dependent EDL predictions. To obtain a tractable formulation, we adopt the affiliate-function-based transformation proposed by D. Zhang et al. (2017), which yields an equivalent linear representation while preserving the economic interpretation of future demand loss.

Let $\Delta_i^{tt'}$ denote the expected demand loss at area i over the interval $[t, t']$ when no rebalancing action is applied at time t , given the expected inventory state EX_i^t :

$$\Delta_i^{tt'} = \mathcal{F}_i(EX_i^t, t, t').$$

This term is precomputed from the Markovian prediction model and represents the baseline EDL trajectory in the absence of intervention.

We define the affiliate function $\tilde{\mathcal{F}}_i(\cdot)$ as the incremental deviation in expected demand loss induced by a rebalancing action that alters the inventory state at time t :

$$\tilde{\mathcal{F}}_i(S_i^t, t, t') = \mathcal{F}_i(S_i^t, t, t') - \Delta_i^{tt'} \quad (3.43)$$

By construction, whenever there is no intervention, we have $S_i^t = E\mathcal{X}_i^t$ and therefore $\tilde{\mathcal{F}}_i(S_i^t, t, t') = 0$. This decomposition separates EDL into a constant baseline component and an action dependent adjustment. Substituting

$$\mathcal{F}_i(S_i^t, t, t') = \tilde{\mathcal{F}}_i(S_i^t, t, t') + \Delta_i^{tt'}$$

into Equation (3.10) eliminates bilinear interactions between rebalancing decisions and EDL terms. The resulting expression is given by:

$$\sum_{t=0}^T \sum_{i \in N} \sum_{v \in V} \sum_{j \in N_0} \gamma \Delta_i^{tt_f} y_{ijv}^t + \sum_{t=0}^T \sum_{i \in N} \gamma \tilde{\mathcal{F}}_i(S_i^t, t, t_f) \quad (3.44a)$$

$$+ \sum_{\substack{t=0 \\ t+rt_{od} \leq T \\ t+rt_{oi} \leq T}}^T \sum_{o, i \in N} \sum_{d \in N_i} \gamma (\Delta_d^{t+rt_{od}t_f} + \Delta_i^{t+rt_{oi}t_f}) x_{oi}^{dt} \\ + \sum_{\substack{t=0 \\ t+rt_{od} \leq T \\ t+rt_{oi} \leq T}}^T \sum_{i \in N} \sum_{d \in N_i} \gamma (\tilde{\mathcal{F}}_d(S_d^t, t + rt_{od}, t_f) + \tilde{\mathcal{F}}_i(S_i^t, t + rt_{oi}, t_f)) \quad (3.44b)$$

The remaining nonlinearity arises from the functional dependence of $\tilde{\mathcal{F}}_i(\cdot)$ on the integer-valued inventory state. Following Kaspi et al., 2017 and Zhou, Lin, et al., 2023, we exploit the convexity of the EDL function with respect to inventory levels. Convexity under the three battery state representation is formally established in B.2.

Let $f(s_i^{tn}, s_i^{tl}, s_i^{th})$ denote the convex EDL function over the feasible inventory domain

$$\varepsilon = \{(s_i^{tn}, s_i^{tl}, s_i^{th}) \in \mathbb{Z}^3 \mid s_i^{tn}, s_i^{tl}, s_i^{th} \geq 0, s_i^{tn} + s_i^{tl} + s_i^{th} \leq C_i\}.$$

For each $\tilde{S}_i \in \varepsilon$, there exists a supporting hyperplane satisfying

$$\alpha_{\tilde{S}_i}^n s_i^{tn} + \alpha_{\tilde{S}_i}^l s_i^{tl} + \alpha_{\tilde{S}_i}^h s_i^{th} + \delta_{\tilde{S}_i} = f(\tilde{S}_i), \\ \alpha_{\tilde{S}_i}^n s_i^{tn} + \alpha_{\tilde{S}_i}^l s_i^{tl} + \alpha_{\tilde{S}_i}^h s_i^{th} + \delta_{\tilde{S}_i} \leq f(s_i^{tn}, s_i^{tl}, s_i^{th}), \quad \forall s_i \in \varepsilon.$$

Accordingly, the convex EDL function admits the representation

$$\widetilde{f}(s_i^{tn}, s_i^{tl}, s_i^{th}) = \max_{(\tilde{s}_i^{tn}, \tilde{s}_i^{tl}, \tilde{s}_i^{th}) \in \varepsilon} \left(\alpha_{(\tilde{s}_i^{tn}, \tilde{s}_i^{tl}, \tilde{s}_i^{th})}^n s_i^{tn} + \alpha_{(\tilde{s}_i^{tn}, \tilde{s}_i^{tl}, \tilde{s}_i^{th})}^l s_i^{tl} \right. \\ \left. + \alpha_{(\tilde{s}_i^{tn}, \tilde{s}_i^{tl}, \tilde{s}_i^{th})}^h s_i^{th} + \delta_{(\tilde{s}_i^{tn}, \tilde{s}_i^{tl}, \tilde{s}_i^{th})} \right) \quad (3.45)$$

Let SPF_{it} denote the set of supporting planes associated with area i at time t . Introducing auxiliary variable η_{it} , the affiliate function is incorporated through the linear constraints

$$\eta_{it} \geq \alpha_{spf}^n s_i^{tn} + \alpha_{spf}^l s_i^{tl} + \alpha_{spf}^h s_i^{th} + \delta_{spf}, \quad \forall spf \in SPF_{it}. \quad (3.46)$$

The resulting formulation is a mixed-integer linear program that jointly optimizes operational costs and monetized expected demand loss over the look-ahead horizon, subject to Constraints (3.11)–(3.42).

3.2.8 Results Analysis

This section examines the operational performance of the proposed DL-HR framework through a real-world case study conducted in collaboration with a major shared e-scooter operator in Rotterdam, the Netherlands (Section 3.2.8). To disentangle the value of hybrid coordination and identify the contribution of its individual components, we consider four operational scenarios (Section 3.2), ranging from a no-control benchmark with no rebalancing to increasingly comprehensive strategies reflecting current industry practice and the DL-HR approach.

Across all scenarios, rebalancing decisions are derived from predicted expected demand loss, while system performance is evaluated using realized demand simulated from historical trip data. In Section 3.2, we first compare the four scenarios in terms of service level and operational cost, then evaluate the computational performance and scalability of *DL-HR* across varying network sizes, time-step granularities, and operational parameters, and finally quantify the value of the usability perspective relative to an availability-only predictor under different initial battery distributions. All computational experiments were implemented in Python 3.9.13 using Gurobi 9.5.2 as the MIP solver and executed on an Apple M1 system with 16 GB of RAM.

Case study

This subsection describes the empirical setting used to evaluate the proposed rebalancing framework. The case study is based on a shared e-scooter system operating in Rotterdam, the Netherlands, an urban environment characterized by high and temporally heterogeneous demand, dense land use, and strong multimodal connectivity through bus, metro, and micromobility services. These features make the study area well suited for assessing dynamic rebalancing and recharging strategies under realistic demand uncertainty.

Geo-fenced areas. The service region is discretized into geo-fenced zones that aggregate trips at fine spatial resolution. Each zone corresponds to a hexagonal cell, with inter-area distances computed as the shortest-path distance between zone centroids. The hexagons have a side length of 65 m, which lies below the maximum walking distance users are willing to accept between neighboring areas. These distances define the neighborhood structure introduced in Equation 3.5. The resulting partition consists of 109 geo-fenced zones.

Demand characteristics. The analysis relies on one year of trip-level operational data, including vehicle identifiers, timestamps, and origin–destination coordinates. Demand exhibits pronounced temporal variation across time of day. Empirical observations indicate that peak evening pickup demand for e-scooters concentrates between 16:00 and 18:00.

E-scooter types and battery states. The operator deploys two e-scooter types differentiated by max speed, 25 km/h and 45 km/h. Because vehicle-type identifiers are not available in the dataset and observed trip speeds are consistent with the lower-speed class, all e-scooters are treated as homogeneous 25 km/h vehicles in the analysis. The qualitative battery classes defined in Section 3.2.5 are operationalized as follows, based on the operator’s withdrawal policy and the trip-length distribution observed in the data. E-scooters below 10% are classified as inactive and withdrawn from service. The low-power class spans 10%–25%, a range that covers the average observed trip but falls short of longer trips and may induce range anxiety. The high-power class lies above 25% and provides sufficient range to serve any observed trip. The same thresholds apply uniformly across areas and times.

Flow of high-power e-scooters between areas. Flows of high-power e-scooters across geo-fenced areas are treated as exogenous inputs to the user-based rebalancing component. These flows are estimated from historical data by computing time-dependent origin-destination probabilities conditional on time of day and weekday versus weekend. This representation preserves observed travel patterns while isolating the effect of incentive-based redirection decisions.

Rebalancing plan parameters. The study considers a rebalancing truck with the capacity of carrying up to 10 e-scooters and 20 batteries. Each geo-fenced area has a maximum parking capacity of 10 e-scooters, and the operating day spans from 6:00 to 20:00. Rebalancing decisions are computed over two-hour planning horizons discretized into 15-minute time steps. To prevent myopic interventions, the optimization objective includes a four hour prediction of expected demand loss. The system employs a rolling horizon method where vehicle locations and battery levels information are updated through hourly data reports. After receiving these hourly updates, the model generates a two hour rebalancing schedule but executes only the actions planned for the first hour. It then optimizes the schedule again once the next hourly data report arrives. The simulation begins with a total fleet of 300 e-scooters and an initial battery state distribution of (0.2, 0.5, 0.3), matching the respective proportions of inactive, low power, and high power vehicles at the beginning of day.

Table (3.5) summarizes the pricing and rebalancing parameters used in the experiments. For incentivized trips, the per-minute fee is waived ($\rho_1 = 0$), and riders pay only the unlock fee (ρ_0). Walking time, riding time, and truck travel time are computed using average speeds of 1.5 m/s for walking, 20 km/h for e-scooters, and 45 km/h for trucks, respectively Emami and Ramezani (2024).

Parameters of the user choice model introduced in Section (3.2.6) are reported in B.1 (Table (3.11)). The model is estimated using stated-preference survey data in Rotterdam, the Netherlands, and is applied here under a homogeneous user behavior assumption. The

Table 3.5 Experiment setup pricing and rebalancing parameters

Parameter	Description	Unit	Value	Reference
ρ_0	Unlock fee for e-scooter trip	€	1	State of practice
ρ_1	Per-minute ride fee	€/min	0.3	State of practice
c_v	Fixed daily truck acquisition cost	€	100	State of practice
c	Unit travel cost of rebalancing trucks	€/km	1.2	
θ_1	Unit e-scooter load/unload cost	€	0.5	X. Li et al. (2024)
θ_2	Unit battery swapping cost	€	0.1	Emami and Ramezani (2024)
$\bar{w}$	Acceptable walking distance	m	500	Hoobroeckx et al. (2023)
B	Incentive budget	€	150	Equal to truck acquisition cost

choice model is treated as exogenous to the prediction and optimization processes and captures user preferences over battery level, walking distance, and pricing attributes when selecting an e-scooter.

Experimental plan

We assess the performance of the proposed *DL-HR* framework through a set of four scenarios that represent increasing levels of operational control over relocation and recharging decisions. These scenarios span the spectrum from no intervention to fully integrated coordination between operator- and user-based actions.

The *No rebalancing (NR)* quantifies the intrinsic service loss caused by ride-induced battery depletion in the absence of intraday control. The *Relocation-only (REL)* scenario allows a truck to load and unload e-scooters across areas but prohibits battery swapping, isolating the effect of dynamic vehicle relocation. The *Relocation with battery swapping (REL+SW)* scenario additionally activates on-street battery swapping, representing an operator-only relocation–recharging strategy. Finally, the proposed *DL-HR* scenario activates the fully hybrid control: truck-based relocation and battery swapping are coordinated with user-based incentives that redirect drop-off locations of high-power e-scooters in exchange for per-minute fee discounts. Across all scenarios, system performance is evaluated in terms of demand satisfaction, measured by both expected and realized demand loss, and total rebalancing costs, including truck operations and user incentives.

Rebalancing decisions in each planning horizon are guided by the look-ahead EDL prediction model, while realized performance is assessed through simulation. Trip demand is simulated using historical trip data with time-varying, area-level arrival rates calibrated from observed pickups and drop-offs and capped by historical hourly maxima. Simulated trip requests are matched against the scenario-specific inventory trajectories induced by each rebalancing strategy, yielding realized demand loss, truck utilization, and user-based rebalancing activities.

Experiment results

In this section, we first analyze the performance of different rebalancing scenarios regarding service levels and operational costs. We then report the computational performance of the rebalancing plans and analyze the scalability of the DL-HR framework under different spatio-temporal granularities. Building on these operational metrics, we delve into the core premise of our study by contrasting how a usability focused perspective alters rebalancing outcomes compared to a traditional availability only approach. Finally, we test the performance of DL-HR across various user behavior profiles and analyze the impact of the user behavior component on rebalancing decisions. This emphasizes that a rebalancing plan must adapt not only to spatial and temporal demand changes but also to the user behavior.

Comparative performance of various rebalancing plans

We compare system performance across scenarios using service level (SL), defined as the ratio of served trips to total potential demand; details of the SL computation are provided in B.3. Table 3.6 reports the weekday average SL, total truck operations cost and total incentive expenditure under the four rebalancing scenarios introduced in Section 3.2.

As shown in Table 3.6, truck-based relocation alone (*REL*) fails to improve average service level over the no-rebalancing baseline (*NR*), confirming that spatial redistribution without recharging cannot offset the growth of inactive inventory that drives demand loss in battery-dependent systems. Adding battery swap (*REL*+*SW*) raises SL by 6.4 percentage points over *REL*, identifying swap as the dominant operator-side lever. Layering user-mediated incentives on top of swap in *DL-HR* adds a further 5.8 percentage points and simultaneously reduces truck operations cost relative to *REL*+*SW*. The operational efficiency of truck-based rebalancing, measured as kilometers travelled per 100 trips served, is 0.89 for *REL*, 0.72 for *REL*+*SW*, and 0.51 for *DL-HR*. The DL-HR therefore serves more demand with less truck travel, an improvement that is environmentally as well as economically meaningful.

Table 3.6 Overview of system average service level and rebalancing costs across scenarios

	NR	REL	REL+SW	DL-HR
Average service level (%)	64.1%	64.5%	70.9%	76.7%
Total truck operations cost (euro)	0	236.8	291.21	275.05
Total incentivization cost (euro)	0	0	0	149.96

Figure (3.5) reports hourly SL and total system cost, defined as the sum of operational expenditure and monetized realized demand loss. All four scenarios begin the operating day above 90% SL. Service level then diverges across scenarios as cumulative riding depletes the fleet. Under *NR*, SL falls to 43% by the end of the operating day; under *REL* the trajectory closely tracks *NR* despite incurring routing cost, confirming the limited value of recharging-free relocation. *REL*+*SW* stabilizes the system service level above 57% during the operating day, with the operational cost of swap partially offset by

reduced demand-loss cost. Finally, *DL-HR* sustains SL above 64% throughout the day and maintains the lowest total cost across most hours. The early-morning cost peak visible for the three active scenarios reflects truck acquisition cost incurred at the start of operations; the secondary early-morning peak for *DL-HR* cost reflects incentive expenditure that prepositions high-power inventory ahead of the afternoon demand peak.

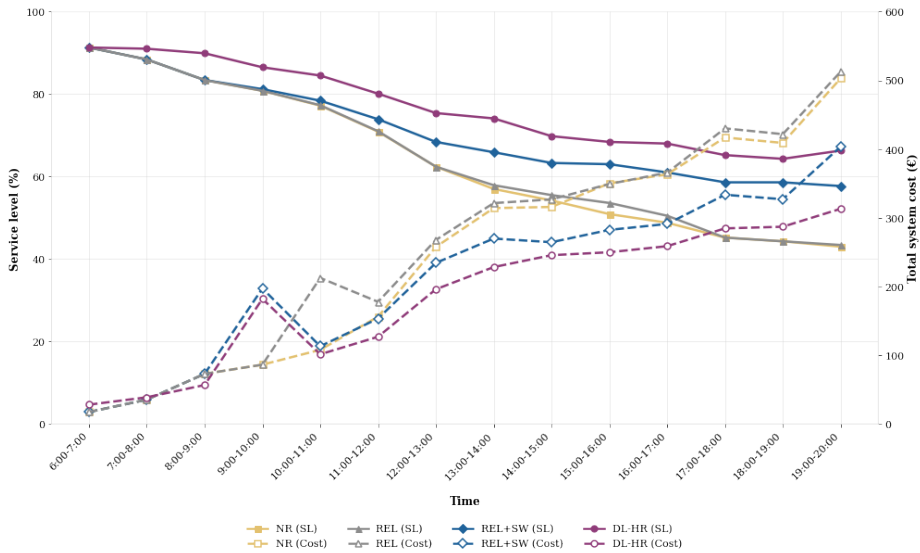


Figure 3.5 Hourly service level and total system cost (operations plus demand loss) for various scenarios and the proposed *DL-HR* method.

Figure (3.6) decomposes *DL-HR* costs by time of day into truck routing, loading and unloading, battery swapping, and user incentives. Incentive expenditure is spread across the operating day but peaks before 11:00 and again in the early afternoon, when the framework redirects high-power scooters into areas that expect demand peak during the afternoon peak (16:00-18:00). Truck activity carries 276 load/unload operations and 135 battery swaps across the day, distributed across mid-morning and afternoon hours. Battery swapping costs increased in the afternoon to maintain the decreased service level caused by power depletion.

Computational performance and sensitivity to problem scale. A predictive rebalancing framework is useful in practice only if it returns high-quality decisions within the time available between two consecutive system updates. The mixed-integer program is solved in an exact way with Gurobi at each planning period and re-optimized every hour within a rolling-horizon scheme. The solver time limit is set to 600 seconds per period, so that a revised plan is returned in time for the next 15-minute decision. We first compare average solve times and optimality gaps across the rebalancing scenarios (Table 3.7). We then test the *DL-HR* under varying spatial and temporal discretizations (Table 3.8), and finally

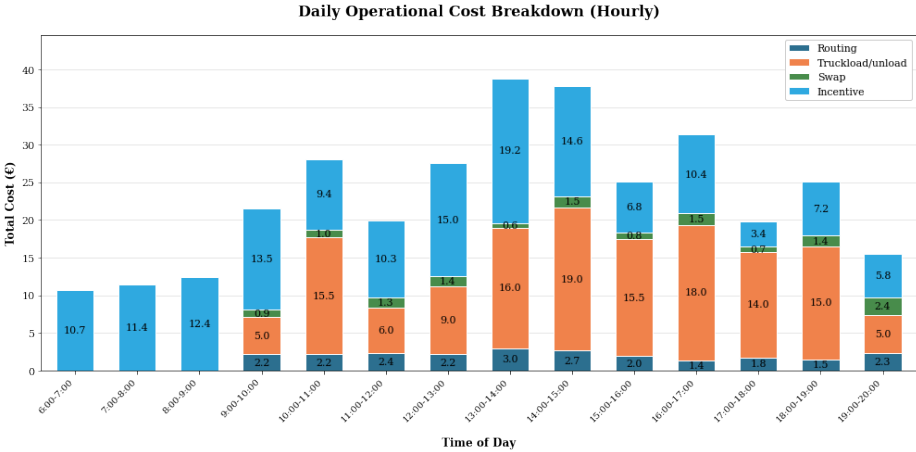


Figure 3.6 Hourly decomposition of DL-HR operational cost by intervention type.

examine the cost of additional rebalancing trucks and incentive budget on solution quality (Table 3.9).

Table 3.7 reports the average planning period optimality gap, the average Markov prediction time, and the average MIP solve time across the four rebalancing scenarios on the 110 zone network using the baseline temporal granularity ($\tau = 15$ minutes). All scenarios achieve proven optimality within the computational time limit, and the required prediction times remain comparable across each scenario. Incorporating battery swap decisions alongside load and unload actions in the REL+SW scenario increases the average MIP solve time, yet it does not degrade the optimality achieved within the allocated time. Integrating user mediated incentive decisions under the *DL-HR* framework introduces a marginal solve time increase of only 14.8 seconds (3.4%) while maintaining strict optimality. Consequently, the slight computational overhead associated with user incentives is negligible compared to the previously discussed improvements in system service levels.

Table 3.7 Average per-planning period computational performance across scenarios

Scenarios	Gap (%)	Predict (s)	MIP (s)
REL	0	2.8	82.1
REL+SW	0	3.1	438.5
DL-HR	0	3.3	453.3

We evaluate *DL-HR* across 27 configurations spanning three network sizes (50, 110, 160 areas), three per-area capacities (5, 10, 15 scooters), and three time-step lengths ($\tau \in \{5, 15, 30\}$ minutes). All values reported in Table 3.8 are averaged across the planning periods of one operating day. The look-ahead horizon for EDL prediction is fixed

at four hours and the rebalancing plan is for each two hours; the truck travel time per arc is set to 15 minutes and rounded up to one slot when $\tau = 30$ min.

Table 3.8 Per-period average computation time, average optimality gap, and average service level of *DL-HR* across spatio-temporal granularities. The baseline configuration (110 areas, capacity 10, $\tau = 15$ min) is shown in bold.

# of zone	capacity	$\tau = 5$ min				$\tau = 15$ min				$\tau = 30$ min			
		Predict(s)	MIP(s)	Gap(%)	SL(%)	Predict(s)	MIP(s)	Gap(%)	SL(%)	Predict(s)	MIP(s)	Gap(%)	SL(%)
50	5	0.4	600	76	48.1	0.18	43.5	0	33.3	0.12	0.36	0	23.6
	10	3.3	600	53	73.6	1.37	600	1.8	57.9	0.6	2.34	0	49.9
	15	13.8	600	68	83	5.7	600	5.8	69.6	3	9.3	0	60.3
110	5	1.4	600	35	69.3	0.77	166.4	0	61.4	0.5	0.9	0	52.7
	10	8.8	600	59	81	3.3	453.3	0	76.7	1.6	3.1	0	73.7
	15	24.6	600	71	79.4	11.9	600	4.2	79.2	7.1	5.2	0	77.4
160	5	2.99	600	32	72.6	2	61.1	0	73	1.8	2.5	0	71.7
	10	10.7	600	36	72.2	4.2	47.9	0	72.7	2.7	5	0	73.6
	15	49.3	442.1	0	71.5	18.4	13.5	0	72.7	14	7.1	0	73.8

First, as expected, the time step length is the dominant driver of solve time variability and optimality gap. At the finest temporal granularity ($\tau = 5$ min), all three 110-area instances exceed the 600 second time limit, closing with optimality gaps between 35% and 71%. The corresponding service levels are comparable to the $\tau = 15$ min baseline (69.3%–81.0% versus 76.7%), but these values are reported under non-optimal solutions and therefore do not indicate a reliable improvement attributable to finer time discretization. Second, the spatial granularity does not monotonically increase MIP solve time and does not improve service level on its own. Finer spatial discretization reduces per-area demand, which lowers the predicted expected demand loss at most areas and allows the time-and-space pruning to eliminate more candidate truck routes and incentive arcs as economically infeasible. Prediction time grows mildly with the number of areas, since the Markov forecast is evaluated per area. Finer spatial aggregations can therefore be computationally cheaper than coarser ones at fixed temporal granularity. Third, per-area capacity expands the Markov state space and raises the achievable service-level ceiling by reducing parking saturation, but the marginal gain diminishes beyond capacity 10 once the 300-scooter fleet becomes the binding constraint rather than parking.

Table 3.9 Per-period average computation time, average optimality gap, average service level, and truck operational efficiency of *DL-HR* under variation in the truck fleet size and incentive budget.

Incentive Budget (B)	MIP CPU (s)	Gap (%)	SL (%)	Truck operational efficiency
Truck = 1				
100	426.5	0	73.4	0.007
150	453.3	0	76.7	0.006
200	451.6	0	77.1	0.007
Truck = 2				
100	600	29	79.3	0.02
150	600	31	79.5	0.019
200	600	29	78.5	0.018

Table 3.9 reports *DL-HR* performance under variation in the number of rebalancing trucks and in the incentive budget B , holding the spatio-temporal discretization at the baseline configuration (110 areas, capacity 10, $\tau = 15$ min). Truck operational efficiency is defined as truck-kilometers travelled per trip served; lower values indicate higher efficiency. The case study uses one truck and $B = 150$ euro as the reference setting. Adding a second truck raises service level by 1.4 to 6 percentage points across all budget levels, but pushes MIP solve time beyond the 600 second limit and leaves an optimality gap of approximately 30%. Truck operational efficiency degrades under two trucks compared to one. This indicates that multi-truck deployment would benefit from a dedicated solution algorithm. Regarding incentive budget, service level is less sensitive to the incentive budget than to the truck fleet size, and its response to budget increases is non-monotone, because the hybrid decisions treats incentives as one of several substitutable rebalancing levers. Truck fleet size therefore remains the dominant operational decision for service-level outcomes, with the incentive budget playing a complementary role whose marginal value depends on the prevailing operator-side capacity.

Usability versus availability perspectives in DL-HR

Having established the computational efficiency and overall operational performance of the *DL-HR* framework, we now examine its core behavioral premise. In this subsection, we investigate how the perspective of usability versus availability impacts the resulting service levels of the rebalancing plan. To isolate this distinction, we execute the *DL-HR* while solely varying the predictor for expected demand loss. The availability variant treats every visible scooter (low-power and high-power e-scooters) as equally usable, mirroring the assumption embedded in prior look ahead rebalancing models. Under this variant, the Markov prediction model reduces to tracking the physical inventory of scooters and parking spaces without distinguishing between low and high power e-scooters or incorporating user choice dynamics. Conversely, the usability variant adopts the expected demand loss prediction that considers vehicle battery classes and the user behavior modeled in Section 3.2.6. Both variants employ the exact same operational levers (truck based relocation, battery swapping, and user mediated incentives) and face identical demand realizations. The sole difference lies in what the optimizer considers as usable inventory during the planning phase.

Because the initial power distribution of e-scooter at the beginning of the day influences both the rebalancing effort and the realized service level, we evaluate the two variants under four initial power distributions chosen to highlight the conditions under which usability and availability diverge most strongly. The *Baseline* power distribution (0.2, 0.5, 0.3) reflects the operator's observed start of day state regarding the share of inactive, low-power and high-power e-scooters in the studied area. The *Degraded* power distribution (0.4, 0.5, 0.1) increases the share of inactive scooters with the same low-power e-scooter as baseline to represent a poorly maintained fleet. The *No high-power* distribution (0.3, 0.7, 0) removes high-power inventory entirely, so every visible scooter is low-power. The *No low-power* distribution (0.3, 0, 0.7) removes low-power inventory entirely. Under the availability perspective the latter two distributions look operationally similar, since each contains only

one class of visible scooter. Under the usability perspective they differ sharply, because users readily accept high-power scooters but reject low-power ones.

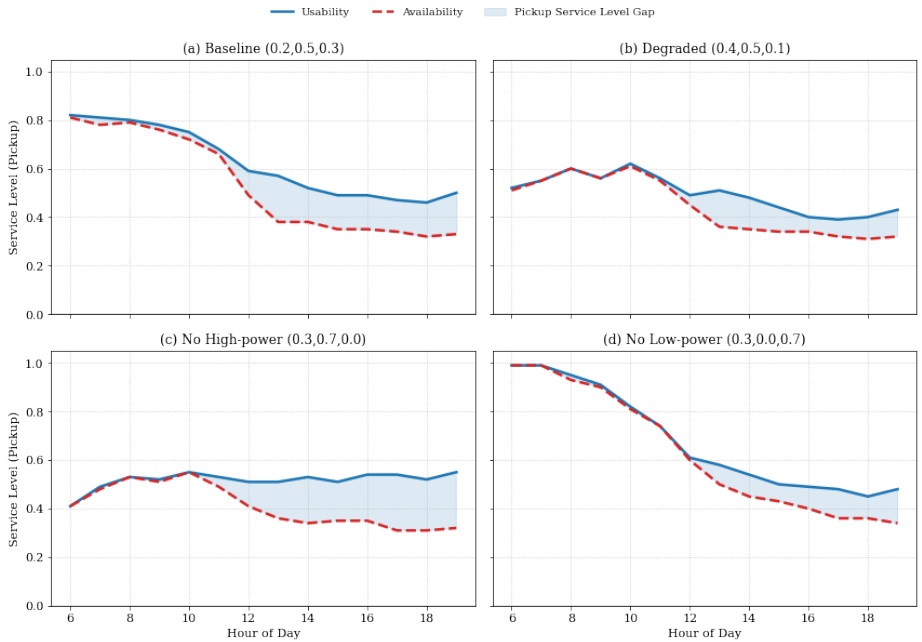


Figure 3.7 Hourly pickup service level of *DL-HR* under the availability (red dashed) and usability (blue solid) perspectives, evaluated under four initial power distributions. Shaded regions indicate the service-level gap between the two perspectives.

Figure 3.7 reports hourly pickup service level under each initial power distribution. First finding is the service level gap between the two perspectives is largest under the *No high-power* distribution, because the availability predictor cannot anticipate that users will reject the entire visible fleet, while the usability predictor correctly forecasts elevated demand loss and triggers compensating rebalancing. The gap is narrowest under the *No low-power* distribution, where the absence of low-power vehicles eliminates the source of behavioral filtering that the two predictors model differently. Second finding is both predictors agree closely in the early morning across all four initial power distributions and diverge progressively as cumulative riding depletes the fleet, with the largest gaps appearing during the afternoon peak. The distinction between physical availability and perceived usability perspective for rebalancing operations management is operationally consequential.

Behavioral sensitivity analysis

This subsection assesses the ability of rebalancing scenarios to maintain service level performance when the user population deviates from the average behavior obtained from

the estimated discrete choice model. The *Average* class corresponds to the population mean values of the random coefficients in the mixed logit specification of Section 3.2.6 and is the calibration used throughout the preceding subsections. To analyze the behavioral sensitivity, we vary two random coefficients of the discrete choice model. The battery level coefficient β_p captures range anxiety, and the per minute ride fee coefficient β_{ρ_1} captures price sensitivity. We define three classes: (i) *Average*, characterized by mean coefficient values; (ii) *Range-sensitive*, with elevated range anxiety; and (iii) *Price- & range-sensitive*, exhibiting stronger disutility for low battery levels and greater responsiveness to price incentives. Class-specific values are drawn from the estimated random-coefficient distributions reported in B.1, Table 3.11.

We first evaluate the robustness of a the rebalancing plan optimized for the *Average* class when it is deployed to a population that does not match the calibration. Table 3.10 reports the realized service level when the plans built for the *Average* class under each of the three rebalancing scenarios are evaluated against the three user classes. *DL-HR* attains the highest average service level for all user classes, indicating that its relative advantage over *REL* and *REL+SW* is preserved under behavioral misspecification. The fixed-plan analysis therefore shows that *DL-HR* retains the strategy ordering across user populations but suffers a proportionate service level penalty when the plan is not adapted to the prevailing user class.

Table 3.10 Average service level for different user profiles based on a fixed rebalancing plan for average users among different rebalancing scenarios

User profile	REL	REL+SW	DL-HR
Average	64.5%	70.9%	76.7%
Range-sensitive	52.9%	60.1%	61.7%
Price- & range-sensitive	53.1%	60.3%	61.9%

We next re-optimize the *DL-HR* plan for each user class to quantify the value of behavioral adaptation. Adapting the plan to the *Range-sensitive* class raises service level from 61.7% to 67.7%, and adapting to the *Price- and range-sensitive* class raises it from 61.9% to 68.4%. Figure 3.8 decomposes the resulting operational cost of the adapted plans into truck routing, on-station load and unload, battery swap, and user incentives. Total operational cost decreases as user behavior becomes more demanding, falling from €324.9 under the *Average* class to €257.7 under *Range-sensitive* and €287.2 under *Price- and range-sensitive*. Under more demanding user classes the opt-out probability rises and a larger share of unmet demand becomes structurally unrecoverable through rebalancing, which lowers the marginal value of each intervention. The framework responds by scaling down total expenditure and reallocating the remaining effort toward the lever with the highest preserved marginal value.

The composition of that reallocation differs across the two demanding classes. Under the *Range-sensitive* class, the framework shifts effort toward truck-based interventions, expanding both routing and swap operations to preserve high-power inventory at required locations. Under the *Price- & range-sensitive* class, the framework relies more on

incentives. Because these users respond more strongly to ride-fee discounts, redirecting their drop-offs through incentivized trips becomes a cost effective substitute for truck travel, and the adapted plan allocates a larger share of the incentive budget to exploit this responsiveness.

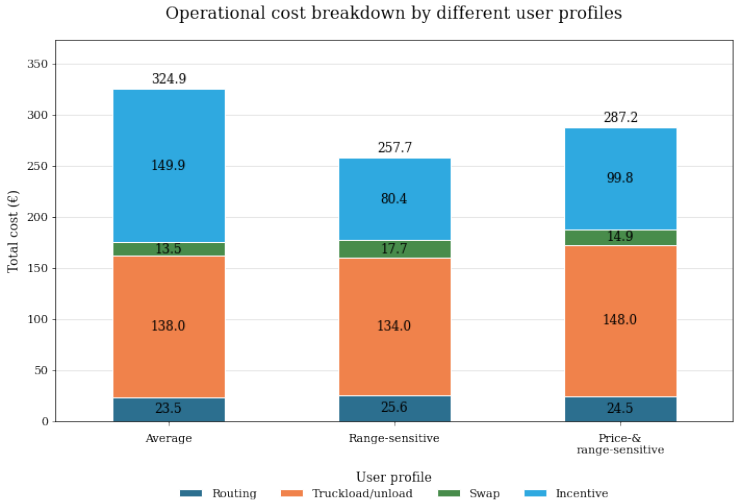


Figure 3.8 Decomposition of *DL-HR* operational cost for plans adapted to each user class.

3.2.9 Conclusion

In this paper, we propose a hybrid operator, user, and battery control framework for rebalancing in geofenced shared electric scooter systems. We introduce the Direct Look Ahead Hybrid Rebalancing (*DL-HR*) framework, which embeds a three state Markov forecast of perceived usability into a mixed integer optimization that coordinates truck based relocation, on street battery swapping, and user mediated drop off incentives. The model is solved exactly for each planning period and subsequently updates the plan when new information regarding system states arrives using a rolling horizon approach. Experiments on a real world case study in Rotterdam yielded three main findings with direct implications for the modeling and deployment of predictive rebalancing in battery dependent micromobility systems.

First, the distinction between physical availability and perceived usability is operationally consequential rather than a mere theoretical refinement. Look ahead frameworks built on inventory only state representations will therefore systematically misallocate effort in battery dependent systems. Second, the operator and user side levers of *DL-HR* are complementary rather than substitutable. Incentives are deployed before the afternoon peak to address the demand for high power e-scooters, while battery swapping is deployed during and after the peak to recover depleted vehicles. The lever mix adapts endogenously to the prevailing behavioral profile. Third, hybrid coordination improves

truck operational efficiency in addition to overall service levels. Truck kilometers traveled per trip served decrease under the *DL-HR* scenario compared to truck-only rebalancing, ensuring a sustainable and environmentally friendly approach.

Future work can strengthen the state prediction model by incorporating real time availability models that account for contextual factors such as weather, time of day, and trip purpose. The framework's behavioral endogeneity is deliberately targeted at the margin rebalancing can influence while total demand and origin–destination flows are held to their historically calibrated values; endogenizing trip generation and destination choice is a worthwhile extension left to future work. On the optimization side, the model can be extended to jointly optimize pricing decisions for incentives. Modeling real time user arrivals and dynamic incentive design would yield a fully real time decision problem with substantially higher computational complexity. This is therefore beyond the scope of this study, which focuses on system level rebalancing planning. However, such real time extensions remain a promising direction for high demand settings where fine grained adaptive control is critical.

Appendix B

B.1 User behavior parameters

The socio-demographic vector $\mathbf{X}_{soc}$ and the latent attitudinal vector $\mathbf{X}_{lat}$ in Equation (4.1) are defined as follows. $\mathbf{X}_{soc}$ collects user-specific characteristics including prior e-scooter usage (*exp*), bike ownership (*bike*), low-income status (*income*), and household composition (living alone or in a shared household). $\mathbf{X}_{lat}$ collects latent attitudinal constructs including the user’s attitude toward shared e-scooter systems (*perception*), perceived range anxiety (*range.anx*), and an interaction term between the two (*interaction*). Table 3.11 reports the parameters used to model users’ behavior.

Table 3.11 Users’ choice parameters

Parameter	Description	Unit	Mean	Standard deviation	Lower bound	Upper bound
ASC_{es}	Alternative specific constant for selecting e-scooter	-	10.514	-	-	-
β_w	Utility coefficient for e-scooter access walking time	1/min	-0.342	-	-	-
β_{ρ_0}	Utility coefficient for trip unlock fee	1/€	-1.419	-	-	-
β_{ρ_1}	Utility coefficient for per minute trip ride fee	1/(€.min)	-25.147	8.68	-45.9	-12.3
β_p	Utility coefficient for e-scooter battery level	1/km	0.27	0.08	0.15	0.46
β_{type}	Utility coefficient for e-scooter type	-	-1.02	-	-	-
β_{exp}	Utility coefficient for previous usage of shared e-scooter systems	-	-1.79	-	-	-
β_{bike}	Utility coefficient for bike ownership	-	-2.21	-	-	-
β_{income}	Utility coefficient for low-income users	-	-1.18	-	-	-
$\beta_{live.alone}$	Utility coefficient for users live alone	-	1.21	-	-	-
$\beta_{live.shared}$	Utility coefficient for users live in shared houses	-	-0.86	-	-	-
$\beta_{perception}$	Utility coefficient for latent variable: attitude toward shared e-scooter	-	0.82	-	-	-
$\beta_{range.anx}$	Utility coefficient for latent variable: perceived range anxiety	-	-0.58	-	-	-
$\beta_{interaction}$	Utility coefficient for latent variables’ interactions	-	0.033	-	-	-

Note: Values are sourced from Burghardt et al. (2025).

B.2 Proof of convexity

The convexity of the bivariate EDL with usable and unusable vehicles has been shown in Raviv and Kolka (2013), Kaspi et al. (2017) and Zhou, Lin, et al. (2023). Our EDL function has the same structure by defining “available” scooters as high- and low-power units together and “unusable” scooters as inactive units. However, to model range-anxious users who require a high-power scooter, we must also handle situations where there is no high-power e-scooter but low-power e-scooters are available and the request is still lost. Hence the convexity must be shown in all three inventories (inactive, low, high). The EDL $F(n_0, \ell_0, h_0)$ is convex in the initial inventory of each scooter class. In particular:

$$\begin{aligned}
 F(n_0, \ell_0, h_0+2) - F(n_0, \ell_0, h_0+1) &\geq F(n_0, \ell_0, h_0+1) - F(n_0, \ell_0, h_0), \\
 F(n_0, \ell_0+2, h_0) - F(n_0, \ell_0+1, h_0) &\geq F(n_0, \ell_0+1, h_0) - F(n_0, \ell_0, h_0), \\
 F(n_0+2, \ell_0, h_0) - F(n_0+1, \ell_0, h_0) &\geq F(n_0+1, \ell_0, h_0) - F(n_0, \ell_0, h_0), \\
 F(n_0, l_0+1, h_0+2) - F(n_0, l_0+1, h_0+1) &\geq F(n_0, l_0, h_0+1) - F(n_0, l_0, h_0), \\
 F(n_0+1, l_0, h_0+2) - F(n_0+1, l_0, h_0+1) &\geq F(n_0, l_0, h_0+1) - F(n_0, l_0, h_0), \\
 F(n_0+1, l_0+2, h_0=0) - F(n_0+1, l_0+1, h_0=0) \\
 &\geq F(n_0, l_0+1, h_0=0) - F(n_0, l_0, h_0=0).
 \end{aligned}$$

The first three inequalities ensure that EDL is convex in each of the variables high-power, low-power, and inactive independently. The last three inequalities corresponds to the mixed terms in Hessian matrix in the $M^\natural$ -convexity condition Moriguchi and Murota (2011), where:

A function $f : \mathbb{Z}^n \rightarrow \mathbb{R}$ is $M^\natural$ -convex iff its discrete Hessian $H(x)$ satisfies, for all x and all distinct i, j, k ,

$$\begin{aligned}
 H_{ij}(x) &\geq \min\{H_{ik}(x), H_{jk}(x)\}, \\
 H_{ij}(x) &\geq 0 \text{ for all } i, j.
 \end{aligned}$$

Proof. Fix a demand/return realization and compare three coupled initial states that differ only in one inventory component. For the high-power case these states are (n_0, l_0, h_0+2) , (n_0, l_0, h_0+1) , (n_0, l_0, h_0) ; the low-power and inactive cases are defined analogously. In each comparison the other two inventories are kept constant, so any difference in shortages comes only from the extra unit of that class.

We distinguish three event types: (i) high-power request (*H-scooter*), which is lost only when $X_h = 0$; (ii) available-scooter request (*Scooter*), which is lost only when $X_h + X_l = 0$; and (iii) *Parking*, which is lost only when $X_h + X_l + X_n = C$. Under a coupled evolution, an extra unit can only postpone the first shortage of the corresponding type; it cannot create a new shortage. Therefore, for each pair of consecutive states, the shortage count at the first shortage event differs by at most $-1, 0$, or $+1$, and after that event the paths equalize. Each H_{ij} is the difference of two one-step comparisons under a common realization. In our serving rules: H-scooter shortages depend only on h_0 , Scooter on $h_0 + l_0$, and parking on $n_0 + l_0 + h_0$. Using the event-based tables in Tables 3.12–3.17, we obtain the discrete Hessian entries of $F(n_0, l_0, h_0)$ as follows.

Table 3.12 Possible combinations of first shortage occurrence with initial inventories $(n_0, l_0, h_0 + 2)$, $(n_0, l_0, h_0 + 1)$, and (n_0, l_0, h_0)

$F(n_0, l_0, h_0 + 2) - F(n_0, l_0, h_0 + 1)$		$F(n_0, l_0, h_0 + 1) - F(n_0, l_0, h_0)$	
First shortage occurrence	Difference	First shortage occurrence	Difference
Parking	1	H-scooter	-1
Parking	1	Scooter	-1
Parking	1	Parking	1
Parking	1	None	0
Scooter	0	Scooter	-1
None	0	None	0
None	0	H-scooter	-1

Table 3.13 Possible combinations of first shortage occurrence with initial inventories $(n_0, l_0 + 2, h_0 = 0)$, $(n_0, l_0 + 1, h_0 = 0)$, and $(n_0, l_0, h_0 = 0)$

$F(n_0, l_0 + 2, h_0 = 0) - F(n_0, l_0 + 1, h_0 = 0)$		$F(n_0, l_0 + 1, h_0 = 0) - F(n_0, l_0, h_0 = 0)$	
First shortage occurrence	Difference	First shortage occurrence	Difference
Parking	1	H-scooter	0
Parking	1	Scooter	-1
Parking	1	Parking	1
Parking	1	None	0
None	0	Scooter	-1
None	0	None	0

Tables 3.12, 3.13, and 3.14 satisfy the inequalities in Lemma B.2. Hence, the EDL is convex in each inventory variable independently. Then, Tables 3.15–3.17 indicate the second differences between high-power and low-power; high-power and inactive, and low-power and inactive, respectively. All the second differences are nonnegative for every realization. Moreover, $H_{hl}(x) \geq \min\{H_{hn}(x), H_{ln}(x)\}$. Hence both discrete-Hessian conditions of Moriguchi and Murota (2011) are satisfied, and $F(n_0, l_0, h_0)$ is $M^{\natural}$ -convex.

Table 3.14 Possible combinations of first shortage occurrence with initial inventories $(n_0 + 2, l_0, h_0)$, $(n_0 + 1, l_0, h_0)$, and (n_0, l_0, h_0)

$F(n_0 + 2, l_0, h_0) - F(n_0 + 1, l_0, h_0)$		$F(n_0 + 1, l_0, h_0) - F(n_0, l_0, h_0)$	
First shortage occurrence	Difference	First shortage occurrence	Difference
Parking	1	H-scooter	0
Parking	1	Scooter	0
Parking	1	Parking	1
Parking	1	None	0
None	0	None	0

Table 3.15 Possible combinations of first shortage occurrence with initial inventories $(n_0, l_0 + 1, h_0 + 2)$, $(n_0, l_0 + 1, h_0 + 1)$, $(n_0, l_0, h_0 + 1)$, and (n_0, l_0, h_0)

$F(n_0, l_0 + 1, h_0 + 2) - F(n_0, l_0 + 1, h_0 + 1)$		$F(n_0, l_0, h_0 + 1) - F(n_0, l_0, h_0)$	
First shortage occurrence	Difference	First shortage occurrence	Difference
Parking	1	H-scooter	-1
Parking	1	Scooter	-1
Parking	1	Parking	1
Parking	1	None	0
Scooter	0	Scooter	-1
None	0	None	0
None	0	H-scooter	-1

Table 3.16 Possible combinations of first shortage occurrence with initial inventories $(n_0 + 1, l_0, h_0 + 2)$, $(n_0 + 1, l_0, h_0 + 1)$, $(n_0, l_0, h_0 + 1)$, and (n_0, l_0, h_0)

$F(n_0 + 1, l_0, h_0 + 2) - F(n_0 + 1, l_0, h_0 + 1)$		$F(n_0, l_0, h_0 + 1) - F(n_0, l_0, h_0)$	
First shortage occurrence	Difference	First shortage occurrence	Difference
Parking	1	H-scooter	-1
Parking	1	Scooter	-1
Parking	1	Parking	1
Parking	1	None	0
None	0	Scooter	-1
None	0	None	0
None	0	H-scooter	-1

Table 3.17 Possible combinations of first shortage occurrence with initial inventories $(n_0 + 1, l_0 + 2, h_0 = 0)$, $(n_0 + 1, l_0 + 1, h_0 = 0)$, $(n_0, l_0 + 1, h_0 = 0)$, and $(n_0, l_0, h_0 = 0)$

$F(n_0 + 1, l_0 + 2, h_0 = 0) - F(n_0 + 1, l_0 + 1, h_0 = 0)$		$F(n_0, l_0 + 1, h_0 = 0) - F(n_0, l_0, h_0 = 0)$	
First shortage occurrence	Difference	First shortage occurrence	Difference
Parking	1	H-scooter	0
Parking	1	Scooter	-1
Parking	1	Parking	1
Parking	1	None	0
None	0	Scooter	-1
None	0	None	0
None	0	H-scooter	-1

B.3 System service level simulation

Algorithm 2 presents the pseudo-code of the service-level simulation, following the event order described above.

Algorithm 2 System service level simulation

- 1: **Input:** Planning window $\mathcal{T}$; zones N ; capacities C_i ; simulated demand per zone/time: pickups $\{p_i^k(t)\}_{k \in P \setminus \{n\}}$, drop-offs $\{d_i^k(t)\}_{k \in P}$; initial inventories $\{X_i^k(0)\}_{k \in P}$; optimal rebalancing plan $\{\Delta_i^k(t)\}_{k \in P}$; number of runs R
 - 2: **Output:** Per-zone demand loss and service level; system mean service level; end-of-window inventories
 - 3: **for** run $r = 1$ to R **do**
 - 4: Initialize $X_i^k \leftarrow X_i^k(0)$ for all $i \in N, k \in P$; set served $\leftarrow 0$, total $\leftarrow 0$
 - 5: **for** each $t \in \mathcal{T}$ **do**
 - 6: **for** each zone $i \in N$ **do**
 - 7: **Rebalancing:** $X_i^k \leftarrow X_i^k + \Delta_i^k(t)$ for $k \in P$
 - 8: **Drop-offs:** let free-parking $\leftarrow C_i - \sum_{k \in P} X_i^k$ and $r_k \leftarrow d_i^k(t)$ for $k \in P$
 - 9: Proportional acceptance: allocate free-parking across $k \in P$ in proportion to r_k
 - 10: $X_i^k \leftarrow X_i^k + a_k$ for $k \in P$; served $\leftarrow \sum_{k \in P} a_k$; total $\leftarrow \sum_{k \in P} r_k$
 - 11: **Pickups:** for $k \in P \setminus \{n\}$ set $s^k \leftarrow \min(p_i^k(t), X_i^k)$; then $X_i^k \leftarrow X_i^k - s^k$
 - 12: served $\leftarrow \sum_{k \in P \setminus \{n\}} s^k$; total $\leftarrow \sum_{k \in P \setminus \{n\}} p_i^k(t)$
 - 13: **end for**
 - 14: **end for**
 - 15: Record service for this run: $SL^{(r)} \leftarrow 1 - \frac{\text{demand loss}}{\text{total demand}}$ and end inventories $\{X_i^k\}$
 - 16: **end for**
 - 17: Report per-zone averages, system mean service level $\frac{1}{R} \sum_{r=1}^R SL^{(r)}$, and average end-of-window inventories =0
-

Chapter 4

Reliable Multimodal Trip Planning with Shared E-Micromobility: a User Welfare Maximization Approach under Battery and Behavioral Uncertainty

Transitioning from strategic design to the operational leg of urban multimodal planning, this chapter focuses on offering reliable, welfare-maximizing trip options to passengers using a combination of e-buses and e-scooters. A major operational challenge is that the success of these multimodal trips hinges on the usability of micromobility vehicles, which is inherently volatile due to uncertain pickup and drop-off rates, as well as battery discharge. To offer reliable options at the time of trip execution, a multimodal trip planner requires accurate, near-future state predictions of the micromobility system.

To achieve this, this chapter draws directly on the outputs of the preceding chapters: the robust e-bus network from Chapter 2 provides the scheduled transit (Momen et al., 2025), while the calibrated passenger behavioral model and e-micromobility state predictions from Chapter 3 enter as exogenous inputs. Using these components, we formulate a flow-based mixed-integer nonlinear optimization framework that is able to recommend a multimodal trip option. Crucially, we introduce a reliability threshold that filters out micromobility pickup zones whose predicted usability for a specific passenger falls below the specified threshold. By jointly embedding the supply-side prediction and demand-side behavioral uncertainties, the trip planner prevents recommendations that are likely to fail at execution, thereby substantially reducing the overall trip failure rate.

This chapter is based on the journal article:

1. Momen, S., Maknoon, Y., van Arem, B., & Azadeh, S. S. (2026). Reliable Multimodal Trip Planning with Shared E-Micromobility: a User Welfare Maximization Approach under Battery and Behavioral Uncertainty. *submission planned*.

Abstract

Multimodal trip planners combine public transport and shared e-micromobility to improve first- and last-mile connectivity. In practice, however, vehicle availability and battery levels fluctuate continuously. A transfer that appears feasible at the time of recommendation may fail when the traveler arrives to change mode trip. Such operational failures weaken the reliability of multimodal transport. We consider a reliability-aware recommendation problem that embeds state of the charge uncertainty of the e-micromobility fleet and passenger behavior directly into multimodal trip planning. To achieve this, we first define the usability of a micromobility transfer by capturing both physical availability and remaining battery capacity, together with passenger sensitivity to battery level and range anxiety. We formulate a welfare-maximizing multimodal trip recommendation problem that coordinates buses with shared electric micromobility while conditioning micromobility transfers on predicted usability. Transfers whose predicted success probability falls below an operator-defined threshold are excluded from the feasible set of the recommended trips. We implemented this approach on Rotterdam's multimodal network. The method is evaluated through a simulation designed to reflect real-world uncertainty by testing the planner's predictions against actual system outcomes. Introducing moderate reliability thresholds reduces micromobility-leg failure rates from roughly 25% under myopic planning to below 5%, at the cost of about four additional minutes of walking on average. When we enforce strict reliability thresholds on longer urban trips, micromobility transitions from a main mode of transport to a last mile connectivity solution to bus trips. Additionally, behavioral heterogeneity further alters success rate of recommended trips, and ignoring dispersion in passenger behavior leads to systematic misestimation of e-micromobility trip execution reliability.

4.1 Introduction

Multimodal trip planning increasingly integrates shared micromobility as first- and last-mile connections to public transport (A. Li et al., 2024). In electrified fleets, vehicle availability and their associated charge levels vary in real time, therefore, a micromobility vehicle that appears present in the system may be unusable when the traveler arrives to the pickup point. As a result, the micromobility leg of a recommended itinerary may be infeasible upon arrival at pickup point through recommended at departure point. These failures are not isolated anomalies but a structural feature of electrified shared mobility.

Furthermore, the e-micromobility availability does not guarantee a successful transfer because its usability is subjective and passengers experience different range anxiety regarding the state of charge of the e-micromobility. A physically present vehicle may still be rejected if its remaining battery falls below an individual traveler's preference for their intended trip. Empirical evidence indicates that range anxiety toward shared electric vehicles varies substantially across individuals and shapes how displayed battery information influences choice model (Burghardt et al., 2025). As a result, the same predicted fleet condition may generate distinct feasible sets across users. In electrified shared fleets, service reliability therefore depends on both physical availability of the

vehicle and the acceptability of its state of charge for the user with a particular range anxiety. Despite increasing attention to micromobility integration, multimodal trip planning models largely represent vehicle availability as a deterministic input and assume that a displayed vehicle remains usable at the pickup point. User-specific state of charge level acceptance thresholds are rarely embedded directly in the admissible set of recommended itineraries. Consequently, the interaction between stochasticity of fleet usability and heterogeneous traveler range anxiety remains unattended in the current literature.

This study embeds user-dependent range anxiety directly into a multimodal trip recommendation problem. First, a Markovian model predicts e-micromobility usability. This usability score determines if a transfer zone meets a specific user's battery needs. Next, we apply a service reliability threshold. A shared e-micromobility leg is defined as *reliable* if the predicted usability that at least one user-acceptable e-scooter is available at the designated pickup zone at the passenger's expected arrival time exceeds the service reliability threshold. Reliability is evaluated for each request, geo-fenced zone, and arrival time. Our framework demonstrates how different threshold values reshape the structure of recommended multimodal trips. Finally, it measures the service-level distortions in terms of number of successful trips, that occur when differences in range anxiety are ignored.

Our proposed approach is evaluated on a shared e-scooter system integrated with electric bus transit in Rotterdam, the Netherlands. The results show that higher service reliability thresholds reduce micromobility-leg failure rates from approximately 25% under myopic planning to below 5% under our proposed method. As a result, average walking time increases by about four minutes. Our evaluation shows that for longer urban trips, stricter reliability thresholds does not eliminate e-scooters from recommended routes. Instead, it repositions them as a practical first/last-mile connection to public transit. Recommended trips' failure rates also rise when passengers differ in battery acceptance thresholds, even under identical fleet conditions. Ignoring this behavioral dispersion therefore leads to systematic overestimation of realized service reliability under stochastic supply.

The paper is organized as follows. Section 4.2 reviews the literature on multimodal trip planning and uncertainty in shared mobility systems. Section 4.3 outlines the problem setting and core components of the proposed trip recommendation approach. Section 4.4 develops welfare maximizing optimization model. Section 4.5 presents the experimental design and empirical findings under varying service reliability thresholds and passenger range anxiety. Section 4.6 is dedicated to conclusions, discussions and future work.

4.2 Related Literature

In this section, we review the literature on multimodal transport planning. We organize the review around two dimensions that define the scope of our contribution, namely the perspective of the decision-maker in multimodal transportation (Section 4.2.1) and the management of service reliability under uncertainty (Section 4.2.2). Finally, in Section 4.2.3 the contributions of our study is highlighted.

4.2.1 The perspective of the decision-maker in multimodal transport planning

Multimodal trip planning models differ fundamentally based on whose perspective they prioritize. This choice of decision-maker shapes how the trip recommendation problem is formulated. A large stream of research adopts an operator-level perspective, in which services, schedules, or fleet deployments are designed to optimize system-wide objectives such as cost minimization, demand coverage, or service frequency. For instance, Posada et al. (2017) examine how bike-sharing infrastructure extends transit reach within a network design framework, while Molenbruch et al. (2021) address routing and scheduling decisions for flexible on-demand transport. These formulations focus on fleet configuration and system performance rather than on generating individualized trip recommendations at the passenger level.

A second stream incorporates passenger preferences into system-level design decisions. Azadeh, Atasoy, et al. (2022) embed discrete choice models to anticipate demand in fixed-line and demand responsive buses service network design, and Guan et al. (2024) integrate choice-based path adoption behavior into the design of on-demand multimodal systems. Although traveler behavior is modeled explicitly, the decision variable remains the service configuration itself. The problem of providing real-time, multimodal trip recommendations to users is therefore conceptually distinct from these design-oriented formulations.

User-level multimodal trip planning models determine an itinerary for a given passenger, typically by minimizing generalized travel cost or maximizing individual utility. Atasoy et al. (2015) generate optimized travel options through flexible vehicle allocation across services, although transfers and fully multimodal trip structures are not explicitly represented. More recent work by Y. Zhang et al. (2025) develops a dynamic, preference-based trip planner that coordinates public transport and shared mobility and produces a single optimized plan for each request. Despite this behavioral orientation, shared modes are assumed to be bookable with certainty, and electric and conventional vehicles are treated as operationally equivalent. Execution-stage availability risk and battery-conditioned usability therefore do not enter the recommendation problem.

4.2.2 Service reliability and uncertainty in shared modes

A central operational challenge in multimodal trip planning is related to the reliability of shared mobility services. Unlike scheduled public transport, shared micromobility operates without fixed timetables and vehicles may be unavailable due to prior use, relocation, technical issues, or charging operations. In electrified fleets, level of charge introduces an additional layer of uncertainty, since physical presence does not ensure usability for a specific trip.

A substantial body of research incorporates e-micromobility availability and battery dynamics within supply-side operational planning problems such as rebalancing and recharging. Zhou, Lin, et al. (2023) optimizes swapping and relocation strategies considering battery evolution across multiple charge states. Emami and Ramezani (2024)

incorporate battery constraints into integrated rebalancing decisions for dockless systems. Momen et al. (2026) forecast perceived vehicle usability and embed behavioral response in rebalancing models. Although these models provide short-term forecasts of fleet availability and usability, their primary objective is to optimize system-level operations rather than recommending multimodal trips to individual travelers.

A parallel stream incorporates uncertainty into multimodal optimization through stochastic demand, travel time variability, or service disruptions (Ding et al., 2024; Mo et al., 2025). Two-stage stochastic and robust formulations address hub location, fleet sizing, routing, and timetabling under such uncertainty Luo et al. (2021), Martin-Idrati et al. (2024), and R. Zhang et al. (2025). Related studies examine path re-planning during public transport disruptions (Akyüz et al., 2023; Mo et al., 2025). Existing literature primarily views uncertainty as an external shock to the multimodal network, such as transit delays and traffic variability. The feasibility of an e-micromobility trip, however, is seldom defined as the joint outcome of predicted battery-state and associated user acceptance behavior in a trip recommendation system. Therefore, existing planning models fail to fully address whether a recommended micromobility transfer will be usable for the user at the moment of trip execution.

4.2.3 Contributions

Table 4.1 categorizes the reviewed studies by their core problem, transport modes, decision-making perspective (DM), and mode transfer possibility (Trans.). The table represents model dynamism (Dyn.) alongside the considerations of three factors related to the usability of shared mobility, i.e., physical vehicle availability (Avail.), battery transition uncertainty (Batt.), and user behavior (Behav.). The final column outlines the methodology used in each study.

Several key observations emerge from this comparison. Models that explicitly capture e-micromobility battery dynamics and vehicle availability are directed exclusively toward supply-side planning, such as rebalancing and recharging problem, rather than toward generating reliable trip recommendations for individual travelers. Studies that incorporate user preferences either address static planning decisions or focus on exogenous disruption scenarios in scheduled public transport. Consequently, there is a research need to have a complete view of the e-micromobility state evolution within a multimodal trip recommendation model by considering all three shared e-micromobility usability dimensions, i.e., shared mode availability, battery state uncertainty, and behavioral heterogeneity in battery acceptance. Battery usability is therefore not defined conditioned on individual passenger characteristics in existing trip recommendation models.

This study addresses this gap through three specific contributions. First, we define e-micromobility usability as a joint function of predicted usability and passenger-specific range anxiety. Second, we embed this usability definition into a service reliability filter that conditions the admissible set of multimodal nodes on the predicted probability that a user-acceptable vehicle will be present at the planned pickup zone. Third, we formulate a welfare-maximizing multimodal trip recommendation model that operates under a rolling

Table 4.1 Comparison between the proposed approach and related literature.

Paper	Problem	Mode	DM	Trans.	Dyn.	Usability of shared modes			Methodology
						Avail.	Batt.	Behav.	
Atasoy et al. (2015)	FMOD	Taxi, shared-taxi, mini-bus	Operator + User						MIP, Assortment Opt. MIP
Posada et al. (2017)	IDARP	PT + RP	Operator	✓					
Molenbruch et al. (2021)	IDARP	PT + RP	Operator	✓					LNS (Metaheuristic)
Azadeh, Atasoy, et al. (2022)	SND	Fixed line and demand responsive bus	Operator	✓				✓	MIP, ALNS
Momen et al. (2026)	EMR	Dockless E-micro	Operator		✓ (RH)	✓	✓	✓	Markovian prediction, MIP
Guan et al. (2024)	ODMTS	Fixed line PT + dynamic shuttle	Operator + user	✓				✓	Bilevel Optimization
Mo et al. (2025)	IPR	PT + Shared Mobility	Operator user	+	✓			✓	Stochastic Opt.
Ding et al. (2024)	IPR	Tourist transport	User						Stochastic Opt. (chance constraint)
Y. Zhang et al. (2025)	MMTP	PT + Shared Mobility	Sysem-level + User	✓	✓ (RH)				MIP, Algorithms
This study	Reliable MMTP	PT (E-bus) + Shared E-micro	Sysem-level + User	✓	✓ (RH)	✓	✓	✓	Markovian Prediction, Flow-based MIP

Note: DM= Decision maker; Trans.=Transfer; Dyn.=Dynamic; Avail.=Shared mode availability; Batt.=Battery level; Behav.=Passenger behavior;

FMOD= Flexible mobility on demand; IDARP= Integrated dial-a-ride problem; SND= Service Network Design; EMR= E-Micromobility rebalancing; ODMTS= On-Demand Multimodal Transit System; IPR= Individual path Recommendation; MMTP= Multi-modal Trip Planning; PT= Public Transport; RP= Ride Pooling;

MIP= Mixed Integer Programming; (A)LNS= (Adaptive) Large Neighborhood Search

horizon, enabling real-time updates to usability predictions as successive requests are assigned and e-micromobility states evolve. Together, these contributions yield a trip recommendation model that maintains both service reliability at the pickup point and user welfare.

4.3 Problem Description

We consider a choice-based multimodal trip planner that coordinates scheduled public transport with shared electric micromobility. Public transport consists of electric buses operating on fixed routes and timetables, while shared mobility is provided by geo-fenced e-scooters. The planner operates on a single coordinating platform without inter-operator competition and processes trip requests sequentially, one at a time. For each request at each time, it recommends a welfare-maximizing itinerary.

When a request arrives, the platform generates and evaluates feasible travel alternatives and recommends one to the passenger. We allow the following types of services:

1. PT as the main mode of trip combined with shared e-micromobility as a first- and/or last-mile connector,
2. PT as the main mode,
3. shared e-micromobility as the main mode,
4. pure walking.

Transfers between public transport and e-scooters are permitted, and multiple e-micromobility legs may occur within a single trip. Passengers are presumed to be captive in the system, as a result, every request is assigned to exactly one feasible itinerary.

4.3.1 Demand specification

Each passenger submits a trip request r defined by an origin o_r , a destination d_r , and a time window $[a_r, b_r]$ specifying the earliest departure and the latest acceptable arrival. Planning is performed at the level of individual requests.

Passengers may register sociodemographic attributes such as gender, age, education, income, and familiarity with shared micromobility. These attributes determine a passenger's mode-specific characteristics preference, in particular the range anxiety. When passenger's profile information is unavailable, the average parameters for the population are considered for the passenger. Preference parameters are exogenous inputs obtained from calibrated discrete choice models (Burghardt et al., 2025), and are not estimated within the optimization model.

4.3.2 State of e-micromobility supply

The e-micromobility is distributed across geo-fenced zones within the operating area, and its spatial-temporal state evolves through user activity (trips) and battery discharge pattern. Battery charge is discretized into three categories $p \in P\{n, l, h\}$, representing inactive, low-power, and high-power vehicles. Only low-power and high-power vehicles are eligible for recommendation, while inactive e-micromobilities are excluded. For each zone and future time step, the trip planner platform receives the predicted number of vehicles in each battery class, generated by a Markovian prediction model of pickup, drop-off, and discharge processes. We define the belief state of the system based on the predicted spatio-temporal availability of usable e-micromobilities across all geo-fenced and time steps. The trip recommender platform conditions all multimodal recommendations on the belief state. The belief state provides a short-term probabilistic representation of e-micromobility conditions, yet a planned micromobility leg may still fail at the pickup point due to the following uncertainties.

Stochastic e-micromobility availability. E-micromobility counts evolve through passengers' trip requests such as pickup and drop-off processes. A geofenced zone predicted to contain e-micromobilities may be empty upon passenger's arrival at the pickup point due to this stochasticity.

Battery charge state uncertainty. When vehicles are physically available, remaining battery charge may be insufficient for the intended passenger's trip request. Battery charge changes through prior usage and recharging plans.

Passenger behavioral heterogeneity. Usability depends not only on physical availability and battery charge level sufficiency for the trip but also on individual battery acceptance thresholds due to range anxiety.

Integrating all three dimensions of e-micromobility usability provides a comprehensive, realistic view of the system, enabling personalized trip recommendations. Failing to account for any of these factors leads to a systematic overestimation of both vehicle usability and real-world trip success rates.

4.3.3 E-micromobility service reliability

A shared mobility leg is defined as *reliable* if the predicted usability that at least one user-acceptable e-scooter is available at the designated pickup zone at the passenger's expected arrival time exceeds a reliability threshold Θ . Reliability is therefore evaluated for each request, geo-fenced zone, and arrival time.

Let $\rho_i^{r,t}$ denote the predicted usability for passenger's request r at geo-fenced zone i and arrival time t . This probability captures the likelihood that the zone contains at least one e-scooter whose battery level satisfies the passenger acceptance condition. It is derived from a Markovian forecast of zone-level battery-class counts and incorporates behavioral parameters.

Figure 4.1 illustrates how passenger demand, multimodal trip optimization under uncertainty, and prediction of e-micromobility usability interact within the framework.

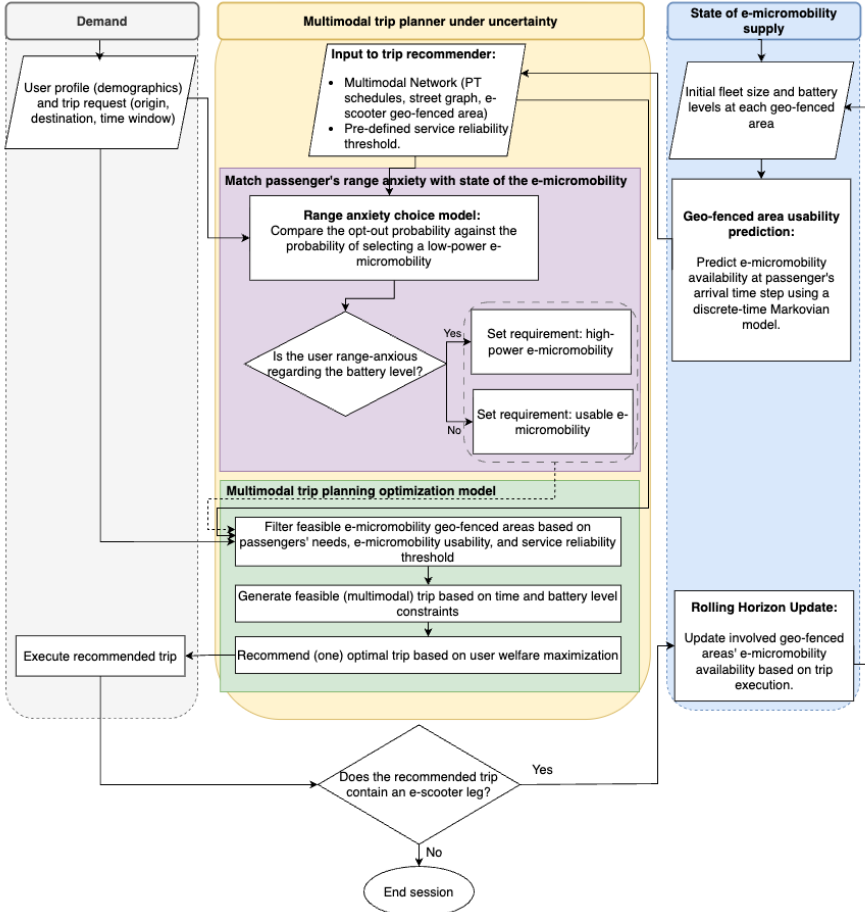


Figure 4.1 Flowchart of the reliable multimodal trip planning.

Passenger demand and the initial state of the e-micromobility supply serve as exogenous inputs to the recommendation model. The service reliability threshold operates as a deterministic pre-processing step prior to optimization (green box in Figure 4.1). For each request, pickup zones with $\rho_i^{r,t} < \Theta$ are excluded from the admissible set. The threshold Θ is an operator-controlled planning parameter that regulates the trade-off between trip success reliability and the feasible search space among the e-micromobility geo-fenced zones. Higher values yield more conservative recommendations and reduce the number of admissible shared mobility legs.

The threshold governs ex-ante feasibility, whereas realized service level is an ex-post performance metric measuring the proportion of successful recommended trips. Because fleet conditions evolve stochastically and users compete for vehicles, zones satisfying

$\rho_i^{r_t} \geq \Theta$ at planning time may still fail at realization. The filter therefore reduces but does not eliminate execution risk.

The problem is solved sequentially by assigning requests on a first-come, first-served basis. In the event of batch arrivals, where multiple travel requests occur simultaneously, the requests are randomly ordered and processed individually. After each trip assignment involving a shared e-micromobility leg, the observed fleet state in involved geo-fenced zones is updated. The usability probabilities are recomputed in a rolling horizon manner before processing the next request. Previously assigned itineraries remain fixed. This rolling-horizon structure maintains consistency between feasibility assignment and updated fleet conditions while limiting forecast error accumulation.

4

4.4 Mathematical Model for Reliable Multimodal Trip Planning

This section develops the reliability-aware multimodal trip planning model. Passenger specific behavioral parameters derived from discrete choice models enter the planner as exogenous inputs in Section 4.4.1. The trip planning problem is formulated on a flow-based, time-expanded network that maximizes user welfare for all users subject to feasibility constraints. Micromobility feasibility is restricted through a reliability threshold based on predicted usability probabilities in Section 4.4.2.

4.4.1 Passenger behavioral models

Behavioral models are exogenous to trip recommender model. Choice-based optimization framework incorporates two choice models, one used to model range anxiety and one modal choice. Both models are estimated from stated-preference surveys data in Rotterdam (Burghardt et al., 2025; Montes et al., 2023), whose studies focus on the same geographic area as our research to ensure methodological consistency.

Range anxiety choice model

This model governs battery-conditioned acceptance and defines e-micromobility usability for each passenger. It specifies the probability that a passenger selects an e-scooter as a function of vehicle attributes and individual characteristics. The systematic utility of selecting an e-scooter of battery class p in geo-fenced zone i is:

$$\begin{aligned} V_i^p = & ASC_{es} + \beta_w walk_i + \beta_{\gamma_0} \gamma_0 + \beta_{\gamma_1} \gamma_1 + \beta_p p + \beta_{type} Type \\ & + \beta_{exp} Use + \beta_{bike} Bike + \beta_{income} Income + \beta_{live.alone} Alone \\ & + \beta_{live.shared} Shared + \beta_{perception} Att + \beta_{range.anx} Anx + \beta_{interaction} Inter \end{aligned} \quad (4.1)$$

where walking time to zone i is denoted as ($walk_i$); γ_0 and γ_1 represent the unlock and per-minute fee; and p denotes expected remaining driving range (in km) associate with the battery class. The remaining variables capture observed heterogeneity and latent

constructs, including prior shared e-micromobility experience, bike ownership, income, living arrangement, attitude toward shared e-scooters, range anxiety, and their interaction. β_{es} indicates the utility constant for selecting an e-micromobility. The coefficient β_p is specified as random to capture heterogeneity in battery sensitivity. Parameter estimates and description are reported in Appendix B.1.

For each arriving passenger, battery acceptance is evaluated using a standardized reference trip to isolate intrinsic tolerance for low battery levels independent of route-specific attributes. Individual realizations of the random coefficient β_p are drawn to reflect heterogeneity. Passenger chooses among a low-power e-micromobility, a high-power e-micromobility, and an opt-out alternative, normalized to zero. A passenger is classified as *range-anxious* if $\Pr^{\text{opt-out}} > \Pr^l$, meaning the utility of declining micromobility exceeds that of selecting a low-power vehicle. In this case, the service reliability filter requires the predicted usability of at least one high-power e-micromobility. Otherwise, the passenger is classified as *flexible*, and both low- and high-power vehicles are considered usable. Choice probabilities follow a multinomial logit structure:

$$Pr_i^a = \frac{e^{V_i^a}}{\sum_{a=\{l,h,opt-out\}} e^{V_i^a}} \quad (4.2)$$

Modal choice model

The second choice model determines passenger valuation of travel time and monetary cost across multimodal trip alternatives and provides the passenger welfare for the objective function. For request r , the deterministic utility of alternative a is specified as

$$V_r^a = ASC^a + \beta_{\text{cost}} \cdot \text{cost}_r^a + \beta_{\text{time}} \cdot \text{time}_r^a, \quad (4.3)$$

where ASC^a captures intrinsic mode preferences, cost_r^a denotes total monetary expenditure, and time_r^a denotes total travel time.

Parameter values are adopted from Montes et al. (2023). Only the deterministic component of utility enters the optimization problem. In the flow-based formulation, arc-level time and cost are aggregated along feasible paths to construct V_r^a , which defines the welfare-maximizing objective of the trip planner. This objective constitutes a welfare maximization in the sense that it maximizes the aggregate utility across all passengers, as expressed in Equation (4.5).

4.4.2 Flow-based time-expanded graph

The multimodal transportation network is represented as a directed graph $G = (\mathcal{N}, \mathcal{A})$ composed of three interconnected layers with distinct temporal structure. The walking layer $\mathcal{N}^{\text{walk}}$ contains static nodes (i, walk) for each physical location $i \in N$, linked by pedestrian arcs with fixed travel times. The micromobility layer $\mathcal{N}^{\text{micro}}$ consists of nodes (i, micro) representing geo-fenced zones. The public transport layer $\mathcal{N}^{PT}$ is time-expanded, where each node (i, k) corresponds to the scheduled arrival or departure of bus trip $k \in \mathcal{K}^{PT}$ at stop i .

Accessibility of micromobility later is governed by the reliability filter. For a request r_t , e-micromobility rentals associated with zone i are retained only if the predicted usability satisfies $\rho_i^{r_t} \geq \Theta$. After filtering, the resulting graph $G^{r_t} = (\mathcal{N}, \mathcal{A}^{r_t})$ is deterministic and defines the feasible search space for optimizing request r_t .

The arc set $\mathcal{A}$ is partitioned into three mode-specific subsets which are $\mathcal{A}^{\text{walk}}$, $\mathcal{A}^{\text{micro}}$, and $\mathcal{A}^{PT}$. The walking subset $\mathcal{A}^{\text{walk}}$ consists exclusively of travel arcs connecting nodes within $\mathcal{N}^{\text{walk}}$. The micromobility subset $\mathcal{A}^{\text{micro}}$ comprises pickup arcs $\mathcal{A}^{\text{rent}}$ from $\mathcal{N}^{\text{walk}}$ to $\mathcal{N}^{\text{micro}}$ representing vehicle unlocking, riding arcs $\mathcal{A}^{\text{travel}}$ within $\mathcal{N}^{\text{micro}}$, and drop-off arcs from $\mathcal{N}^{\text{micro}}$ to $\mathcal{N}^{\text{walk}}$ representing vehicle locking. The public transport subset $\mathcal{A}^{PT}$ comprises boarding arcs $\mathcal{A}^{\text{board}}$ from $\mathcal{N}^{\text{walk}}$ to $\mathcal{N}^{PT}$, in-vehicle travel arcs $\mathcal{A}^{\text{travel}}$ within $\mathcal{N}^{PT}$, and alighting arcs $\mathcal{A}^{\text{alight}}$ from $\mathcal{N}^{PT}$ to $\mathcal{N}^{\text{walk}}$. All sets and parameters are summarized in Table 4.2.

Table 4.2 Sets and parameters notations

Set	Description
$\mathcal{N}$	Set of physical/geo-fenced locations; $i, j \in \mathcal{N}$.
$\mathcal{M}$	Set of mobility modes, indexed $m = \{\text{Walk}, \text{micro}, \text{PT}\} \in \mathcal{M}$
$\mathcal{K}^{PT}$	Set of specific PT (bus) vehicle trips; $k \in \mathcal{K}^{PT}$.
$\mathcal{N}$	Set of tuple (node, mode) in the layered graph, with layer specific node subset $\mathcal{N}^{\text{walk}}, \mathcal{N}^{\text{micro}}, \mathcal{N}^{PT}$
$\mathcal{A}$	Set of arcs (u, v) , partitioned into $\mathcal{A}^{\text{travel}}, \mathcal{A}^{\text{board}}, \mathcal{A}^{\text{alight}}, \mathcal{A}^{\text{rent}}$
R_t	Set of active requests at time t .
Parameters	
$[a_r, b_r]$	Desired time window for request r (earliest departure, latest arrival)
$td_{i,k}$	Scheduled departure time of bus k at stop i
$tb_{i,k}$	Scheduled arrival time of bus k at stop i
τ_{uv}	Travel time on arc (u, v) (including unlock/lock time where applicable)
c_{uv}	Monetary cost of traversing arc (u, v)
$\rho_i^{r_t}$	Predicted probability of finding a required e-scooter at zone i for request r_t , conditional on the passenger's behavioral type (Section 4.4.1)
Θ	Operator-specified reliability threshold. Pickup allowed only if $\rho_i^{r_t} \geq \Theta$.
M	A sufficiently large constant

As a pre-processing step, micromobility pickup arcs that fail to meet the service reliability criterion are removed from the search space. The definition of usability depends on passenger classification. For *range-anxious* passengers, $\rho_i^{r_t}$ denotes the probability that at least one high-power e-micromobility be available at the expected arrival time at pickup point. For *flexible* passengers, defined in Section 4.4.1, it denotes the probability that at least one usable vehicle, either low- or high-power, will be available. These probabilities are derived from the exogenous Markovian forecast of zone-level battery-class counts. Formally, the admissible arc set for request r_t is

$$\mathcal{A}^{r_t} = \mathcal{A} \setminus \{(u, v) \in \mathcal{A}^{\text{rent}} : v = (i, \text{micro}), \rho_i^{r_t} < \Theta\}.$$

The threshold Θ operates on the belief state and defines usability at planning time. Realized service level, by contrast, is measured ex post and reflects the stochastic evolution of the physical system. The filter therefore reduces but does not eliminate the recommended trip's failure possibility.

Table 4.3 Decision variables

Variable	Description
g_r	Binary variable; 1 if the trip is multimodal.
z_r^m	Binary variable; 1 if the mode m is used for request r
x_{uv}^r	Binary flow variable; 1 if request r uses arc (u, v) .
t_u^r	Continuous variable; Arrival time of request r at node u .
w_u^r	Continuous variable; Waiting time of request r at node u (specifically at Walk nodes before boarding).

Objective function

For each request r , deterministic utility is computed by aggregating arc-level travel times and monetary costs along the selected path in the time-expanded graph. Binary variable g_r indicates whether request r follows a multimodal itinerary combining public transport and micromobility ($g_r = 1$) or a unimodal itinerary ($g_r = 0$). Decision variables are summarized in Table 4.3. The resulting deterministic utility for request r is given by

$$\begin{aligned}
 V_r = & \sum_{m \in \mathcal{M}} ASC^m \cdot z_r^m + \sum_{(u,v) \in \mathcal{A}^{walk}} x_{uv}^r \beta_r^{walk} \tau_{uv} \\
 & + g_r \left(\sum_{(u,v) \in \mathcal{A}^{PT}} x_{uv}^r (\beta_r^{mainTime} \tau_{uv} + \beta_r^{PTwait} w_u^r + \beta_r^{mainCost} c_{uv}) \right. \\
 & \quad \left. + \sum_{(u,v) \in \mathcal{A}^{micro}} x_{uv}^r (\beta_r^{subTime} \tau_{uv} + \beta_r^{subCost} c_{uv}) \right) \\
 & + (1 - g_r) \left(\sum_{(u,v) \in \mathcal{A}^{micro}} x_{uv}^r (\beta_r^{mainTime} \tau_{uv} + \beta_r^{mainCost} c_{uv}) \right),
 \end{aligned} \tag{4.4}$$

The monetary cost associated with arc (u, v) is defined as

$$c_{uv} = c_{uv}^{fixed} + \tau_{uv} c_{uv}^{time} + d_{uv} c_{uv}^{distance},$$

where τ_{uv} and d_{uv} denote travel time and distance. Cost parameters are mode-specific; inapplicable components are set to zero. Requests are processed sequentially within a rolling-horizon framework. When request r_t arrives at time t , previously assigned requests $R_t \setminus \{r_t\}$ retain their itineraries and associated utilities. The objective function at time t

therefore maximizes social welfare of all passengers R_t who have not arrived at their destinations.

$$\max F(t) = \sum_{r \in R_t} V_r = \sum_{r \in R_t \setminus \{r_t\}} V_r + V_{r_t}. \quad (4.5)$$

Due to the fact that the utilities of previously assigned requests ($R_t \setminus r_t$) have already been optimized in previous time steps, the problem reduces to selecting the feasible path for r_t that maximizes its deterministic utility V_{r_t} subject to reliability and resource constraints inherited from earlier decisions. It is important noting that the objective function maximizes the incremental welfare of the active travel request, conditional on the updated usability prediction of the network.

4

Constraints

The optimization is subject to the following operational constraints.

Flow conservation. Each request is routed along a connected path from origin o_r to destination d_r :

$$\sum_{v \in \mathcal{N}} x_{uv}^r - \sum_{v \in \mathcal{N}} x_{vu}^r = \begin{cases} 1 & \text{if } u = o_r \\ -1 & \text{if } u = d_r \\ 0 & \text{otherwise} \end{cases} \quad \forall r \in \mathcal{R}_t, \forall u \in \mathcal{N}. \quad (4.6)$$

Strictly positive travel times preclude cyclic solutions.

Mode activation and multimodality. Binary variables z_r^{PT} and z_r^{micro} indicate whether public transport or micromobility arcs are used. Variable g_r equals one if and only if both modes are activated:

$$g_r \leq z_r^{PT} \quad \forall r \in \mathcal{R}_t, \quad (4.7)$$

$$g_r \leq z_r^{micro} \quad \forall r \in \mathcal{R}_t, \quad (4.8)$$

$$g_r \geq z_r^{PT} + z_r^{micro} - 1 \quad \forall r \in \mathcal{R}_t. \quad (4.9)$$

Mode activation is linked to arc usage as shown in Equation (4.10)-(4.13). The lower-bound constraints ensure that if any arc of a specific mode is traversed, the corresponding mode variable is activated. Similarly, the upper-bound constraints prevent the use of any arcs belonging to a mode that has not been selected. M is a sufficiently large positive constant and is parameterized to exceed the maximum number of arcs a user

could feasibly traverse in any single multimodal trip within the network.

$$\sum_{(u,v) \in \mathcal{A}^{PT}} x_{uv}^r \geq z_r^{PT} \quad \forall r \in \mathcal{R}_t, \quad (4.10)$$

$$\sum_{(u,v) \in \mathcal{A}^{micro}} x_{uv}^r \geq z_r^{micro} \quad \forall r \in \mathcal{R}_t. \quad (4.11)$$

$$\sum_{(u,v) \in \mathcal{A}^{PT}} x_{uv}^r \leq M z_r^{PT} \quad \forall r \in \mathcal{R}_t, \quad (4.12)$$

$$\sum_{(u,v) \in \mathcal{A}^{micro}} x_{uv}^r \leq M z_r^{micro} \quad \forall r \in \mathcal{R}_t, \quad (4.13)$$

Public transport (bus) scheduling. Boarding arcs (u, v) with $v = (i, k)$ enforce timetable consistency, the arrival time of passenger plus waiting time must equal the scheduled departure $td_{i,k}$ as shown in Equations 4.14 and 4.15.

$$t_u^r + w_u^r \geq td_{i,k} - M(1 - x_{uv}^r) \quad \forall (u, v) \in \mathcal{A}^{board}, \quad (4.14)$$

$$t_u^r + w_u^r \leq td_{i,k} + M(1 - x_{uv}^r) \quad \forall (u, v) \in \mathcal{A}^{board}. \quad (4.15)$$

For alighting arcs:

$$t_v^r \geq tb_{j,k} - M(1 - x_{uv}^r) \quad \forall (u, v) \in \mathcal{A}^{alight}. \quad (4.16)$$

Waiting is allowed only if boarding occurs, and there is no waiting time for e-micromobility usage.

$$w_u^r \leq M \sum_{v \in \mathcal{N}^{PT}} x_{uv}^r \quad \forall u \in \mathcal{N}^{walk}. \quad (4.17)$$

Time continuity. For all non-boarding arcs, the arrival time at the downstream node respects the travel duration τ_{uv} , which incorporates in-vehicle time, unlock time, and lock time as applicable:

$$t_v^r \geq t_u^r + \tau_{uv} - M(1 - x_{uv}^r) \quad \forall (u, v) \in \mathcal{A} \setminus \mathcal{A}^{board}. \quad (4.18)$$

Trip request time windows. Each request must depart no earlier than its earliest departure time and arrive no later than its latest acceptable arrival time:

$$t_{o_r}^r \geq a_r \quad \forall r \in \mathcal{R}_t, \quad (4.19)$$

$$t_{d_r}^r \leq b_r \quad \forall r \in \mathcal{R}_t. \quad (4.20)$$

Variable domains. The variables domain are defined in Constraints 4.21 and 4.22.

$$x_{uv}^r, g_r, z_r^{PT}, z_r^{micro} \in \{0, 1\} \quad \forall r \in \mathcal{R}_t, (u, v) \in \mathcal{A}, \quad (4.21)$$

$$t_u^r, w_u^r \geq 0 \quad \forall r \in \mathcal{R}_t, u \in \mathcal{N}. \quad (4.22)$$

4.4.3 Dynamism through Rolling-Horizon approach

The model is implemented in a sequential rolling-horizon framework in which the incremental welfare maximization is solved once for each arriving request. Let r_t denote the request arriving at time t . Upon assignment of an itinerary to r_t , the system state is updated along two dimensions.

If the selected itinerary includes an e-micromobility leg, the usability prediction of the involved geo-fenced zones are updated to reflect the execution of the planned trip. The Markovian prediction model is then reinitialized from this revised e-micromobility state to compute updated zone-level usability probabilities for subsequent requests.

Assigned arcs and timing variables for r_t are fixed and carried forward as constraints. Previously assigned itineraries are not re-optimized. The next request r_{t+1} is solved on the resulting feasible arc set $\mathcal{A}^{t+1}$, constructed using the updated usability probabilities. This solve-update sequence continues throughout the planning horizon.

The rolling-horizon structure captures the endogenous interaction between successive trip assignments and shared resource availability while preserving computational tractability. Although future demand is not anticipated explicitly, each decision internalizes the cumulative resource impact of earlier assignments through the evolving belief state.

4.5 Results

This section evaluates the performance of the proposed reliable multimodal trip planner. The results reveal that reliability constraints reshape the functional role of shared e-micromobility within multimodal chains. Under conditions where e-micromobility availability fluctuates, enforcing a strict 90% reliability threshold causes e-micromobility usage to shift toward first-/last-mile connectivity to PT rather than serving as the main mode. We further show that behavioral heterogeneity in passenger range anxiety interacts with stochastic e-micromobility usability, amplifying execution risk in the absence of reliability filtering. Incorporating service reliability thresholds effectively hedges against this behavioral uncertainty, improving realized service levels under stochastic supply.

The section proceeds as follows. Section 4.5.1 describes the case study, data sources, and simulation framework. Section 4.5.2 introduces the experimental design and reliability scenarios. Section 4.5.3 analyzes how service reliability thresholds alter planned mode distributions. Section 4.5.4 quantifies welfare impacts based on travel time and cost. The per-request computational time and scalability report of the proposed approach are discussed in Section 4.5.5. Section 4.5.6 examines behavioral sensitivity against range anxiety. All computational experiments were implemented in Python 3.9.13 using Gurobi 9.5.2 as the MIP solver and executed on an Apple M1 system with 16 GB of RAM.

4.5.1 Experimental setup

The numerical experiments are conducted on an urban network centered on Rotterdam Centraal and surrounding districts in Rotterdam, the Netherlands (see Figure 4.2). The

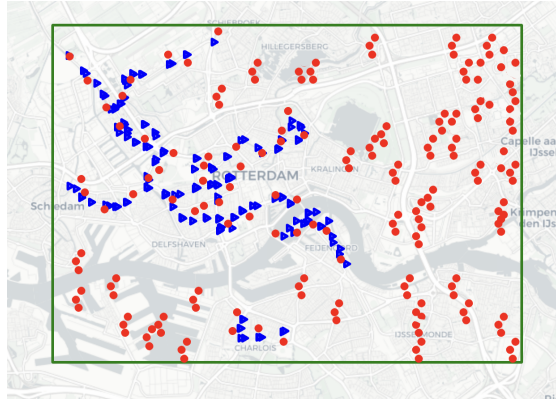


Figure 4.2 The studied area in Rotterdam (green box) and bus stops passing the Rotterdam Centrum (blue triangles) and e-micromobility geo-fenced centers (red color).

study area includes scheduled bus services and dockless shared e-scooter operations distributed across geo-fenced zones.

Public transport data are obtained in GTFS format (MobilityData, 2026), comprising 1,190 active bus schedules for January 20, 2026, as buses constitute the exclusive public transport mode considered in this study. The trip recommender processes requests over a planning horizon spanning 07:00 to 22:00. The micromobility system is represented by spatially defined zones covering the study area. Fare structures for both public transport and shared e-scooters are calibrated using published pricing information from Rotterdam's primary public transport provider (RET, 2025) and prevailing micromobility pricing schemes. Public transport capacity is assumed non-binding. The resulting multimodal network combines fixed-schedule bus operations with spatially distributed micromobility zones. Bus stops and e-micromobility geo-fenced zones' centers are illustrated in Figure 4.2.

Passenger demand is synthetically generated to evaluate system performance under controlled conditions. Each request is defined by an origin, destination, arrival time, and maximum acceptable travel time. Access to public transport stops and micromobility zones is limited by a maximum walking distance constraint.

To assess how reliability thresholds interact with trip length, three categories are defined based on shortest path walking time between origin and destination: short (less than 30 minutes), medium (30-60 minutes), and long (more than 60 minutes). For each category, 100 origin destination pairs satisfying the respective distance criterion are randomly sampled. Passenger arrivals follow a time dependent Poisson process over a full day horizon, with peak-hour intensity of 10 and off peak intensity of 5. Maximum acceptable travel times are drawn uniformly between 30 and 120 minutes.

Behavioral parameters for the multimodal trip choice model and the e-scooter pickup model are adopted from Montes et al. (2023) and Burghardt et al. (2025), both calibrated

on stated-preference data from Rotterdam. The pickup model links e-scooter choice probability to battery level, access distance, pricing structure, vehicle type, and user characteristics, including perceived range anxiety. In the experiments, systematic utility parameters are held homogeneous across passengers, while range-anxiety classification is incorporated through the reliability filter.

4.5.2 Experiment design

Planner performance is evaluated under four service reliability thresholds scenarios defined by $\Theta \in \{0, 0.7, 0.8, 0.9\}$. The benchmark *Myopic* scenario sets $\Theta = 0$, ignoring predicted availability and battery state and treating any displayed e-scooter's zone as feasible set. The remaining scenarios impose minimum usability probabilities of 70%, 80%, and 90%, respectively. These specific thresholds were selected to represent high assurance operational tiers; lower thresholds (e.g., 50%) essentially equate to a coin toss, which is behaviorally unacceptable for travelers seeking reliable connections. Increasing Θ progressively restricts the feasible search space by excluding pickup zones with lower predicted reliability, thereby trading solution flexibility for execution assurance.

Performance is assessed using an event-based simulation over a full operational day with dynamically arriving trip requests. The framework separates planning time beliefs from execution time realizations by maintaining two parallel system states: (i) a stochastic physical state representing actual fleet evolution, and (ii) a belief state used by the optimizer. Events, including trip requests, pickup attempts, vehicle returns, and belief updates, are processed chronologically. Recommendations are generated using the belief state, while pickup success is validated upon passenger arrival against the physical state. This structure enables identification of "false-positive" recommendations, i.e., itineraries that satisfy the imposed reliability threshold at planning time but fail at execution due to stochastic drift or resource competition.

To evaluate robustness with respect to behavioral uncertainty, the population share of range-anxious passengers is varied across three levels: 50%, 70%, and 100%. These values allow us to systematically observe system performance as range-anxious passengers constitute an increasing majority of the population. We examine how battery acceptance interacts with service reliability filtering and whether higher thresholds mitigate execution risk under increasingly conservative user behavior.

4.5.3 Impact of e-micromobility service reliability on recommended multimodal trip

Figure 4.3 illustrates how reliability thresholds alter the composition of planned itineraries across trip lengths. The impact of reliability control is strongly dependent on trip characteristics.

For short trips, mode shares remain largely stable across thresholds. Bus dominates, while approximately 35% of trips are completed by pure walking and only about 1% involve shared e-micromobility as the primary mode. Because micromobility offers limited

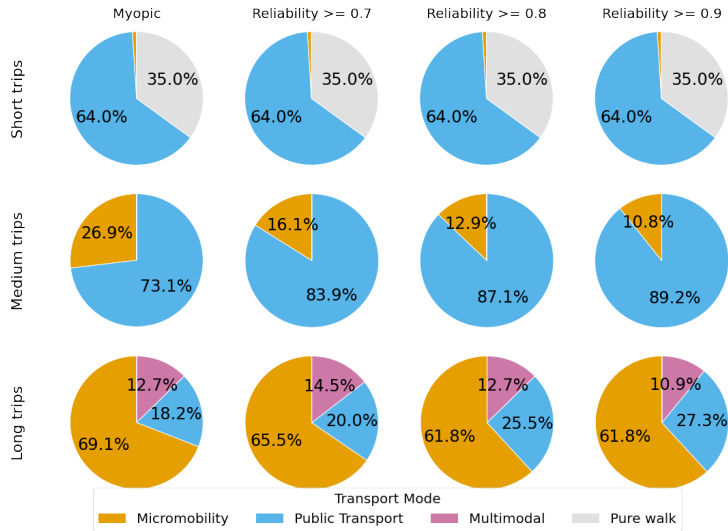


Figure 4.3 Planned trip distribution across different reliability scenarios

spatial advantage over walking at short distances, restricting its usability has negligible influence on optimal plans.

For medium trips, micromobility accounts for nearly 27% of itineraries as the main mode under the *Myopic* scenario. As the service reliability threshold increases from to 90%, this share declines to 10.8%, with demand shifting toward scheduled public transport. The reduction in micromobility only trips indicates that service reliability filtering eliminates itineraries predicated on moderately risky scooter availability, shifting passengers toward more predictable, single-mode transit and highlighting a distinct aversion to multimodality for medium-length urban trips.

For long trips, the adjustment follows a different pattern. Although stricter service reliability thresholds reduce micromobility only itineraries, micromobility remains present in more than 72% of recommended trips. Rather than being eliminated, it is retained primarily as a first- and last-mile connectivity to public transport. This shift demonstrates that reliability control does not uniformly suppress micromobility usage; instead, it restructures its functional role.

4.5.4 Impact of micromobility service reliability threshold on users' welfare

Travel time and monetary cost jointly determine passenger welfare in the proposed planner. Their variation across reliability scenarios quantifies the trade-off associated with service assurance.

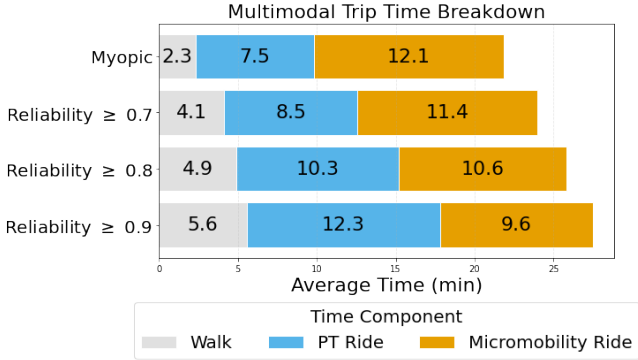


Figure 4.4 Breakdown of average travel time components across imposed reliability thresholds.

Figures 4.4 and 4.5 report average travel time and cost components under different service reliability thresholds for passengers during the long trips. As the threshold increases from the *Myopic* case to $\Theta = 0.9$, average total travel time rises. The increase is driven primarily by walking time, which grows from 2.3 to 5.6 minutes on average, and by public transport in-vehicle time. Passengers therefore incur approximately 3 additional minutes of walking to access zones or stops that satisfy higher predicted usability requirements. By the decrease in micromobility usage as the main and sub mode, the average micromobility riding time declines from 12.1 to 9.6 minutes. Despite the increase in total travel time (by 5.6 minutes, as shown in Figure 4.4, comparing the *myopic* scenario to a service reliability of 90%), the average total cost decreases, as shown in Figure 4.5. Higher service reliability thresholds shift itineraries toward fixed fare public transport (buses) and reduce exposure to time dependent micromobility charges. Service reliability control therefore increases total time while lowering monetary cost. The total cost reduction indicates that the service reliability threshold alters not only execution risk but also the cost structure of recommended trips.

Figure 4.6 reports the distribution of travel time components for long trips under varying service reliability thresholds. Box plots decompose total time into walking, public transport in-vehicle time, and e-micromobility riding time, revealing how reliability control affects modal composition beyond mean values. Walking time range increases as the service reliability threshold rises. The median grows from approximately 3 minutes in the *Myopic* case to about 5 minutes at the 90% threshold, while the interquartile range expands from 2-5 minutes to 3-8 minutes. The widening dispersion indicates that a subset of passengers is rerouted toward more distant yet more reliable pickup zones or bus stops.

The micromobility riding component persists across all thresholds, with a stable median of approximately 12-14 minutes, as shown in Figure 4.6. For long trips, micromobility therefore remains embedded in the optimal recommended trips. In parallel, public transport in-vehicle time increases, reflecting greater reliance on scheduled and more reliable services. The joint increase in public transport use and persistence of micromobility indicates a redistribution of modal split rather than elimination. Micromobility continues to

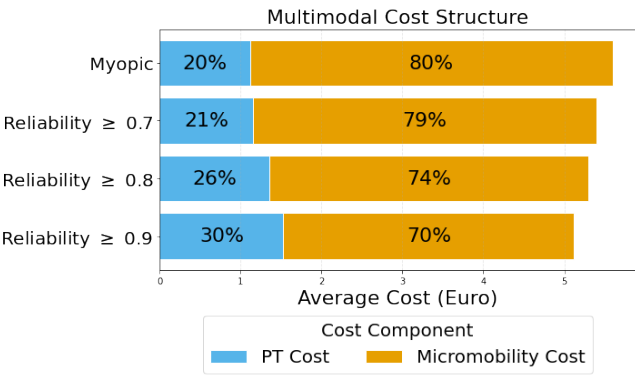


Figure 4.5 Breakdown of average travel cost structures across imposed reliability thresholds.

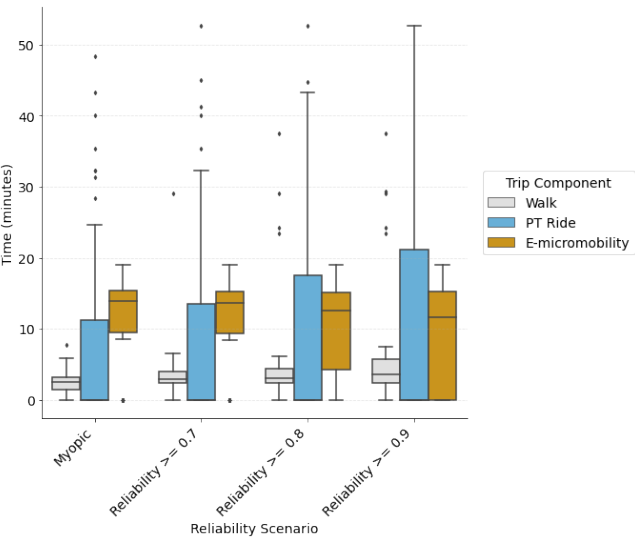


Figure 4.6 Trip time components for long trips.

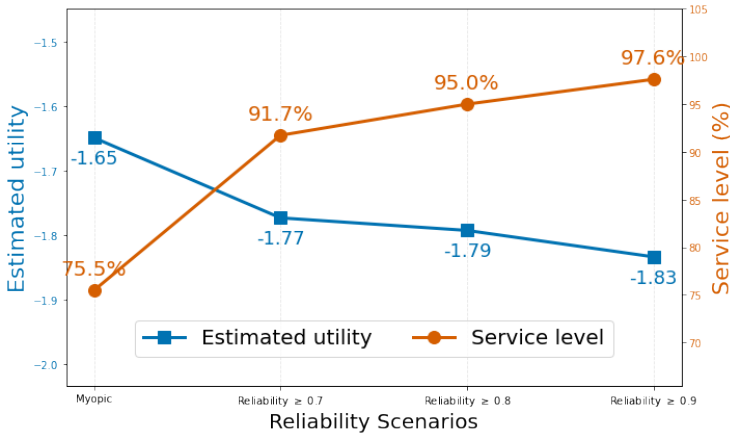


Figure 4.7 Trade-off analysis between estimated utility and system service level.

provide access to the public transport network, while stricter service reliability thresholds shift its positioning within the trip. Outliers with walking times exceeding 30 minutes under high thresholds illustrate the limits of substituting micromobility with walking for long-distance access.

The trade-off between realized service level (measured as the recommended and realized trips) and estimated utility for itineraries containing an e-micromobility leg is shown in Figure 4.7. Increasing the reliability threshold generates two opposing effects. First, higher thresholds substantially reduce execution failures; under the *Myopic* scenario, nearly 25% of micromobility-including trips fail at execution. Imposing a service reliability threshold of 80% reduces the failure rate to 5%, capturing most of the attainable reliability improvement. Second, stricter thresholds restrict the feasible search space of the planner. As Θ increases, itineraries involving moderate service risk are excluded, leading to a monotonic decline in estimated utility. Raising the threshold from 80% to 90% yields only an additional 2.6% increase in service level with reduction in estimated utility. The relationship therefore exhibits diminishing returns to increasingly conservative reliability control. A threshold of 80% achieves an improvement in execution success while retaining flexibility for the optimizer to identify high utility multimodal alternatives.

4.5.5 Computational performance

Table 4.4 reports the computational performance of the proposed reliable trip recommender across all requests processed during a full 15-hour operational day (07:00–22:00). Pre-processing time measures the duration required to construct the user-specific time-expanded arc set via Markovian fleet-state propagation and admissible geofenced zone filtering; MIP solve time measures the duration required to identify the welfare-maximizing itinerary over the resulting feasible network.

Mean total processing time decreases monotonically from 6.98 s under the Myopic scenario to 2.60 s at $\Theta=0.9$, averaging 3.17 s across all reliability-aware configurations. Higher reliability thresholds contract the admissible zone set earlier in the pre-processing pipeline. The reliability filter is therefore simultaneously a service quality mechanism and a computational accelerant. The observed standard deviations reflect heterogeneity in trip request information.

The framework is computationally scalable to city-level deployment. The rolling-horizon assignment updates e-micromobility usability through a Markovian prediction model in which each request requires only the current fleet belief state rather than the full assignment history, bounding the state that must be maintained as demand grows. The per-request processing times observed over the full operational day in the Rotterdam case study confirm that the proposed reliability-aware operation becomes cheaper to run at scale precisely when service guarantees are most stringent.

Table 4.4 Computational performance of the proposed reliable trip recommender across reliability thresholds.

Θ	Preprocessing Time (s)		MIP Solve Time (s)	
	Mean	Std. Dev.	Mean	Std. Dev.
Myopic	5.88	2.90	1.09	2.19
0.7	3.21	2.19	0.63	0.92
0.8	2.51	1.80	0.56	0.88
0.9	2.07	1.41	0.51	0.94

4.5.6 Range anxiety behavior sensitivity analysis

While system level service reliability constraints address stochastic vehicle availability and battery state, passenger behavior introduces an additional execution risk. An e-micromobility with sufficient charge may still be rejected due to range anxiety. The effectiveness of the reliability filter must therefore be evaluated under varying degrees of behavioral heterogeneity.

Figure 4.8 reports failure rates for medium and long trips under different population shares of range anxious passengers (50%-100%) and reliability thresholds. The heatmap, Figure 4.8, shows the percentage of micromobility including trips that fail because the assigned vehicle is rejected upon arrival. The *Myopic* scenario exhibits pronounced sensitivity to behavioral composition. Under a fully range anxious population, failure rates reach 17.4% for medium trips and 16.1% for long trips. Physically feasible itineraries are therefore invalidated when subjective acceptance thresholds are ignored. Increasing the service reliability threshold reduces failure rates across all anxiety compositions and compresses the dispersion of outcomes. At $\Theta = 0.8$ and 0.9 , differences in failure rate across different behavioral scenarios become limited, less than 3%, indicating that service reliability thresholds hedges against both usability uncertainty and acceptance heterogeneity. Battery usability thus operates jointly as a physical and behavioral

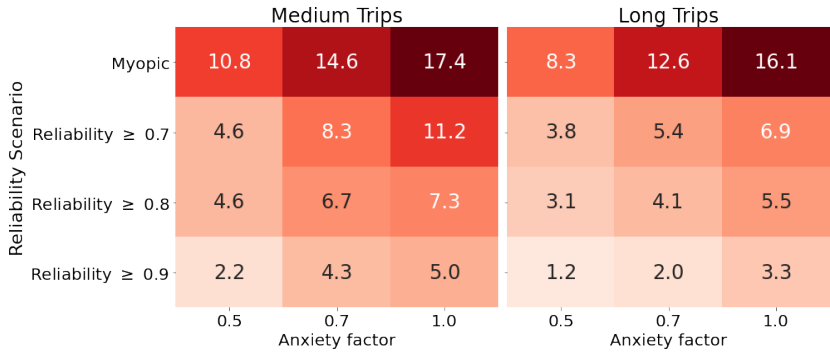


Figure 4.8 Impact of passenger range anxiety on e-micromobility trip failure rates (%).

constraint. Modeling predicted availability without accounting for passenger specific acceptance systematically overstates execution feasibility.

4.6 Conclusion

Reliable multimodal trip planning depends on aligning predictive fleet information, battery dynamics, and passenger behavior within a unified feasibility definition. The proposed framework integrates scheduled public transport and shared e-micromobility while accounting for stochastic vehicle availability, battery charge evolution, and heterogeneity in range anxiety. By conditioning the admissible search space on battery-conditioned usability probabilities, the model reduces ghost trip recommendations without eliminating micromobility where it enhances network connectivity.

The results show that reliability control reshapes rather than suppresses micromobility usage. For long urban trips, e-scooters persist as first- and last-mile connectors to public transport under stringent reliability thresholds, accompanied by on average three minutes increases in walking time. Behavioral acceptance of battery levels emerges as a structural determinant of execution success meaning ignoring range anxiety inflates failure rates even when vehicles are physically capable of completing the trip. Embedding both objective battery constraints and subjective acceptance thresholds improves realized service performance under stochastic supply. The reliability threshold operates as a design parameter governing the trade-off between execution stability and solution flexibility. Computational results reveal that the proposed reliable approach simultaneously enhances the recommended trip success rate and is a computational accelerant to find the trip with maximum welfare for each requests in 3.17 seconds on average.

In summary, this study offers actionable insights for multimodal transport manager and policymakers, providing a mathematical model that is empowered by prediction of e-micromobility usability upon passenger’s arrival time that supports more informed decision-making and the development of adaptable electrified urban mobility systems. While the current study validates the proposed approach using simulated scenarios and

demand, the future studies will involve testing the framework in a larger transport network with different transportation modes, further evaluating its applicability and scalability in real-world settings. Furthermore, extended simulations could be utilized to evaluate the comparative efficiency of shared-mode reservation systems versus the proposed predictive usability approach on the long-term success rate of recommended trips. The current approach assumes centralized coordination and a single decision-maker. Extending the approach to multi-operator settings would require addressing strategic interaction, data sharing, and incentive alignment in addition to predictive uncertainty. Further research could incorporate richer behavioral segmentation or evaluate the framework in pilot implementations to assess performance under operational deployment.

Chapter 5

Conclusions and Discussions

In this final chapter, we reflect on the significance of the studies conducted in this thesis by answering the main research question: *“How can electrified multimodal transport networks be designed and operated reliably by integrating user behavior, vehicle characteristics, and operator costs under uncertainty?”* This question, which grew out of the knowledge gaps identified in the introduction, has guided our investigation and shaped the methodologies applied. Throughout this dissertation, we developed mathematical optimization models to support reliable decision-making for electrified urban multimodal transport networks. We start by summarizing the main findings from each chapter. Next, we discuss the implications of our findings and acknowledge the limitations of this study. Finally, we suggest directions for future research and formulate recommendations for practitioners, policymakers, and society.

5.1 Main Findings

As combined electric public transport and shared e-micromobility is an important backbone for sustainable urban transport, the need for decision-making tools that systematically convert uncertain data into reliable strategies becomes increasingly urgent. This dissertation has taken steps toward that goal by connecting strategic infrastructure design, tactical fleet management, and operational trip planning within an architecture that accounts for user behavior, vehicle characteristics, and operator objectives under real-world uncertainty. By examining key decisions at different decision-making levels and their impact on operators and passengers in terms of long-term investment costs, operational costs, service level, and passenger welfare, we have identified insights crucial for making informed decisions toward this transition.

In **Chapter 2**, we developed a data-driven distributionally robust chance-constrained charging infrastructure design model for electrifying an existing bus network with battery electric buses. The results demonstrate the importance of uncertainty quantification for both the system’s service level and investment costs. With a tailored robust optimization approach, even with sparse data, decision-makers can exploit richer distributional characteristics of the data beyond conventional estimates such as mean and worst-case values to produce designs that are both robust in ensuring the system’s service level and effective in managing long-term investment costs. The data-driven distributionally robust model reduces total electrification costs by 28% compared to the worst-case robust (box

uncertainty) model while maintaining reliability, especially in scenarios where extreme energy consumption values are rare and data exhibit skewness. The cost reduction is achieved primarily through optimized battery capacity allocation, which reduces the need for costly charging station installations. The choice of optimization approach affects not only strategic objectives such as investment costs but also tactical performance: the resulting charge–discharge patterns extend battery lifetime, reducing long-term battery cost per cycle by over 48%. A sensitivity analysis on data sample size confirms that feasibility of the optimal design improves as the number of observations increases, underscoring the value of structured data collection campaigns for new technology deployment.

Next, we focus on shared e-micromobility systems to investigate the main factors affecting user adoption behavior and how to manage these systems efficiently as a substantial mode in multimodal transport that facilitates sustainable transportation. We first identify the factors governing whether a passenger selects a shared e-micromobility, using hybrid choice modeling that jointly captures vehicle characteristics and behavioral constructs in **Sub-chapter 3.1**. The central finding is that range anxiety varies across passengers and has a significant impact on vehicle selection behavior with considerable heterogeneity, a factor that has not been quantified in the shared e-micromobility literature. Battery level, walking distance to the vehicle, unlock and per-minute ride fees, vehicle type, and prior experience with shared systems all influence vehicle selection probability. The interaction between range anxiety and displayed battery level implies that physical vehicle availability is an insufficient measure of effective supply; *perceived usability*, as shaped by passenger-specific behavioral thresholds, must be accounted for in both fleet management and trip planning. This reveals that in addition to spatial and temporal demand patterns, passenger behavior toward vehicle characteristics is a factor that operators need to consider to estimate demand comprehensively.

Sub-chapter 3.2 formulates a predictive hybrid rebalancing and recharging model that controls *perceived usability* rather than physical inventory. The findings show how truck-based and user-mediated rebalancing actions can be coordinated to minimize demand loss while keeping operational costs managed. User-mediated relocations reduce truck-kilometers per unit of served demand. The behavioral sensitivity analysis reveals that for price-and-range-sensitive users, a 50% increase in incentive budget reduces truck costs by 33% at unchanged service levels, demonstrating substitution between user-based and operator-based rebalancing. These findings shed light on the previously unquantified impact of incorporating passenger behavior into rebalancing planning decisions.

Building on the robust electrified bus network from Chapter 2 and the e-micromobility state prediction model from Sub-chapter 3.2, **Chapter 4** demonstrates that multimodal trip planning must consider passenger-specific welfare and shared e-micromobility usability predictions at the passenger's arrival time in order to ensure reliable door-to-door trip options. Implemented on the Rotterdam Centraal greater area, the findings reveal that without reliability consideration for shared e-micromobility usability, 25% of itineraries involving e-micromobility fail at execution. By enforcing a reliability threshold for e-micromobility zone usability tailored to each passenger's trip request, this failure rate is reduced to below 5%, incurring a modest trade-off of approximately three additional

minutes of average walking time. Importantly, filtering out zones that do not meet the reliability threshold at the passenger's predicted arrival time does not eliminate e-micromobility usage in the multimodal system; for longer trips, the approach preserves e-micromobility as a first- and last-mile connection to public transport. Sensitivity analyses on battery-dependent vehicle selection behavior confirm that passenger behavioral heterogeneity is a distinct source of service degradation, and that the proposed approach successfully hedges against this behavioral uncertainty. These insights are instrumental for shared e-micromobility operators and trip planner platforms, which need to account for this behavioral dimension to provide reliable trip recommendations.

This thesis also connects different fields of research, including operations research, choice modeling, and prediction methods. Integrating these approaches allowed us to quantify uncertainty sources that have been largely overlooked in the literature, such as passenger behavior in vehicle selection, and to develop a comprehensive perspective on system evolution across spatial zones and time periods. A key finding is that identical system states can be perceived differently by different passenger groups, which points to the influence of underlying latent factors such as range anxiety. These models enable decision-makers to differentiate between passenger segments and make informed planning and operational decisions for each group based on a defined service level.

5.2 Conclusions

The findings of this dissertation, lead to several overarching conclusions about the design and operation of electrified multimodal urban transport systems.

Sparse data is sufficient for robust infrastructure decisions, provided that distributional information is exploited rather than reduced to point estimates or worst-case bounds. The results of Chapter 2 demonstrate that even a limited number of field observations can support cost-efficient and reliable infrastructure design when the shape of the data distribution is incorporated into the optimization. Implemented on the Rotterdam bus network, relying on mean estimates alone leads to designs that fail in up to 55% of simulated scenarios, while worst-case bounds inflate costs by 67%. The distributionally robust approach avoids both extremes and produces designs that remain stable across conservatism levels.

Perceived usability, not vehicle counts, governs real service quality in shared e-micromobility. Chapter 3 establishes that identical fleet conditions produce markedly different effective service levels across users due to heterogeneity in range anxiety. A vehicle that is physically present and capable of completing a trip may nonetheless be avoided by a range-anxious passenger. This finding challenges the conventional approach of measuring service quality through vehicle counts and calls for behavioral models to be embedded into fleet management decisions. In Chapter 4, the results consistently show that behavioral acceptance of battery levels determines whether a recommended trip succeeds at execution time. Even when vehicles are present and charged, ignoring range anxiety inflates trip failure rates. Therefore, passenger behavior constitutes a structurally distinct source of service uncertainty in the shared e-micromobility management.

The consequences of not adopting the proposed approaches are quantifiable. The experiments across all chapters provide concrete evidence of what happens without the proposed models. Infrastructure designed on mean energy consumption fails in a majority of scenarios. Truck-only rebalancing underperforms the hybrid strategy in service level. Myopic trip planning without shared e-micromobility usability prediction strands a substantial share of passengers on e-micromobility legs. These are not hypothetical risks but outcomes observed in simulation experiments calibrated on real-world data from the Rotterdam transport network.

From a methodological perspective, a distinctive feature of this dissertation is the systematic integration of discrete choice models from behavioral research into mathematical optimization models from operations research. In Chapters 3 and 4, the optimization models without behavioral input would have an incomplete perspective of the system's evolution and produce structurally different decisions. The predict-then-optimize architecture adopted in these chapters offers a practical way to integrate behavioral and operational models in the system's evolution in a sequential manner. Calibrated prediction models feed into mixed-integer optimization models to guide the decision based on its impact on future states of the system. This modular structure allows each component to be updated independently as new data or improved behavioral models become available.

Mathematical optimization models applied in this thesis provide the interpretability that is essential for stakeholder adoption. Municipalities investing in infrastructure, operators designing rebalancing policies, and platform providers recommending trips all require models whose recommendations can be explained, audited, and traced to their underlying assumptions. The transparent structure of mathematical optimization, with explicitly defined objectives, constraints, and decision variables, supports this requirement in a way that end-to-end learning-based methods currently lack.

5.3 Limitations and future research directions

While the models developed in this thesis advance the state of knowledge on electrified multimodal transport planning, several limitations should be acknowledged, along with their consequences and opportunities for future research.

Data and empirical limitations. The behavioral models in Chapters 3 and 4 are calibrated using stated-preference survey data. Stated-preference surveys allow the analyst to vary attribute levels systematically, but respondents may behave differently in real travel situations, particularly under time pressure, unfamiliar conditions, or when cognitive effort differs from the survey setting. As a consequence, the estimated range anxiety parameters and vehicle selection probabilities may not fully reflect actual behavior in the field. Future work could extend these findings through expanded surveys that cover trip characteristics such as time of day and trip purpose, or through revealed-preference observations derived from real trip data, which would strengthen the empirical foundation of both the rebalancing and trip planning models.

All case studies are conducted in Rotterdam, the Netherlands which ensures the methodological consistency of our studies. Although the methods are formulated in a general manner, the empirical validation is confined to one urban context. Network structure, fleet size, regulatory environment, cycling culture, and weather patterns all vary across cities, and the quantitative results (cost savings, failure rates, service level improvements) should be interpreted as context-specific rather than universally transferable.

Modeling assumptions. Several assumptions are made in this thesis to build the decision-making architecture, and relaxing them presents opportunities for future work. The rebalancing model in Chapter 3 treats trip flows between geo-fenced zones for e-micromobility as exogenous inputs estimated from historical data. Endogenous and real-time demand responses to rebalancing actions are not captured. This may lead to underestimation of the benefits and effectiveness of rebalancing under different demand conditions.

The model developed in Chapter 4 is capable of finding optimal trip options for different passenger segments. However, for the experimental analysis we focused on a homogeneous passenger population in terms of multimodal trip preferences. In practice, passengers differ not only in range anxiety (which is captured) but also in their preferences for travel time and cost and mode combinations. Extending the trip planner to accommodate distinct passenger segments with different preference parameters would enable more tailored recommendations. This is particularly relevant for populations with varying levels of familiarity with shared e-micromobility, different mobility constraints, or different willingness to walk.

Scope limitations. This thesis builds a comprehensive understanding of the electric multimodal urban transport system focusing on electric buses and e-micromobility, from a single operator or planner perspective. The scope can be extended by considering other shared and electric modes into the trip recommendation problem. In many cities, multiple shared micromobility operators compete for the same users, and data sharing between operators may be constrained by commercial interests. In competitive settings, the achievable service levels may be lower, and the data-sharing prerequisites identified in Chapter 4 may be harder to establish. Multi-operator game-theoretic models that balance data exchange with commercial confidentiality are needed to operationalize multimodal integration at scale. Such models could explore minimum information-sharing requirements that still enable reliable trip planning.

Another potential direction is the study of reservation systems for shared e-micromobility in multimodal transport. Since reservations are made at planning time, which can differ from the passenger's arrival time, the interaction between reservation mechanisms and the predictive models proposed in this thesis deserves investigation, particularly in competitive settings where multiple operators serve the same area.

Adaptive prediction models. The predict-then-optimize models in Chapters 3 and 4 rely on prediction models calibrated from historical data. Integrating online learning mechanisms that update demand forecasts, battery depletion models, and behavioral

parameters as new observations arrive would improve responsiveness to non-stationary demand patterns, seasonal shifts, and unexpected disruptions.

From zone-level incentive planning to trip-level incentives. The hybrid rebalancing model in Chapter 3 prescribes zone-level drop-off incentives that do not account for the specific trip context of each individual passenger. Operationalizing hybrid rebalancing at a finer granularity requires a deeper understanding of passenger behavior at the individual and trip level. Reinforcement learning approaches offers a promising direction, where an agent learns personalized real-time incentives (destination suggestions, pricing discounts) based on spatiotemporal demand patterns, battery depletion dynamics, and heterogeneous user responses. This would bridge the gap between the zone-level plans produced by the current model and the real-time decisions passengers face when completing a trip.

5.4 Recommendations for Practice

The models developed in this dissertation are designed to support practitioners at different levels of the multimodal transport system. This section formulates recommendations for three stakeholder groups.

For transit authorities and municipalities. Transit authorities should treat early-stage data collection as a strategic investment rather than a preliminary step. The results of Chapter 2 demonstrate that each additional field observation tightens the ambiguity set of the distributionally robust model and translates into measurable infrastructure cost savings. Structured data collection campaigns covering diverse weather, passenger load, and route conditions should be embedded into the earliest phases of electrification procurement, so that they inform long-term design decisions.

For shared e-micromobility operators. Operators should invest in understanding how passengers respond to vehicle characteristics, particularly battery levels and pricing strategies, and embed these behavioral insights into fleet management planning. The results show that conventional inventory-based metrics systematically misestimate the effective supply of the fleet. The joint coordination of truck-based and user-mediated interventions offers a cost-efficient rebalancing architecture that operators can implement incrementally: begin with drop-off incentive pilots to quantify user response, then integrate incentive-aware routing into existing truck dispatch systems. The behavioral sensitivity analysis further reveals that the optimal balance between truck-based and user-based interventions shifts across user populations, meaning that a single rebalancing policy will not perform uniformly across all operating environments.

For multimodal platform providers. Platform developers and mobility-as-a-service providers should prioritize establishing data-sharing agreements or prediction-service interfaces with micromobility operators, as Chapter 4 identifies this as a prerequisite for reliable trip planning. A practical starting point is to expose zone-level availability and battery-state forecasts via standardized APIs, enabling trip planners to evaluate shared-mode reliability before recommending itineraries. Policymakers should adopt a moderately stringent reliability threshold as a planning standard to maintain a balance

between reliability gains and the flexibility needed for the optimizer to identify desirable multimodal alternatives.

From a societal perspective, the long-term viability of shared e-micromobility as a complement to public transport relies on sustained user adoption, which fundamentally depends on reliable service. The finding that myopic trip recommendations strand approximately one in four passengers on e-micromobility legs highlights a critical barrier to adoption. By implementing reliability-aware trip planning, cities can ensure that the promised convenience of multimodal systems is met in practice, thereby fostering the user trust necessary for widespread adoption.

Real-world pilot deployment. All models in this dissertation are validated through simulation experiments calibrated on real-world data. A next step can be a real-world pilot deployment with a transport operator that tests the models under live operational conditions, validates the behavioral assumptions with field observations, and identifies implementation barriers not captured in simulation based evaluations.

In summary, the transition toward reliable electrified multimodal urban transport demands informed decisions across infrastructure planning, fleet operations, and passenger-facing services. The models and findings presented in this dissertation provide a foundation for this goal by accounting for real-world conditions, including multiple interacting sources of uncertainty and the role of passenger behavior in shaping system performance.

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About the Author

Sara Momen was born in Tehran, Iran. She obtained her Bachelor's degree in Industrial Engineering from Alzahra University, followed by a Master's degree in Industrial Engineering from University of Tehran in 2020.

In May 2022 she joined the Department of Transport and Planning at Delft University of Technology as a doctoral candidate, under the supervision of Prof. dr. ir. Bart van Arem, Dr. Shadi Sharif Azadeh, and Dr. Yousef Maknoon. Her research was carried out within the Sustainable Urban Multimodal Mobility (SUM) Lab and focused on mathematical optimization for electrified urban multimodal transport. She developed robust optimization models for different electric transport modes across strategic, tactical, and operational levels of decision-making, with an emphasis on embedding uncertainty and passenger behavior into each decision layer.

During her doctoral studies she was a member of the TRAIL Research School. She also contributed to teaching and supervising Master's thesis projects.



List of publications

Journal Papers

1. **Momen, S.**, Maknoon, Y., van Arem, B., & Azadeh, S. S. (2025). Designing a robust and cost-efficient electrified bus network with sparse energy consumption data. *Transportation Research Part C: Emerging Technologies*, 171, 105020. [Link](#)
2. Burghardt, S. P., **Momen, S.**, Maknoon, Y., Azadeh, S. S., & Kavta, K. (2025). Behavioral impact of range anxiety and unlock fees on shared electric-moped usage. *Transportation Research Part D: Transport and Environment*, 145, 104772. [Link](#)
3. **S. Momen**, SA. Torabi. "Omni-channel retailing: A data-driven distributionally robust approach for integrated fulfillment services under competition with traditional and online retailers." *Computers and Industrial Engineering* (2021). [Link](#)
4. M. Rabbani, **S. Momen**, N. Akbarian-Saravi, H. Farrokhi-Asl, and Z. Ghelichi. "Optimal design for sustainable bioethanol supply chain considering the bioethanol production strategies: A case study." *Computers and Chemical Engineering* (2020). [Link](#)

Under review

1. **Momen, S.**, Maknoon, Y., van Arem, B., & Sharif Azadeh, S. (2026). Hybrid Predictive Rebalancing Control of Perceived Usability in Shared E-Scooter Systems. Submitted to *Transportation Research Part C: Emerging Technologies* (major revision). [Link](#)
2. **Momen, S.**, Maknoon, Y., van Arem, B., & Azadeh, S. S. (2026). Reliable multimodal trip planning with shared e-micromobility: a user welfare maximization approach under battery and behavioral uncertainty. (Submitted to a journal)

Conference contributions

1. **Momen, S.**, Maknoon, Y., van Arem, B., Azadeh, S. S. (2026) Reliable Multimodal Trip Planning with Shared E-Micromobility under Battery and Behavioral Uncertainty, in: Proceedings of the 14th Symposium of the European Association for Research in Transportation (hEART 2026), Paris.
2. **Momen, S.**, Maknoon, Y., van Arem, B., Azadeh, S. S. (2026) Hybrid Predictive Rebalancing Control of Perceived Usability in Shared E-Scooter Systems. Accepted for presentation at the 24th Conference of the International Federation of Operational Research Societies (IFORS 2026), Vienna.
3. **Momen, S.**, Maknoon, Y., van Arem, B., Azadeh, S. S. (2025) Designing a Robust Charging Infrastructure for Battery-Electric Buses with Sparse Energy Consumption Data,

- in: Proceedings of the 13th Symposium of the European Association for Research in Transportation (hEART 2025), Munich.
4. **Momen, S.**, Burghardt, S. P., Kavta, K., Azadeh, S. S. (2025) Behavioral Impact of Battery Range and Unlock Fees on Shared E-Moped Usage, in: Proceedings of the 16th International Conference on Advanced Systems in Public Transport (CASPT 2025), Kyoto.
 5. **Momen, S.**, Maknoon, Y., van Arem, B., Azadeh, S. S. (2024) Cost-Efficient Robust Network Design for BEBs: Tackling Energy Uncertainty with Limited Data, in: Proceedings of the 12th Symposium of the European Association for Research in Transportation (hEART 2024), Espoo.
 6. **Momen, S.**, van Arem, B., Azadeh, S. S. (2023) Dynamic location for charging operations of shared free-floating e-scooters, in: Proceedings of the 11th Symposium of the European Association for Research in Transportation (hEART 2023), Zürich.

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Summary

A combined electric public transport and shared e-micromobility system forms a backbone for sustainable urban mobility, yet electrification introduces interacting uncertainties at every decision level. This dissertation embeds uncertainty modeling and passenger behavior jointly into optimization across strategic, tactical, and operational planning. The resulting models design bus charging infrastructure from sparse data, rebalance shared fleets toward perceived usability, and recommend door-to-door trips that remain executable under uncertainty.

About the Author

Sara Momen holds an MSc in Industrial Engineering and completed her PhD at the Department of Transport and Planning, Delft University of Technology. Her research interests include operations research, prediction methods, and optimization under uncertainty.

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