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Exact and Approximate Methods for Multimodal City Logistics

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Exact and Approximate Methods for Multimodal City Logistics

Çiğdem KARADEMIR

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Exact and Approximate Methods for Multimodal City Logistics

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Contents

Chapter 1

Introduction

The escalating population and tourist numbers in cities, coupled with tightening restrictions on freight vehicle access, have created a complex challenge for urban logistics. As a result, there is a growing interest in leveraging waterborne freight transportation as a means to alleviate traffic congestion and reduce associated costs. To fully realize the potential benefits of integrating waterborne transportation into city logistics, efficient and reliable service network design is essential. On the strategic level, the trade-offs lie between the initial investment costs of the transshipment facilities and the costs incurred by stakeholders in the cities. On the tactical level, trade-offs exist between the logistics costs of waterborne and city freighters, sharing these facilities to transfer the freight flow from one network to the other. Furthermore, introducing flexibility into multimodal transport—by allowing more transshipment places and on-demand resource allocation—brings the trade-offs between strategic and operational costs.

This thesis proposes a series of methodologies to assess the potential of integrated waterborne transport systems to improve city logistics. We show how these systems can contribute to the development of sustainable logistics using efficient synchronization and coordination in light of new vehicle and computing technologies. First, in Section 1.1, we introduce the motivations, challenges, and innovations in city logistics. Then, in Section 1.2, we summarize real-life practices considering various sectors and cities across the world. Next, in Section 1.3, we discuss the challenges in addressing such complex real-life problems in the literature. Finally, we present the research objectives and questions in Section 1.4, while Section 1.5 frames the scope and the contributions of this thesis. In Section 1.6, we conclude with an overview of this thesis.

1.1 City logistics and integrated water- and land-based transportation (IWLT)

City logistics seeks to optimize freight movement within urban areas by mitigating negative impacts such as congestion and pollution while supporting economic growth. The complex interplay of stakeholders, operations, and resources necessitates integrated planning approaches, including network design, to address the challenges of efficient and sustainable urban freight transport (Crainic et al. 2021b).

Growing populations and tourism in metropolitan areas increase the need for food, package delivery, and waste management services. The increase in the demand for freight transportation attracts more Logistics Service Providers (LSPs) targeting more profits in cities. However, this urban expansion and increased economic activity have come at a cost. Nieuwenhuijsen (2024) emphasizes the contribution of dense urban populations to elevated air pollution due to increased emissions from heating and transportation. The challenges, including health-related risks, push policymakers toward regulations on fuel types, vehicle size, and city access hours to build emission-free cities and improve mobility in public spaces (Alarcón et al. 2023).

The stakeholders and actors within city logistics have distinct roles in shaping urban freight transport. Actors like shippers, carriers, and local authorities directly influence the system's efficiency and sustainability through operational decisions and policies (Ballantyne et al. 2013). Stakeholders, such as citizens, landowners, and vehicle manufacturers, indirectly shape logistics through their demands and market forces. While their influence is indirect, it is significant, particularly regarding land use and transportation demand (Ballantyne et al. 2013, Gonzalez-Feliu et al. 2018). This complex interplay between direct and indirect actors necessitates integrated planning and management strategies that optimize urban space and quality of life, especially as competition for urban space intensifies (Zhu et al. 2023).

LSPs are increasingly exploring the implementation of innovative technologies to comply with the regulations and capitalize on the increased demand (Yu et al. 2020). While Light Electric Freight Vehicles (LEFVs) have been invested in for over a decade for their versatility, their economic success in urban freight transport depends on coordinating and synchronizing them with conventional vehicles instead of using them solely (Moolenburgh et al. 2020). This integration encompasses vehicle type selection and urban spatial planning (Kin & Quak 2024). Policymakers are in charge of initiating more sustainable logistics solutions through infrastructure policies that enhance LSPs' access to fuel stations and consolidation hubs to meet the demand. By focusing narrowly on the final leg of the service delivery process, studies frequently neglect the impacts of upstream activities such as land use planning, middle-mile transport, and the location of consolidation facilities (Fried et al. 2024).

Integrating inland waterways into urban freight transport offers a viable alternative to address congestion, environmental impact, and limited space challenges in city logistics (Janjevic & Ndiaye 2014, Takman & Gonzalez-Aregall 2024). Besides transporting bulk materials for construction, there exist several applications for last-mile parcel and retail logistics using inland waterways in various ways coordinated with LEFVs, e.g., floating barges in Sweden, autonomous vessels in Germany, and vessels in the Netherlands (Brauner et al. 2021). Recent studies have reflected this trend by focusing on route optimization and cost evaluation for new last-mile delivery systems, replacing traditional delivery methods with alternatives such as electric vehicles or cargo bikes (Divieso et al. 2021). However, most studies focus on case-specific last-mile operations and ignore expensive transshipment operations in cost calculations. Consequently, the economic benefits of such integrated systems are unclear to all stakeholders.

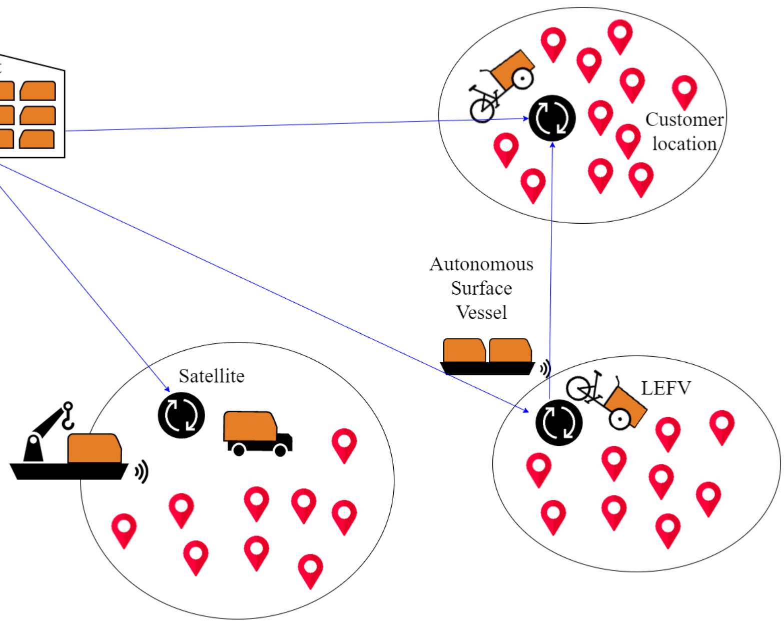


Figure 1.1: An illustration of a two-echelon distribution system for an IWLT system, with a centralized depot feeding into intermediary satellite locations, which then distribute goods to customers' locations through smaller, efficient vehicles.

Multimodal applications in city logistics involve transporting goods across multiple stages, referred to as echelons (Cuda et al. 2015). At the top of this hierarchy, the depot serves as the central location where goods are stored. The next level in the network consists of satellites, which serve as intermediate hubs closer to the final customer. Satellites receive goods from the depot and either hold them temporarily or transfer them directly to LEFVs for the last-mile service to the customers. In the final step of the distribution, smaller vehicles transport goods from the satellite and distribute them to the customers. This thesis focuses on synchronized two-echelon routing systems within the context of Integrated Water- and Land-based Transportation (IWLT) considering realistic aspects of waterborne transport in urban areas. A typical two-echelon distribution system for an IWLT is illustrated in Figure 1.1.

Utilizing existing transport capacity over waterways to partially shift the freight flow can reduce the burden on road transportation in cities. This shift can lead to a decrease in vehicle kilometers traveled on the streets, ultimately enhancing the lifespan and economic viability of LEFVs in urban freight transportation. However, challenges such as investment costs for integration, limited space in urban areas, and operational complexities hinder widespread implementation (CCNR 2022). Despite these challenges, the potential environmental benefits and successful case studies make waterways an attractive option for addressing the growing demands of urban freight transport (Gemeente Amsterdam 2024).

1.2 Status of practice

The increased demand increases freight flow in cities, burdening roads, causing traffic jams and delays, and increasing emissions. This puts more pressure on LSPs to adopt LEFVs in urban areas for environmental and societal concerns. These vehicles are limited in terms of capacity (fuel or volume) and may not be profitable in meeting all the demand (Moolenburgh et al. 2020). However, they are lighter and more versatile compared to conventional vehicles, such as trucks, vessels, trams, or trains. Coordinating LEFVs with the larger vehicles on another transportation network can reduce the idle times and can increase the efficiency of light vehicles (Yu et al. 2020, Moolenburgh et al. 2020).

Despite the efforts on modal shift, LSPs still heavily depend on road transportation due to the cost, reliability, and simpler operations (Eurostat 2024). Waterborne transport, particularly in cities with extensive waterway networks, has demonstrated promising results in the viability of using waterways for freight transportation. Table 1.1 summarizes various applications of waterway transport gaining popularity in city logistics across different cities and countries. Examples include the use of barges and electric vessels for last-mile deliveries, reverse logistics such as waste collection, and inter-dock transportation. While the integration of waterborne transport provides savings in the number of vehicles used and kilometers traveled, incurring extra transshipment costs or longer last mile distances can be a barrier in being competitive to road transportation (Maes et al. 2015).

The successful implementation of an IWLT system in city logistics faces numerous infrastructural and spatial challenges. A key concern is the high investment costs associated with establishing and maintaining the necessary infrastructure, including the satellites and vessels. Limited space in densely populated urban areas complicates the location problem for satellites, which may require space for docking, transshipment, and storage (Janjevic & Ndiaye 2014). Furthermore, slower vessel speeds compared to road vehicles can also impact delivery times and overall system efficiency. External factors, such as weather conditions and seasonal variations in water levels, can further disrupt operations.

Operational complexities also contribute to the challenges of IWLT implementation compared to road transportation. In a two-echelon system, the need for synchronization between water and land-based vehicles, especially when storage at satellites is limited, demands coordination and dependence between operations (Drexl 2012). The feasibility of the services depends on the operations of the interacting vehicles both downstream and upstream of the integrated system, making these systems sensitive to delays. Policymakers and logistics providers may be hesitant to invest due to uncertainties about economic viability and operational complexities of the coordinated vehicles (Serafimova et al. 2022).

The integration of waterborne transport into urban logistics systems requires a system-wide perspective, accounting for various stakeholders and their spatial requirements when evaluating the feasibility and impact of waterborne transport solutions (Caris et al. 2014). In such a system, it is important to consider

Table 1.1: Applications of waterway transport gaining traction in city logistics.

City, Country	**Application**
Utrecht, Netherlands	Beerboot barge with an electric vehicle with different carts for last-mile deliveries (Maes et al. 2015).
Amsterdam, Netherlands	Pilot program with small electric vessels for waste collection (Dimitrova 2021, Roboat 2024).
Amsterdam, Netherlands	DHL floating distribution center and cargo bikes (Mommens & Macharis 2012).
Berlin, Germany	Pilot project with autonomous vessels for inter-dock transportation, final deliveries by land vehicles (CCNR 2022).
Strasbourg, France	Rental vessel for parcel deliveries, cargo bike last-mile, waste collection on return (CCNR 2022).
Gothenburg, Sweden	Floating barges and vessels for container delivery to ports (Rogerson et al. 2020).
Paris, France	Franprix barges for grocery deliveries near Eiffel Tower, final deliveries by diesel trucks (Mommens & Macharis 2012).
Paris, France	Fludis electric boats for deliveries, e-waste collection on return (Maes et al. 2015).
Ghent, Belgium	Bioboot solar-powered vessel transports crops from production sites to city, dockside pickup or bicycle trailer deliver (Bioboot 2020).
New York City, USA	Barges deliver household waste to port facilities (CBCNY 2015).
London, UK	High-speed vessels deliver freight fast to the city on congestion-free waterways (Clippers 2024).

the service quality for the customers, the profitability of the LSPs, and the impact of the space used in transshipment activities (Gonzalez-Feliu et al. 2018).

1.3 Status of literature

The interest in two-echelon logistics systems is on the rise in both academia and industry, thanks to their relevance and applicability in various fields. These systems involve the optimization of interacting fleets at two levels such as supply chain management, city logistics, and urban planning. Researchers are drawn to these problems because they offer more flexibility in modeling complex and real-world challenges. Furthermore, Alarcón et al. (2023) attribute the growing popularity of such problems to the increasing pressure on LSPs to adapt their services to new regulations targeting emission-free cities. They conclude that advancing the integration of electric vehicles into sustainable cities necessitates incorporating electric logistics vehicles into the multimodal transport chain, using more economic vehicles on a different echelon.

Due to the complex environment of city logistics, there exist several variants of two-echelon distribution systems in the literature to reduce the negative impacts of increased on-street movements on society, economy, and environment (Anderluh et al. 2021). These studies differ in terms of the synchronization degree between the vehicles using common resources during transshipment operations at the satellites for the last-mile delivery. Resource management of the satellites, limited by space, storage, or labor, increases the complexity by forcing the vehicles to synchronize in time, space, and load in different magnitudes (Marques et al. 2020). However, the existing studies often overlook the broader spatial and systemic dimensions of multimodal urban freight transportation, focusing on the logistics costs of the simplified operations and neglecting the impacts of upstream activities in shaping the city environment and society, as highlighted by Fried et al. (2024). De Bok et al. (2024) show that city hubs can improve the logistics costs the most when they are shared among the LSPs. They emphasize that savings in vehicle kilometers and the number of hubs can reduce the claim on the scarce urban space. However, the use of urban space for capacity management at the hubs is not considered for the transshipment operations, thus the cost of use.

The exact studies on the synchronized two-echelon problems mostly adopt a decomposition approach to employ pricing or cutting decisions for the optimality proof. Jepsen et al. (2013) and Santos et al. (2013) propose branch-and-cut for the Two-echelon Vehicle Routing Problem (2E-VRP). Baldacci et al. (2013) develop a bounding procedure combining dynamic programming using a decomposition approach. Dellaert et al. (2019) propose a branch-and-price algorithm for a Two-echelon Vehicle Routing Problem with Satellite Synchronization (2E-VRP-SS) with time windows, while Dellaert et al. (2021) extend the problem to multiple commodities by a decomposition-based exact solution approach for the 2E-VRP-SS. Despite limited capacity, LEFVs can efficiently perform multiple trips if supplied between trips, though this flexibility increases system complexity. Marques et al. (2020) propose a branch-and-cut algorithm for a Two-echelon Multi-trip Vehicle Routing Problem with Satellite Synchronization (2E-MVRP-SS) that first enumerates all solutions for supplying the satellites before optimizing city freighters' routes. Escobar-Vargas et al. (2021) study synchronization in multi-attribute two-echelon distribution systems and propose a compact formulation and a time-space formulation. Mhamedi et al. (2021) also propose a branch-price-and-cut algorithm, for solving the 2E-VRP-SS including time windows and multiple depots. While the analytic optimization methods assist us greatly in evaluating the solution methods for the solution quality, their applicability to realistic-sized problems is limited in terms of computational time required to achieve the convergence.

There exist several studies on the approximation methods, i.e., heuristics and metaheuristics, to solve large-scale two-echelon problems. Li et al. (2018) consider a two-echelon distribution system and provide a non-tractable Mixed Integer Linear Programming (MILP) formulation and solve large-scale problems by a Large Neighborhood Search (LNS). Li et al. (2021b) propose an Adaptive Large Neighborhood Search (ALNS) for the 2E-VRP with pick-ups and deliveries, customer time windows, and satellite bi-synchronization. Grangier et al. (2016) focus on a 2E-MVRP-SS with no storage option and use an ALNS Anderluh et al. (2017) focus on a 2E-MVRP-SS and use a Greedy Randomized Adaptive Search Procedure (GRASP) with path relinking for SE routes for ensuring synchronization between vans and bikes. He & Li (2019) consider a 2E-MVRP-SS and use a memetic algorithm with a local search procedure. Anderluh et al. (2021) use an LNS embedded in a heuristic rectangle/cuboid splitting to solve the two-echelon vehicle routing problem with multi-trip and satellite synchronization. Belgin et al. (2018) introduce the 2E-VRP with simultaneous pick-ups and deliveries and propose a variable neighborhood descent algorithm for solving it Zhou et al. (2022) study a 2E-VRP with time windows, and simultaneous pick-ups and deliveries and propose a tabu search algorithm to solve it. Jia et al. (2023) provide a MILP for the two-echelon vehicle routing problem with multiple depots, time windows, satellite capacity, and satellite synchronization and solve it using ALNS. These heuristics typically adopt a decomposition strategy, dividing the problem into two subproblems corresponding to each echelon. While the majority of studies employ local or LNS methods to address the 2E-VRP, Sluijk et al. (2023) indicate that no single heuristic consistently outperforms others across all problem configurations.

In multimodal transportation, operational resilience is crucial due to the inherent uncertainties that can disrupt transshipment operations and the seamless transition between different modes of transport.

These uncertainties stem from external factors, i.e., accidents, natural disasters, infrastructure failures, and operational variations, i.e., demand fluctuations, cancellations, travel time variability, and service time changes (Delbart et al. 2021). Ultimately, these uncertainties within IWLT systems pose significant risks to operational resilience, potentially leading to delays, disruptions, and increased costs.

Crainic et al. (2016) propose a general two-stage stochastic programming framework for 2E-VRP with various constraints (synchronization, time windows, multi-tours, multi-depots, heterogeneous fleets) under uncertain demand, aiming to provide tactical-level decision strategies. Wang et al. (2017) focus on the 2E-VRP with stochastic demands following a known distribution, an area less explored in the literature. Liu et al. (2017) examine 2E-VRPs with uncertain demands, employing a two-stage stochastic programming approach and Monte Carlo simulation to approximate the cost of a solution. Anderluh et al. (2020) address a synchronized delivery system with vans and bikes using a two-stage greedy randomized adaptive search procedure. They assess the impact of uncertain travel times through the Monte Carlo simulation and introduce a re-optimization procedure to handle real-time infeasibilities, highlighting the importance of real-time planning in highly synchronized systems.

To enhance reliability and robustness in a multi-echelon supply chain, Peng et al. (2011) propose a mixed-integer linear model for logistic network design, incorporating facility disruptions. They employ the p-robustness measure, aiming to minimize total system cost under normal conditions while ensuring that the relative regret of the solution remains within an acceptable threshold (p) for each disruption scenario. Hatefi & Jolai (2014) also apply the p-robustness measure to a multi-echelon forward-reverse network with facility disruptions and uncertainties in demand, quantity, and quality for a single product. They develop a three-stage stochastic programming model using a scenario tree for multi-echelon supply chain network design, catering to customers with uncertain demands and delivery lead time sensitivities in the face of facility disruptions. Azad et al. (2013) employed Benders' decomposition to address a similar problem but allowed for partial facility disruptions or resource sharing among facilities in case of failures. Crainic et al. (2021a) shows significant benefits of using Benders' decomposition in stochastic design problems considering uncertain demand and arc capacities.

To bridge the gap between academia and the industry, it is crucial to develop methodologies that enable us to evaluate various design options by taking into account the impact on all stakeholders, both direct and indirect (He & Haasis 2019). The complexity issue of resource planning in service network design problems constitutes the challenge in taking action to build emission-free cities. Existing practices and studies lack comprehensive models to assess the economic gains of the potential integrated transportation systems, especially when the design options change, i.e., storage options at the satellites. This includes assessing the required infrastructure investments, quantifying economic benefits, and addressing the challenges associated with spatial integration and operational efficiency.

1.4 Research objective and questions

Motivated by the challenges in modeling and practical implementations of two-echelon systems integrating waterborne solutions in real life, this thesis aims to investigate the following main research question **(RQ):**

How can synchronized two-echelon systems leverage new vehicle technologies as well as cities' infrastructure to balance the goals of various stakeholders within the context of IWLT for city logistics?

To address the research challenges encompassed by this question thoroughly, we propose the following key research sub-questions (**SQs**) addressed in the following chapters:

SQ1. How to **model** IWLT systems to account for systematic resource changes and flexibility of various service network designs?

City logistics presents significant challenges for decision-makers. LSPs are exploring alternative logistics system designs to comply with regulations on fleet requirements and city access hours while remaining competitive in the expanding urban logistics market. Governing entities face the dual challenge of providing livable and affordable urban environments while mitigating the negative externalities of freight logistics. Furthermore, city logistics impacts various stakeholders in the cities, including businesses, residents, and the environment. Growing awareness of the need for greener solutions is putting pressure on both LSPs and policymakers.

To effectively assess infrastructure needs and economic benefits in city logistics, we must re-frame urban logistics problems to account for system-wide impacts of emerging technologies like autonomous vehicles, increased waterborne transport, and requirements in service network capacity due to city regulations. However, the literature lacks models that can evaluate potential solutions incorporating synchronization for the flexibility of the multimodal services without intermediate storage while considering the conflicting objectives of these stakeholders, particularly in the context of IWLT systems for city logistics (Crainic et al. 2021b, Caris et al. 2014, Sluijk et al. 2023).

SQ2. How to **design and solve** IWLT systems to evaluate their efficiency against alternative systems in practical scenarios?

While IWLT systems offer a more flexible and potentially greener alternative to traditional distribution systems, their operational complexity requires further investigation to understand optimal decision-making. Optimizing the schedules of multi-trip vehicles at the satellites without storage is particularly challenging due to the complexity of synchronizing interacting vehicles in space and time. To reduce the computational cost, existing literature often relies on approximations (Marques et al. 2020, Dellaert et al. 2019, Grangier et al. 2016). Therefore, developing tractable models is crucial to prove feasibility and validate heuristic methods for solving two-echelon routing problems.

SQ3. How to **scale up** the solution methods for assessment of IWLT systems considering real-life problems?

Existing approaches struggle to address the complexities of designing large-scale synchronized multimodal systems, considering the network of the satellites, resources available at these locations, and fleet composition (Wieberneit 2008). While storage options at the satellites simplify spatiotemporal synchronization, they also intensify competition for urban space and create capacity management challenges at satellite locations. Current methods often rely on approximation algorithms that lack consistency and fail to adequately account for the impact of transshipment lead times, leading to potential delays and inefficiencies (De Bok et al. 2024). This highlights the need for more robust and efficient methods that can accurately capture real-world complexities and optimize the performance of these systems when evaluating potentials of synchronized IWLT solutions for real-life applications (Kin & Quak 2024).

SQ4. How to **model the uncertainty** associated with the flexibility of IWLT systems?

Despite advancements in communication technologies, city logistics, characterized by a complex interplay between multiple LSPs, still lacks effective re-optimization mechanisms to handle uncertainty in two-echelon synchronized systems without storage at the operational level. This gap highlights the need for analytical models (MILPs or stochastic programming) to evaluate performance in such complex urban freight environments (Cuda et al. 2015, Anderluh et al. 2020, Delbart et al. 2021). Although computationally expensive for real-life scale problems, these models enable the development of dynamic strategies crucial for adapting to real-time disruptions.

1.5 Research scope and contributions

The scope of each chapter is provided in more detail in Table 1.2, and the contributions of this thesis are summarized as follows:

- To address **SQ1**, we develop a system-wide MILP model for synchronized two-echelon systems. This model provides a unified framework for modeling various urban freight systems, integrating waterborne transport within a two-echelon setting, and formulating the intricate relationships inherent in resource synchronization problems for capacity planning.

- To address **SQ2**, we develop a decomposition model that reduces computational time and improves solution quality for large-scale instances. We explore various policies to minimize freight movement through service design, considering real-time resource capacities at satellite locations. Furthermore, we evaluate the benefits and challenges of integrated systems compared to alternative approaches in reducing road congestion within cities.
- To address **SQ3**, we develop a multi-purpose metaheuristic for evaluating the trade-offs between strategic, tactical, and operational decisions in service network design for real-life sized IWLT applications. Considering economic and societal stakeholders, several design choices are tested on a case study, including the storage options and space use at the transshipment places for minimizing the fleet requirements and the logistics cost of the service providers on both levels.
- To address **SQ4**, we develop a two-stage stochastic programming with mixed-integer recourse that minimizes the costs of the stakeholders. It integrates the reliability and flexibility of IWLT systems directly into service network design models to assist the decision-makers in shaping the cities.

Table 1.2: The scope of the chapters in this thesis.

Focus Area	Key Concepts & Complexity	Methodology
Chapter 1. Introduction	Motivations for city logistics Challenges in urban freight Innovations & opportunities	Literature review
Chapter 2. Integration & System Modeling **SQ1**	Waterborne transport integration System-wide modeling Scalability challenges	Mixed integer linear programming
Chapter 3. Service Network Design & Methods **SQ2**	Resource synchronization Two-echelon service network design Solution methods	Logic-based Benders' decomposition
Chapter 4. Multimodal Service Networks **SQ3**	Capacity planning in service design Multimodal real-life applications Stakeholder analysis	Metaheuristics
Chapter 5. Reliability & Flexibility **SQ4**	Reliability formulation Flexibility benefits Comparison to resource dedication	Stochastic optimization with recourse
Chapter 6. Conclusion & Future Directions	Thesis conclusions Contributions Future research avenues	

1.6 Thesis outline

The outline of this dissertation is illustrated in Figure 1.2. Chapter 2 addresses **SQ1** and provides a system-wide model for the integration of waterborne transport into city logistics. The problem is defined and formulated as well as the alternative systems on road transport, that are used in the subsequent chapters. The limitation is shown to be the scalability due to the complexity of the underlying multi-trip aspect of the new vehicle technologies. In Chapter 3, the complexity issue is tackled by first enhancing the formulation and then developing a decomposition model. Experiments on the demand networks of up to 100 nodes provide discussions on designing the service networks and the solution methods for IWLT systems and addresses **SQ2**. The decomposition model is further adopted within a metaheuristic in Chapter 4 for tackling more realistic-sized problems, up to 750 demand nodes. It addresses **SQ3** for analyzing the trade-offs between inventory management and resource synchronization issues at the satellites with or without storage. Chapter 5 formulates the reliability problem of IWLT systems to quantify the benefits of service network design. It tackles **SQ4** and provides a discussion on the resource dedication at the satellites in terms of cost, customer satisfaction, and modal shift. Finally, Chapter 6 concludes the thesis, summarizing contributions and outlining future research directions.

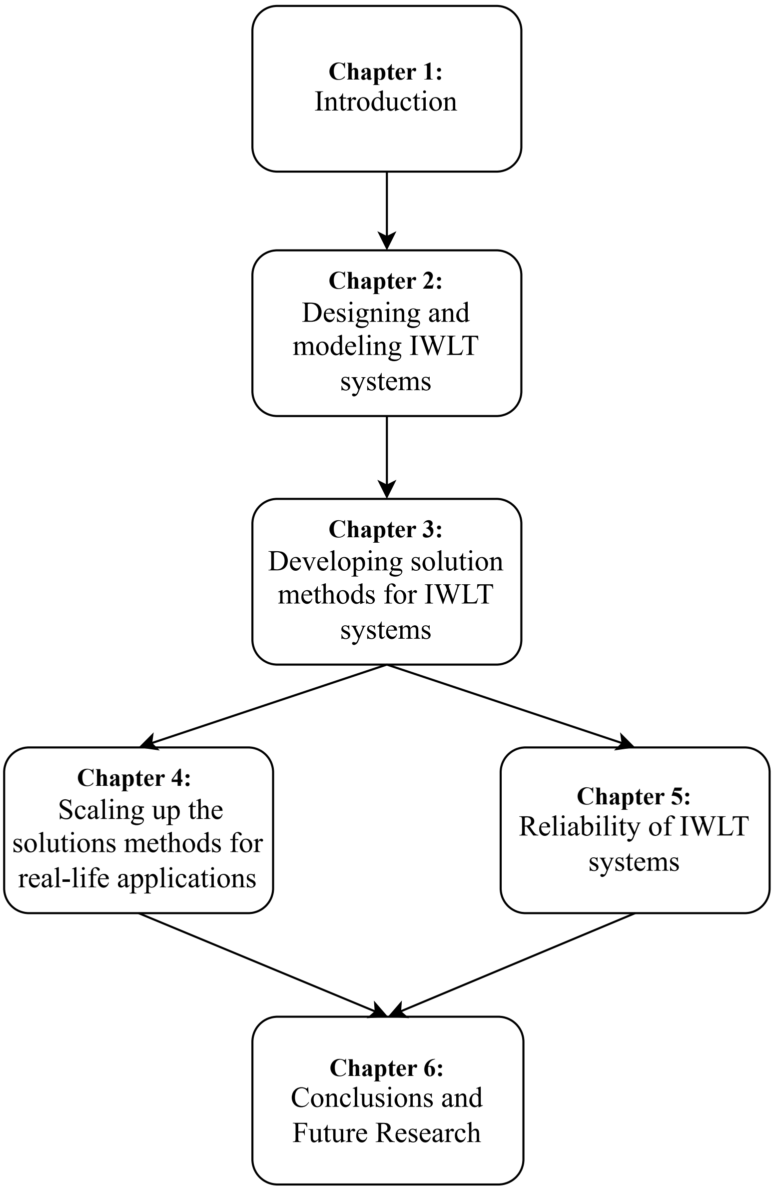


Figure 1.2: The structure of the thesis.

Chapter 2

Designing and modeling IWLT systems

This chapter addresses the challenges of designing shared facilities for transshipment operations in city logistics, lacking a system-wide modeling approach. Through a practical example of waste collection, it introduces the problem and provides a novel MILP model to evaluate the efficiency of two-echelon intermodal systems, considering resource synchronization and capacity planning. Furthermore, the chapter presents plausible service design alternatives for both single and two-echelon settings, which will be further explored in the thesis for the assessment of integrating waterborne transport into city logistics in Chapters 3, 4, and 5. Therefore, this chapter tackles **SQ1** with this developed modeling approach.

The remainder of the chapter is organized as follows. Section 2.1 introduces the research background, and Section 2.2 formulates the problem. Section 2.3 lays out an experimental study where we compare the solution quality of the proposed model with three benchmarks on modified Solomon's 1987 test instances. Finally, Section 2.4 is devoted to the conclusions and further directions.

The research discussed in this chapter is partly published in Karademir et al. (2022b,a).[1]

[1] Karademir, C., Beirigo, B. A., Negenborn, R. R., & Atasoy, B. (2022a). "Multi-trip vehicle routing problem with time windows for waste collection in Amsterdam". *Proceedings of Annual Meeting of the Transportation Research Board.*
Karademir, C., Beirigo, B. A., Negenborn, R. R., & Atasoy, B. (2022b). "Two-echelon Multi-trip Vehicle Routing Problem with Synchronization for An Integrated Water-and Land-based Transportation System". *Proceedings of hEART 2022: 10th Symposium of the European Association for Research in Transportation.*

Table 2.1: Notation for the 2E-MVRPTW-SS in this chapter.

Sets	
d	The depot for electric cars
w	The waste center for vessels
C	Waste points, $\{1,\dots,n\}$
C_d	Waste points and the depot d, $C \cup \{d\}$
S	Hubs
Parameters	
t_{ij}	Shortest travel time from waste point i to j
c_{ij}	Cost of travelling from node i to j
Q_1	Capacity of an electric car
Q_2	Capacity of a vessel
K_1	The number of available electric cars
K_2	The number of available vessels
s_i	Service duration of node
q_i	Waste amount at node
a_i	Earliest collection time of node i
b_i	Latest collection time of node i
U	Constant duration for a transfer task
β_1	The fixed cost of an electric car
β_2	The fixed cost of vessel
M	Sufficiently large number for constraint linearization
Variables	
x_{ij}	(Binary) 1 if node j is visited immediately after node i, 0 otherwise
v_{ip}	(Binary) 1 if the hub p is visited immediately after node i is served, 0 otherwise
m_i	Load on the car after node i is visited
h_i	Service start time at node i
ε_i	Extra travel cost to visit a hub after node i
$y_{ip,jr}$	(Binary) 1 if the transfer task ip is served by a vessel immediately after the transfer task jr
$y_{w,ip}$	(Binary) 1 if the transfer task ip is served as the first task by a vessel
$y_{ip,w}$	(Binary) 1 if the transfer task ip is served as the last task by a vessel
u_i	Service start time for the transfer task requested immediately after visiting node i
l_i	Load on the vessel at the departure from the transfer task requested immediately after visiting i

2.1 Introduction

The interest in logistics over inland waterways has been increasing recently as cities plan to reduce on-street congestion and emissions (Amsterdam.nl 2019). Amsterdam, the Netherlands, for example, aims at further harnessing its extensive waterway network, which covers 25% of the city's central area, to improve its waste collection system. This system is based on heavy garbage trucks, which, besides worsening congestion, contribute to damaging the city's historical and fragile quay walls, resulting in billions of euros in maintenance costs (Dimitrova 2021).

To reduce heavy vehicle movements and prevent quay wall damage, this study proposes an *Integrated Water- and Land-based Transportation (IWLT)* system that eliminates heavy garbage trucks. As pointed out by Anderluh et al. (2021), two-echelon systems may help alleviate the impact of growing freight movements on society, the economy, and the environment caused by the development of e-commerce and same-day delivery services. At the first echelon, small garbage cars collect waste. Next, at the second echelon, waste is consolidated onto larger vessels that meet the cars at the hubs. Finally, full vessels sail to a central waste facility.

We model this hybrid waste collection system as a variant of the *Two-echelon Vehicle Routing Problem (2E-VRP)* introduced by (Gonzalez-Feliu 2008). Typically, 2E-VRP aims at routing and consolidating freight through intermediate satellites connecting echelons before transferring it to a final destination (Perboli et al. 2011). Unlike most 2E-VRP models in the literature, which consider a delivery scenario where items are first consolidated and then dispatched, we model a reverse logistics problem (see Figure 2.1).

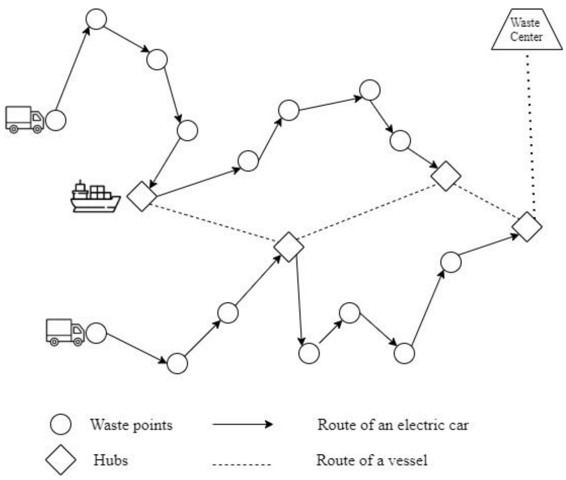


Figure 2.1: Two-echelon waste collection network.

The first echelon problem consists of finding routes for cars and selecting the best hubs for the transfer tasks, while the second echelon problem consists of finding routes for the vessels to serve these transfer tasks. Due to their low capacity, cars may execute multiple transfer tasks, leading to multiple trips to hubs. Therefore, vessels and cars should be in sync to be present at hubs to perform the transfer tasks. Synchronizing vessels and cars is further constrained by time windows (collection hours vary per neighborhood) and physical space (only a single vessel can access a hub at a time and perform a single transfer task at once).

Most studies have focused on the basic variant of 2E-VRP, where the synchronization is required only for cargo flow Cattaruzza et al. (2017). Since satellites may lack storage capabilities or feature temporary storage capacity, temporal synchronization may also be necessary: First echelon vehicles should not arrive after the departure of second echelon vehicles (Li et al. 2021a). Crainic et al. (2009) first introduce the 2E-VRP with time windows and temporal satellite synchronization (2E-MVRP-SS) and propose a general model for a multi-depot multi-trip variant considering heterogeneous vehicles.

Although many studies have focused on 2E-MVRP-SS variants (see, e.g., Grangier et al. (2016), He & Li (2019), Anderluh et al. (2021)), to the best of our knowledge, none has considered vehicle transfer constraints. They assume that multiple transfer operations can occur simultaneously at a hub, which is not feasible for the Amsterdam waste collection use case where space for maneuvering cars and vessels is limited. Hence, in this study, we model a 2E-MVRP-SS with one-to-one transfers at the satellites and time windows at the customers. Additionally, from a practical view, we analyze different logistic systems that integrate water and land for waste collection problems in cities.

2.2 Problem formulation

The 2E-MVRP-SS is formulated as a MILP. The first echelon is the street level, where we have K_1 identical electric cars with a capacity of Q_1 units. These cars start their journey at the main depot (d), visit a set of waste points (C), and return to the main depot without exceeding their capacity at any point. Each waste point i requires q_i units of waste to be collected within a time window of (a_i,b_i) associated with a service time of s_i. t_{ij} and c_{ij} denote the shortest travel time and travel cost between points i and j, respectively. Cars can unload the waste onto vessels at a set of transshipment hubs S over multiple trips. Transferring waste requires U time units. The second echelon is the water level where K_2 identical vessels with a capacity of Q_2 units start at the waste center (w), visit hub(s) if cars require transfer task(s), and return to the waste center.

The x_{ij} variable determines whether a car serves point j immediately after serving point i while v_{is} decides whether the car visits hub s immediately after serving point i. x_{ij} gives the order in which waste points are assigned to a car, while v_{is} provides the selected hub and the last point in a trip. The hub selection decisions by v_{is} enable us to correctly calculate the total load on the car and the earliest arrival time of a car at the hub s according to the service decisions of the last point i. If v_{is} is 1, then there is a transfer task at hub s with a demand equal to the total waste on the car after serving point i denoted by m_i and earliest service start time equal to the service end time at point i denoted by $h_i + s_i$ plus travel time to hub s. In this way, the model jointly decides the first echelon routes and transfer tasks for the second level routing problem. The second echelon sub-problem (vessel routing) is a basic VRP where a fleet of vessels serves all the transfer tasks required by the first echelon decisions respecting the capacity of the vessels and the maximum time duration, operational times represented by a_w and b_w for the waste center. The vessel routing decisions are taken by y variables. The synchronization is achieved by the earliest service start time for a transfer task at a hub and delayed arrival time to the next point, according to the service end time of the transfer task plus travel time to the next point. All sets, parameters, and decision variables are presented in Table 2.1.

$$\begin{aligned}\min\Big(\sum_{i\in C}\beta_1 x_{di} + \sum_{i\in C}\sum_{p\in S}\beta_2 y_{w,ip}\Big) + \Big(\sum_{i,j\in C_d} c_{ij}x_{ij} + \sum_{i\in C}\varepsilon_i\Big)\\ +\Big(\sum_{i,j\in C}\sum_{r,p\in S} c_{pr}y_{ipjr} + \sum_{i\in C}\sum_{p\in S} c_{wp}y_{w,ip} + c_{pw}y_{ip,w}\Big)\end{aligned} \tag{2.1}$$

subject to

$$\sum_{j\in C_d} x_{ij} = 1 \qquad i\in C \tag{2.2}$$

$$\sum_{j\in C_d} x_{ji} = 1 \qquad i\in C \tag{2.3}$$

$$\sum_{i\in C} x_{di} = \sum_{i\in C} x_{id} \le K_1 \tag{2.4}$$

$$\sum_{p\in S} v_{ip} \ge x_{id} \qquad i\in C \tag{2.5}$$

$$\varepsilon_i \ge (c_{ip} + c_{pj} - c_{ij})(x_{ij} + v_{ip} - 1) \qquad i\in C, j\in C_d, i\ne j, p\in S \tag{2.6}$$

$$m_j - m_i \geq q_j - Q_1(1 - x_{ij} + \sum_{p \in S} v_{ip}) \qquad i,j \in C, i \neq j \tag{2.7}$$

$$a_i \leq h_i \leq b_i \qquad i \in C \tag{2.8}$$

$$a_d + t_{dj} \leq h_j \qquad j \in C \tag{2.9}$$

$$h_i + s_i + t_{ij} \leq h_j + M(1 - x_{ij}) \qquad i \in C, j \in C_d, i \neq j \tag{2.10}$$

$$u_i + (U + t_{pj}) v_{ip} \leq h_j + M(1 - x_{ij}) \qquad i \in C, j \in C_d, i \neq j, p \in S \tag{2.11}$$

$$u_i \geq h_i + s_i + t_{ip} v_{ip} \qquad i \in C, p \in S \tag{2.12}$$

$$\sum_{p \in S} v_{ip} \leq 1 \qquad i \in C \tag{2.13}$$

$$y_{w,ip} + \sum_{j \in C} \sum_{r \in S} y_{jr,ip} = v_{ip} \qquad i \in C, p \in S \tag{2.14}$$

$$\sum_{j \in C} \sum_{r \in S} y_{ip,jr} + y_{ip,w} = v_{ip} \qquad i \in , p \in S \tag{2.15}$$

$$\sum_{i \in C} \sum_{p \in S} y_{w,ip} = \sum_{i \in C} \sum_{p \in S} y_{ip,w} \leq K_2 \tag{2.16}$$

$$l_i \geq m_i \qquad i \in C \tag{2.17}$$

$$l_j - l_i \geq m_j - Q_2(1 - \sum_{p \in S} \sum_{r \in S} y_{ip,jr}) \qquad i,j \in C, i \neq j \tag{2.18}$$

$$a_w + t_{wp} v_{ip} \leq u_i \qquad i \in C, p \in S \tag{2.19}$$

$$u_i + U + t_{pr} \leq u_j + M(1 - y_{ip,jr}) \qquad i,j \in C, p,r \in S, i \neq j \tag{2.20}$$

$$u_i + U + t_{pw} v_{ip} \leq b_w \qquad i \in C, p \in S \tag{2.21}$$

$$x_{ij} \in \{0,1\} \qquad i,j \in C_d, i \neq j \tag{2.22}$$

$$v_{ip},\ y_{w,ip},\ y_{ip,w} \in \{0,1\} \qquad i \in C, p \in S \tag{2.23}$$

$$y_{ip,jr} \in \{0,1\} \qquad i,j \in C, i \neq j, p,r \in S \tag{2.24}$$

$$m_i \geq q_i \qquad i \in C \tag{2.25}$$

$$\varepsilon_i \geq 0 \qquad i \in C \tag{2.26}$$

The objective function (2.1) minimizes the total number of used vehicles (vessels or cars) and the transportation costs for cars and vessels. The first part is the number of total vehicles, the second is the transportation cost for street level and the last part is the transportation cost for water level. Constraints (2.2) and (2.3) ensure that each waste point is served exactly once by a car while constraints (2.4) indicate that the number of leaving and returning cars must be equal and should not exceed the available fleet size. Constraints (2.5) guarantee that a car must visit a hub before returning to the depot in order to transfer the collected waste in its last trip. Constraints (2.6) calculate the additional travel cost to visit a hub s between points i and j, assuming triangle inequality holds for all i, j pairs. Constraints (2.7) are capacity constraints. Constraints (2.8)– (2.10) sequentially calculate service start times at the points with respect to their time windows and operational time horizon of the cars. Constraints (2.11) delay the arrival time to the next point j if there exists any transfer task just before point j while constraints (2.12) ensure the transfer task must be performed after the car arrives at the selected hub. Constraints (2.14) and (2.15) assign a single vessel to hub p only if there exists a transfer task decision at that hub. If no transfer task is assigned to a hub p immediately after i, then all second echelon constraints regarding this task become redundant. Constraints (2.16) indicate that the number of leaving and returning vessels to the waste center must be equal and not larger than the fleet size. Constraints (2.17) ensure that the waste load for a transfer task must be at least the amount of collected waste on the car after serving the last point i just before the transfer task occurs, while constraints (2.18) indicate the waste load on the vessel while performing transfer tasks. (2.19)– (2.21) state temporal limitations for transfer tasks. Finally, (2.22) – (2.26) define ranges for each decision variable.

Modeling one-to-one transfers

A hub can only perform one transfer task at a time, meaning that any two operations cannot overlap. Let f_{ij} be the time difference between the service start time of the transfer tasks requested immediately after collecting node i and j. If they are assigned to the same hub p, then we need to ensure that they need to be at least U units of time distance away from each other in order to finish one before starting the other. The temporal distance between two operations assigned to the same hub is equal to:

$$|u_i - u_j| \geq U(v_{ip} + v_{jp} - 1) \qquad i, j \in C, i \neq j, p \in S \qquad (2.27)$$

It can be linearized such that:

$$u_i - u_j \leq f_{ij} \qquad i, j \in C, i < j \qquad (2.28)$$
$$u_j - u_i \leq f_{ij} \qquad i, j \in C, i < j \qquad (2.29)$$
$$f_{ij} = f_{ji} \qquad i, j \in C, i \neq j \qquad (2.30)$$
$$f_{ij} \geq U(v_{ip} + v_{jp} - 1) \qquad i, j \in C, i < j, p \in S \qquad (2.31)$$

2.3 Computational experiments

The proposed IWLT system, where cars and vessels operate in synchronization, is referred to as a two-echelon VRP with flexible vessels system (2-echelon-F) and evaluated with respect to three benchmarks: single echelon VRP with large trucks (1-echelon-T), single echelon VRP with small cars (1-echelon-C), and two-echelon VRP with stationary barges (2-echelon-S) system.

The models are implemented in a computer with Intel Core(TM) i7-3820 3.60 GHz and 32 GB RAM. They are solved by a commercial solver, CPLEX 12.10. The computation time limit is set to an hour for every instance.

2.3.1 Only large trucks: 1-echelon-T

To assess the proposed IWLT collection system, the traditional collection system is modeled assuming that large garbage trucks start from a depot in the city, collect waste, deliver it to the waste center, and return to the depot. It is formulated as a capacitated VRP with time windows considering the collection hours of the neighborhoods. The proposed model by Bard, Kontoravdis, and Yu 2002 is modified to include the trip to the waste center at the end of each route before returning to the depot.

2.3.2 Only small electric cars: 1-echelon-C

Since large trucks will be removed from the streets by 2025 Amsterdam.nl (2019), another option is to use smaller electric cars instead of large trucks. They are allowed to perform multiple trips to the waste center due to their relatively smaller capacities with respect to total waste. The model used in *1-echelon-T* system is modified to include multi-trip for the vehicles such that:

$$m_j \geq m_i + q_j - Q_1(1 - x_{ij} + v_i) \qquad i, j \in C, i \neq j \qquad (2.32)$$
$$h_i + s_i + t_{ij} + \varepsilon_i + U v_i \leq h_j + M(1 - x_{ij}) \qquad i, j \in C, i \neq j \qquad (2.33)$$
$$\varepsilon_i \geq (c_{iw} + c_{wj} - c_{ij})(x_{ij} + v_i - 1) \qquad i \in C, j \in C_d, i \neq j \qquad (2.34)$$

Let m_i be the load on the car after collecting the waste point i, v_i decide whether there is a waste center visit immediately after i, and ε_i be the additional travel time to the waste center. The cost of additional travel time (ε_i) is also added to the objective as a part of the travel cost.

2.3.3 Stationary barges: 2-echelon-S

In this case, large barges are placed along the canals as temporary dump sites for the cars. Instead of delivering the collected waste to the waste center as in the traditional setting or to the vessels as in the proposed setting, the cars dump the waste into these barges that are placed at a hub during collection hours. The barges are taken to the waste center by tugboats when they are full or no longer needed. The number of barges is assigned such that the waste generated in the city can be contained, $b_n = \lceil \frac{\sum_{i \in C} q_i}{Q_b} \rceil$, where Q_b is the capacity of a barge. The objective still includes the travel cost of the tugboats to place the barges to the selected hubs and take them back to the waste center in order to account for the water level logistic costs in the IWLT setting. The proposed 2E-MTVRPTW-SS formulation is modified as follows:

$$v_{ip} \leq z_p \qquad i \in C, p \in S \tag{2.35}$$

$$\sum_{p \in S} z_p = b_n = K_2 \tag{2.36}$$

$$y_{ip,jr} = 0 \qquad i, j \in C, p, r \in S, p \neq r \tag{2.37}$$

Constraints (2.35) allow the cars to use selected hubs as dump sites while constraints (2.36) ensure that at most b_n hubs are selected. Constraints (2.37) prevent inter-movements between hubs, meaning that they can only be placed at a single hub. Note that these constraints are added to the model explained in Section 2.2 and are subject to the hub capacity, multi-trip, synchronization, and time window constraints.

2.3.4 Test instances

We use modified Solomon's VRPTW instances Solomon (1987) as proposed by Grangier et al. 2016 for geographical configuration. The only difference is in locating the hubs, where we choose hubs outside of the city while Grangier et al. 2016 locate them at the center of the network. Keeping the transfer operations away from the public is primarily motivated by hygienic concerns, noise, and the lack of space in the city. Let x_{min}, x_{max}, y_{min}, and y_{max} be the minimum and maximum values of the coordinates of the nodes to collect. Four hubs are located at (x_{min},y_{min}), (x_{min},y_{max}), (x_{max},y_{min}), and (x_{max},y_{max}). The earliest and latest operational times of the hubs and the waste center are equal to the ones of the depot, as given in the instances.

To better observe multiple trips and transfer tasks, the capacity of electric cars is set to 50 units in 1-echelon-C, 2-echelon-S, and 2-echelon-F systems. The capacity of the trucks, barges, and vessels is set to 250 units.

The objective is to minimize the number of trucks or cars first and then minimize the travel cost for 1-echelon-T and 1-echelon-C systems. Similarly, for 2-echelon-S and 2-echelon-F systems, the priority is to minimize the number of cars and then the travel cost. The cost of water-level logistics is also minimized in the same order but relatively less important than the street level cost such that the fixed cost of the cars (β_1) is set to 1000, the travel cost on the streets is equal to 1 while the fixed cost for the vessels (β_2) 100 and the travel cost is 0.1 of the travel times. The main motivation is to reduce the heavy movements and congestion on the streets. Lastly, U is assumed to be 150 time units.

For testing different approaches, we assume that waste points are the first ten nodes of Solomon class "2" instances with wide time windows and long scheduling horizons, which is more similar to the structure of the collection hours for neighborhoods.

2.3.5 Results and discussion

Table 2.2 summarizes the average results of the instances in each type for the problems with ten waste points for all approaches and four hubs for 2-echelon-S and 2-echelon-F systems. Based on the geographical distribution of the waste points, cases are divided into three categories: C type for clustered locations, R type for random locations, and RC type for randomly clustered locations. For both levels, NV is the number of the vehicles (cars, barges, or vessels), $Travel\ Time$ is the total travel time of the vehicles on their network, while $Weighted\ Avg.\ Load$ is the weighted average of the load on the vehicles per travel

Table 2.2: Results on the instances with 10 waste points and four hubs derived from Solomon's VRPTW problems Solomon (1987).

		Street Level			Water Level		
		NV	Travel Time	Weighted Avg. Load	NV	Travel Time	Weighted Avg. Load
C	1-echelon-T	1	227,99 (base)	92,11 (base)	-	-	-
	1-echelon-C	1	392,28 (+72%)	26,52 (-71%)	-	-	-
	2-echelon-S	1	208,65 (-8%)	28,63 (-69%)	1	119,61	79,38
	2-echelon-F	1	181,16 (-21%)	28,19 (-69%)	1	148,24	106,47
R	1-echelon-T	1	277,71 (base)	84,24 (base)	-	-	-
	1-echelon-C	1,3	413,59 (+49%)	27,61 (-67%)	-	-	-
	2-echelon-S	1	263,82 (-5%)	31,02 (-63%)	1	120,44	86,45
	2-echelon-F	1	205,66 (-26%)	26,65 (-68%)	1	191,28	151,46
RC	1-echelon-T	1	209,88 (base)	136,57 (base)	-	-	-
	1-echelon-C	2	408,04 (+94%)	38,71 (-72%)	-	-	-
	2-echelon-S^f	2	250,48 (+19%)	42,02 (-69%)	1	62,43	120,63
	2-echelon-F^f	2	197,56 (-6%)	35,91 (-74%)	1	163,58	146,23

time considering non-empty movements. All instances are solved to optimality except the ones labeled with superscript f, where the best feasible solutions are presented.

1-echelon-T system has typically been preferred by decision-makers for the advantage of easy and direct access to service areas, as well as larger capacity of trucks, which leads to fewer trucks needed for waste collection. Therefore, a 1-echelon-T system cannot be beaten in terms of the number of vehicles for all instances as expected. 1-echelon-C system requires frequent visits to the waste center due to the smaller capacity of electric cars, resulting in under-utilization of the working hours. It causes more cars to use in R type problems on average compared to 2-echelon-S and 2-echelon-F systems, where small cars also operate. 2-echelon IWLT systems can reduce the number of cars down to the number of trucks for R and C type problems but fail to use fewer cars for RC type problems.

Travel Time for the street level represents the vehicle movements on the streets. The models also minimize the travel cost, which is mostly proportional to the travel time. The results show that the proposed 2-echelon-F system reduces the burden on the road infrastructure by partially shifting the movements to inland waterways. It reduces the total travel time on the streets for all types of problems more than the 2-echelon-S system, which shows the added value of the flexibility.

The cost of waste collection in Amsterdam is not only about the logistic cost but also the damage to the quay walls. 2-echelon-S system produces the largest values for *Weighted Avg. Load* among three systems, where the cars are used, compared to 1-echelon-T. 2-echelon-F system can achieve the lowest *Weighted Avg. Load* for almost all scenarios. It shows us 2-echelon-F system has the potential to reduce heavy street movements by providing cheaper solutions in terms of fleet size, total street travel time, and lightweight operating garbage cars.

2.4 Conclusions

In this chapter, we consider an integrated water- and land-based waste collection system that aims to remove heavy large garbage trucks from the streets to reduce the damage on the quay walls as well as the congestion. We provide a new formulation for the 2E-MVRP-SS with time windows considering one-to-one transfers and compare the proposed approach with three different benchmarks in terms of the fleet size, average travel time on the streets, and weighted average load of the vehicles per non-empty movements. The proposed system with synchronized mobile vessels and electric cars is shown to be a promising solution for the issues with the current system. It can reduce the total travel time of the garbage cars on the street by 18% and the weighted average loads of the cars by 70% on average across all scenarios without increasing the fleet size of the cars significantly, even if they have way less capacity than the traditional garbage trucks.

We address **SQ1** in this chapter by developing a system-wide MILP model for synchronized two-echelon systems. This unified framework enables the modeling of diverse urban freight systems, explicitly integrates waterborne transport within a two-echelon structure, and formulates the intricate resource synchronization challenges for capacity planning. The savings observed in small instances indicate potential improvements that can be obtained in larger instances. Recognizing the computational complexity of this model, future work will focus on developing exact decomposition methods or heuristics to solve larger instances and gain more insights into the system's benefits.

The MILP model developed in this chapter is used to design and evaluate the performance of several methodologies for synchronized two-echelon routing problems explored in this thesis, namely joint and decomposed MILP models (Chapter 3), the iterative metaheuristic framework (Chapter 4), and the two-stage stochastic programming with recourse model (Chapter 5).

Chapter 3

Developing solution methods for IWLT systems

This chapter addresses the computational challenges of policy evaluation in two-echelon systems, requiring analytic analysis of various service design network scenarios, shown to be challenging in Chapter 2. Therefore, this chapter tackles **SQ2** by testing two solution methods, joint MILP and a logic-based Benders' decomposition. Extensive numerical experiments show that compared to the joint model, the decomposed model is more robust in terms of solution quality and time and is superior for large-scale instances up to 100 nodes for various problems in city logistics. Furthermore, the chapter presents several economic analyses of multiple design choices from strategic and tactical levels, indicating the potential of integrating waterborne transport to reduce the burden on the streets. This chapter provides the theoretical basis of the development of decomposition-based methods presented in the rest of the thesis, which are the metaheuristic in Chapter 4 and the two-stage stochastic optimization with recourse model in Chapter 5. Additionally, the economic analysis of storage options and synchronization is extended in Chapter 4 to further analyze the flexibility of using on-demand satellites to balance the goals of all freight transportation stakeholders.

The remainder of the chapter is organized as follows. Section 3.1 introduces the problem, and Section 3.2 provides a literature overview related to synchronized two-echelon problems, focusing on important aspects. In Section 3.3, we formulate the problem and discuss its applicability to different variants. Section 3.4 introduces a decomposition method, and Section 3.5 evaluates the performance of the decomposition method, providing managerial insights for IWLT systems. Finally, Section 3.6 is devoted to the conclusions and further directions. The chapter is published as Karademir et al. (2025). [1]

[1] Karademir, C., Beirigo, B. A., & Atasoy, B. (2025). A two-echelon multi-trip vehicle routing problem with synchronization for an integrated water-and land-based transportation system. European Journal of Operational Research, 322(2), 480-499.

Table 3.1: Notation for the 2E-MVRP-SS model used in this chapter.

Sets and Indices	
g, d	garage for LEFVs and central depot for vessels, respectively
C	Customer nodes indexed by i and j
C_s	Customer nodes and the garage g, $C \cup \{g\}$
C_w	Customer nodes and the central depot d, $C \cup \{d\}$
P	Satellites indexed by p
N	All nodes indexed by n, $C \cup \{g\} \cup \{d\} \cup P$
Parameters	
q_i	Demand at node $i \in C$
a_i	Earliest service time of node $i \in N$
b_i	Latest service time of node $i \in N$
τ_i	Service duration of node $i \in C$
U	Constant duration for a transfer task
t_{ij}	Shortest travel time from node $i \in N$ to $j \in N$
c^s/c^w	Cost of traveling a unit of time on the streets/water
Q_s/Q_w	Capacity of a LEFV/vessel
K_s/K_w	Number of available LEFVs/vessels
β_s/β_w	Fixed cost of a LEFV/vessel
M^s_{ij}	Sufficiently large number for constraint linearization, $M^s_{ij} = b_i + \tau_i + t^{max}_{ip} + U + t^{max}_{pj} - a_j$
M^w_{ij}	Sufficiently large number for constraint linearization, $M^w_{ij} = b_i + \tau_i + t^{max}_{ip} + U + t^{max}_{pr} - (a_j + \tau_j + t^{min}_{jp})$
Variables	
x_{ij}	(Binary) 1 if node $j \in C_s$ is visited immediately after node $i \in C_s$ by a LEFV, 0 otherwise
m_i	Total load on the LEFV after visiting node $i \in C$, $q_i \leq m_i \leq Q_s$
h_i	Service start time at node $i \in C$ with an LEFV, $\max\{a_g + t_{gi},\ a_i\} \leq h_i \leq \min\{b_g - t_{ig} - s_i - U,\ b_i\}$
ϕ_i	(Binary) 1 if there is a transfer task immediately after node $i \in C$ is served, 0 otherwise
v_{ip}	(Binary) 1 if satellite $p \in P$ is assigned to the transfer task $i \in C$ (if exists), 0 otherwise
y_{ij}	(Binary) 1 if the transfer task $j \in C_w$ is served immediately after the transfer task $i \in C_w$ by a vessel, 0 otherwise
u_i	Service start time of the transfer task $i \in C$ with a vessel and LEFV
l_i	Total load on the vessel after serving the transfer task $i \in C$
f^s_{ij}	Total travel time for an LEFV from node i to node j if it visits $i, j \in C_s$ consecutively
f^w_{ij}	Total travel time for a vessel from the transfer task $i \in C_w$ to the transfer task $j \in C_w$ if it serves tasks i, j consecutively

3.1 Introduction

Freight activities in metropolitan areas have been increasing as a result of the growth in the need for parcel delivery, food delivery, and waste collection (Chevalier 2021). Due to the greater preference for road infrastructure over more environmentally friendly options, the growth in logistics activities has been escalating the burden on the roads (Pfoser 2022). The increased logistics movements and the increased number of trucks affect the quality of life in cities by contributing to congestion, emissions, and damage to the infrastructure. Logistics service providers (LSPs) are facing challenges to reduce congestion-related costs such as service delays, customer inconveniences, and traffic idling times. On the other hand, the authorities are looking for solutions to achieve emission-free cities by 2030 (EU 2021). Nevertheless, overarching initiatives toward more sustainable and livable cities have not significantly contributed to a modal shift.

LSPs are increasingly exploring the implementation of innovative technologies like electric vehicles, autonomous vehicles, unmanned vessels, and drones in their logistics systems to cut costs. These technologies are still limited in terms of storage space, driving range, or reliability, which limits their suitability to take up transport operations completely. Nevertheless, they can be combined with larger vehicles to supply capacity replenishment (Yu et al. 2020). However, the economic benefits of such systems are still not very clear to the LSPs (Moolenburgh et al. 2020).

According to Sluijk et al. (2023), consolidating cargoes outside of cities via larger vehicles and coordinating them with smaller city freighters at urban transshipment facilities (satellites) can enhance efficiency in the logistics system. Adding another layer to the distribution system can lead us to economies of scale. They highlight the growing interest in such two-tier or two-echelon logistics systems in both academic and commercial applications. Crainic et al. (2009) introduce the city logistics concept to move toward integrated freight systems, particularly using two-echelon systems to meet the increasing demand in cities. To achieve this, they emphasize the importance of synchronization and coordination between fleets on different echelons.

The above-mentioned technological developments and inefficiencies in current road transportation require us to explore alternatives. Groothedde et al. (2005) discuss the efficiency and reliability of intermodal systems for city logistics problems. They conclude that economies of scale can be achieved by advancing service network design methods to include coordination and synchronization costs in real settings. Mostly, the cost of transshipment operations in intermodal systems or two-echelon systems is overlooked in the literature by simplifying the transshipment capacities of satellites regarding the equipment, time, and space at a time. These simplifications ignore possible delays and related costs (Côté et al. 2017). For example, if multiple transfer requests overlap in time, especially when the satellite's resources are limited, delays can occur as the satellite needs to allocate its resources to handle each transfer. This can lead to queuing or prioritization issues, causing delays for specific transfers, which are not taken into account while deciding them.

To address the issues in city logistics, we study an integrated water- and land-based transportation (IWLT) system that aims at achieving a higher level of modal shift to take advantage of the growing worldwide applications over waterways (Janjevic & Ndiaye 2014). In this system, light electric freight vehicles (LEFVs) serve the demand in cities, while vessels act as mobile depots whenever capacity replenishment is needed. Satellites are considered to have the capacity to transship from a single vehicle to another vehicle at a time, providing one-to-one transfers between vessels operating over inland waterways and LEFVs operating as city freighters on streets. We model such a system as a two-echelon multi-trip vehicle routing problem with satellite synchronization (2E-MVRP-SS) considering unitary transshipment real-time capacities at the satellites with no storage and time windows at the customers. Unitary transshipment ensures that the vehicles at the satellite are unloaded and loaded one by one for an average transshipment duration, allowing a non-overlapping operations sequence to eliminate congestion.

The purpose of the proposed system is twofold: (i) alleviating congestion by reducing the burden on street vehicles with the integration of inland waterways and (ii) maximizing the utilization of new vehicle technologies to improve city logistics. The main contributions of our work are listed as follows:

- We provide a two-index compact formulation for a synchronized two-echelon system, 2E-MVRP-SS, with unitary transshipment capacities. To the best of our knowledge, the transshipment capacity of satellites, limited by both space and resources, is not addressed yet for such problems.
- We propose a logic-based Benders'decomposition (LBBD) approach for the 2E-MVRP-SS to tackle the complexity of large-scale problems and show its superiority in terms of quality and solution time.
- We show how to adopt the proposed model under different scenarios regarding the service network design and operational costs. Furthermore, we provide managerial insights about the benefits and challenges of synchronized IWLT systems compared to the on-street alternatives.

3.2 Literature review

Following the introduction of the two-echelon capacitated vehicle routing problem (2E-VRP) by Gonzalez-Feliu (2008), studies have demonstrated that two-echelon routing problems have become more prominent due to the increased freight movements in cities. Thus, many authors have researched two-echelon distribution systems tailored to city logistics to reduce the negative impacts of increased on-street movements on society, economy, and environment (Anderluh et al. 2021). These studies differ in terms of the synchronization degree between the vehicles using common resources during transshipment operations.

In single-echelon systems, vehicles transport goods directly from origin to destination without interacting with other vehicles. However, in two-echelon systems, services involve a combination of vehicles, creating a dependence between their operations for cargo-flow connectivity. This introduces complex decisions regarding transshipment synchronization at satellites. As a result, changing the route of one vehicle in this system can make other routes infeasible. The interdependence problem, as referred to by Drexl (2012), adds complexity compared to conventional solution methods. Resource synchronization at satellites significantly impacts operations and decisions at different echelons, influencing the degree of interdependence. Drexl (2012) defines the requirement such that the total utilization or consumption of a particular resource by all vehicles should not exceed a set limit at any given time.

Integrated vehicle routing problems are commonly used in the literature to describe two-echelon transportation systems. These problems arise when vehicle routing problems result from another optimization problem. According to Côté et al. (2017), solving "strongly interdependent problems" as integrated problems, considering joint decisions' feasibility and cost relations, brings benefits despite increased complexity. Integrated modeling bridges the gap between academia and the real world by reducing assumptions and unexpected costs resulting from simplifications.

Integrating inland waterways into urban freight transport offers a viable alternative to address congestion, environmental impact, and limited space challenges (Janjevic & Ndiaye 2014). Besides transporting bulk materials for construction, there exist several applications for last-mile parcel and retail logistics using inland waterways, e.g., floating barges in combination with electric cargo bikes and LEFVs in Sweden, autonomous vessels with electric bikes in Germany, vessels loaded with electric cubicycles in Belgium, vessels with rolling containers in the Netherlands, ships and diesel trucks in France (Brauner et al. 2021). Recent studies have reflected this trend by focusing on route optimization and cost evaluation for new last-mile delivery systems, in which traditional delivery methods are replaced by alternatives such as electric vehicles (EVs) or cargo bikes (Divieso et al. 2021). However, most of the studies focus on case-specific operations at the last mile and ignore expensive transshipment operations in cost calculations. Thus, the economic gains of such integrated systems are not clear to all stakeholders. Accordingly, He & Haasis (2019) highlight the scarcity of research on the utilization of electric vehicles (EVs) requiring transshipment operations in integrated distribution systems. Caris et al. (2014) emphasize the need for system-wide modeling to evaluate various design options for all stakeholders to determine risks and establish operational schemes to guide policies for the public and private sectors. With advancements in autonomous vehicles and the increased use of waterborne freight transport in cities, re-framing urban logistics problems to account for such a system-wide perspective is essential for assessing the required infrastructural investments and the extent of economic benefits. In this study, we propose a framework to provide managerial insights for the novel integrated systems to improve city logistics by coordination and synchronization compared to traditional logistics.

In order to assess the economic benefits of two-echelon systems, we present a comprehensive overview of the existing studies on synchronized systems, which are characterized by the transshipment capacity of satellites. Additionally, we focus on studies that aim to enhance the utilization of new technologies with limited capacities by exploring the concept of multi-trips. Interaction between vehicles due to their multiple use and limitations on these interactions due to the transshipment capacities increase the complexity of the decisions. To tackle complexity issues, we briefly summarize the LBBD approach, highlighting its effectiveness in integrating existing knowledge to solve integrated problems.

3.2.1 Unlimited transshipment capacity

Most studies have focused on the basic variant, 2E-VRP, where synchronization is required only for the flow of the items (Cattaruzza et al. 2017). They only respect the capacities of the vehicles to supply the assigned flows but ignore the satellites' capacities. All the goods are brought to the satellites without any time dependence. The satellites have unlimited resources and storage to process and store the freight at the satellite until the city freighters arrive.

For 2E-VRP, Jepsen et al. (2013), Santos et al. (2013), Marques et al. (2020) and more recently Mhamedi et al. (2021) propose branch-and-cut or branch-and-price algorithms. Baldacci et al. (2013) develop a bounding procedure combining dynamic programming using a decomposition approach to divide the problem into multi-depot capacitated VRPs. Marques et al. (2020) propose a branch and cut algorithm that first enumerates all solutions for supplying the satellites before optimizing city freighters' routes for each of the enumerated solutions. It outperforms the existing exact algorithms and solves problems with 200 customers and 10 satellites, indicating the potential of such a decomposition-based approach.

Time windows force the system to be semi-synchronized in time, only allowing departures of city freighters after the delivery at the satellites. It is also referred to as the basic variant with time dependence. Dellaert et al. (2019) propose a branch-and-price algorithm for a 2E-VRP with time windows and satellite synchronization (2E-VRP-SS), which can solve the problems with 100 nodes and 5 satellites to optimality. More recently, Dellaert et al. (2021) developed a decomposition-based exact solution approach for the 2E-VRP-SS. An adaptive large neighborhood is proposed by Li et al. (2021b) for 2E-VRP-SS with satellite bi-synchronization that can solve instances with 4,080 nodes and 34 satellites. The 2E-VRP with load synchronization is adequately studied in the literature with various exact and heuristic approaches, and we refer to the recent survey by Sluijk et al. (2023) for more details.

3.2.2 Limited transshipment capacity

For city logistics, due to the limited infrastructure, generally, there exist dedicated spaces with limited storage options or public spaces such as parking lots or public transportation stops with no storage option. Moreover, most studies addressing synchronization in two-echelon settings assume that multiple transshipments can be performed, ignoring the synchronization of resources. Resource synchronization ensures the output rate of a satellite does not exceed its capacity in terms of total transshipped goods, given the employee hours, equipment capacities, and availability of the satellites at any time. In any of these cases, the vehicles operating different networks require semi or exact synchronization in space and time in addition to cargo flow synchronization (Li et al. 2021a).

Li et al. (2018) consider a two-echelon distribution system with maximal transshipment capacity at satellites at any time to serve dedicated customers to the satellites. Capacity is defined as the maximum quantity of goods stored and processed at a time. They provide a non-tractable MILP formulation that becomes exhaustive to solve problems with 10 demand nodes within 4 hours and solve large-scale problems by a large neighborhood search (LNS). A similar problem with maximal transshipment capacity is introduced for simultaneous pickup and delivery problems by Dumez et al. (2023). They provide a MILP formulation, but it also becomes very expensive in terms of memory when the size of the demand nodes increases from 10 to 20. They show that doubling the satellite transshipment capacities provides more savings than doubling the number of satellites, indicating the effect of the resource synchronization is significant in terms of economic gains considering transfer operations. Escobar-Vargas et al. (2021) study the synchronization in multi-attribute two-echelon distribution systems with limited capacities, allowing storage for a limited duration. They propose a compact formulation by three-index vehicle flows and a time-space formulation that can solve problems with up to 10 customer nodes. They further integrate a dynamic discretization method to provide feasible solutions up to 50 nodes, suggesting the efficient use of the compact formulation for large-scale instances.

3.2.3 Multiple use of vehicles under no storage

There exists a limited number of studies for synchronized two-echelon settings considering the multi-trip nature of practical applications like those involving drones, bicycles, or LEFVs under limited satellite capacities. Crainic et al. (2009) introduce first general models and formulations for a 2E-MVRP-SS with time windows, multiple-depot, and heterogeneous vehicles. They stay at the conceptual phase by providing tactical and strategic level analysis for designing and solving such complex systems.

Grangier et al. (2016) focus on a 2E-MVRP-SS with time windows and no storage, requiring a high degree of temporal and spatial synchronization. They assume that the satellites have the resources to operate an unlimited number of transshipments at any time. They suggest incorporating the process times of the transfers into travel times to and from satellites. However, in case of limited resources, it is not possible to know in advance how much time is needed to process given transfers. This simplification ignores the queuing problem at the satellites and underestimates the impact of lead times as well as the number of vehicles. They propose an intractable MILP with a three-index formulation and use an adaptive large neighborhood search (ALNS) to test Solomon's (1987) instances with 100 nodes.

Anderluh et al. (2017) focus on a 2E-MVRP-SS with no storage at the satellites to serve the customers assigned to the vans or cargo bikes. Using a greedy randomized adaptive search procedure (GRASP), they assess the impact of using bikes in combination with vans instead of using only vans for a real-life application of pharmacy wholesale and distributors of vegetable boxes in Vienna. In their (Anderluh et al. 2021) study, they assess the effect of "gray zone" customers that can be served by direct and indirect shipments at any echelon to further improve the economic benefits of using lighter vehicles in city logistics.

He & Li (2019) consider a 2E-MVRP-SS with dynamic satellites with no storage for a harvesting schedule. The transshipments take place at the customer nodes by allowing vehicles to wait up to a maximum duration. This assumption simplifies the location problem and the cost of transshipment operations at customer sites since ensuring the availability of such spaces for city logistics is neither easy nor cheap. A memetic algorithm with a local search procedure is used to solve instances of up to 200 farmlands and 6 harvesters. They show that full synchronization increases the complexity but not necessarily the cost of the system for a given fleet of vehicles. However, pre-defined discretization of time, proposed as time windows for the transshipments, reduces the utilization of the satellite resources.

Our previous work, Karademir et al. (2022b), considers a 2E-MVRP-SS with unitary transshipments and time windows and proposes a MILP with a four-index-based formulation. The real-time capacity is defined only as a single transshipment operation between a vessel and a LEFV at a time without having the option to store any goods between arrivals and departures of the vehicles. However, it also faces difficulties in solving problems with 10 customers and 4 satellites. This is due to the exponential number of choices available in two-echelon systems regarding the allocation of customers to the vehicles and to the satellites, and finally synchronizing the schedules of these vehicles at the allocated satellites. In this study, we enhance the proposed MILP using a new compact two-index formulation that reduces the number of binary variables to address the memory issues in solving problems of up to 100 customer nodes with limited capacitated satellites to perform unitary transshipment operations.

3.2.4 Logic-based Benders'decomposition

Real-life applications often rely on upstream or downstream optimization problems. However, these problems are commonly treated separately, with a focus on solving them quickly by simplifying and making assumptions. This approach sacrifices optimal results in favor of reducing decision complexity.

There has been a growing body of literature exploring the application of LBBD to address integrated optimization problems. This approach involves breaking down complex problems into easier-to-solve problems in any form, typically consisting of a master problem for strategic decision-making and corresponding subproblem(s), leveraging existing knowledge in the literature. For instance, Raidl et al. (2014) focus on a bi-level capacitated VRP and implement an LBBD by assigning the demand to the closest satellites first and minimizing fleets for each satellite. Their proposed decomposition method is enhanced by a variable neighborhood search metaheuristic in order to tackle the scalability of the subproblems at the satellites with larger demand shares. Roshanaei & Naderi (2021) re-formulate the integrated operating room planning and scheduling problem by decomposing the cost function to estimate the cost of strategic location decisions. Their proposed MILP outperforms the existing state-of-the-art branch-price-and-cut algorithm. They further show that when combined with a branch-check-and-cut method at every feasible master solution, an LBBD is more robust in terms of solution time and optimality gap compared to solving the master problem to optimality at every iteration. The LBBD method offers significant benefits for problems involving both assignment and task scheduling, especially when tasks cannot overlap due to resource constraints, such as in operation rooms or process planning problems. For example, Karamyar et al. (2018) study a stochastic location-allocation and scheduling problem for a healthcare system and propose a simulated annealing method to find feasible solutions for locating new hospitals equipped with new machines at the master problem. Similarly, a multi-trip traveling repairman problem with drones is optimized using an LBBD by focusing on customer locations to launch the drones from a truck (Bruni et al. 2022). Martínez et al. (2022) focus on the cost of integrated process configuration decisions and solve related production planning problems. Typically, these models formulate the logic between strategic decisions and optimality using Big-M constraints leading to weak formulations but the LBBD method can exploit the relaxations of the feasible solutions to provide a tighter lower bound or better upper bounds(Rahmaniani et al. 2017).

The 2E-MVRP-SS with unitary transshipment capacity studied in this chapter aims at jointly solving strongly interdependent problems to reduce the cost of integration. We propose an LBBD method to tackle the complexity of the problem based on a two-index compact formulation for solving large-scale instances. Instead of optimizing the resource allocation at the master problem by locating the satellites in space, we first ensure the feasibility of LEFV schedules to cover all the demand within the requested time windows. A subproblem is solved to locate the transshipment operations of these schedules at various satellite locations, considering resource availability for feasibility and cost evaluation. In other words, the master problem provides the temporal precedence graph of the operations, while the subproblem provides the temporal-spatial graph of the transfer operations for global optimality. Despite the increased complexity at the master level, it reduces the time to find feasible solutions for larger-scale instances.

3.3 Problem definition and formulation

In this section, we formally present the 2E-MVRP-SS for an IWLT system. Section 3.3.2 provides a mathematical formulation for only pickup services based on our previous work (Karademir et al. 2022b), proposed for the waste collection problem in Amsterdam using an IWLT system. To avoid congestion at the satellites, Section 3.3.3 is devoted to modeling unitary transshipment constraints to respect satellite capacities, limiting the number of transfers to a maximum of one at a time. Moreover, to show the applicability of the proposed two-index formulation for different variants considering service types, satellite capacities, and charging requirements of the vehicles, we explicitly provide necessary modifications in the formulation for only delivery services in Section 3.3.4.

Instead of using the terms “first and second echelon” as in the literature, we refer to the two levels of operations in our study as the street level and water level. At the water level, vessels transport cargo between the central depot and the satellites. At the street level, LEFVs transport cargo between the satellites and pickup request locations as city freighters.

3.3.1 Problem statement

At the street level, there exists a fleet of K_s identical LEFVs with a capacity of Q_s units. All LEFVs are located at a main garage, g, in the city. They start and end their journeys at the garage while visiting a set of customer nodes, C, and one or more satellites in between to transfer the goods. Each customer node i requires q_i units of goods to be picked up by a single LEFV and associated with a service duration of τ_i within a time window of $[a_i, b_i]$. t_{ij} denotes the shortest travel time between nodes i and j. LEFVs should meet with the vessels for transfer operations at a predefined set of satellites P over multiple times to transfer goods onto a vessel at a time safely. A transfer operation for unloading and loading goods requires U time units.

The water level fleet consists of K_w identical vessels with a capacity of Q_w units. These vessels are located at a central depot, d, that has sufficient space to store them along with the goods collected. The vessels depart from the central depot empty, stop at one or more satellites for transfer tasks, and then return to the central depot loaded. Satellites are public spaces that allow LEFVs and vessels to park while waiting for synchronization. Unlike most of the studies in the literature, there is no storage area where LEFVs can unload cargo before vessels arrive for related transfers. Instead, the synchronized system described in this study enables vehicles to function as temporary and secure storage places while they wait for the vessel at the transshipment location. Moreover, it is assumed that during a transshipment, each LEFV completely unloads its cargo onto a single vessel at the satellite locations.

The 2E-MVRP-SS seeks to minimize overall transportation costs at both levels by (i) routing LEFVs to serve all the city demand while assigning transfer tasks at satellites to them and (ii) routing vessels to serve these transfer tasks. The transportation cost at each level consists of the fixed cost of the vehicles used (β_s for LEFVs and β_w for vessels) and the variable cost of the total traveled duration by all the vehicles (c^s for LEFVs and c^w for vessels). The fixed cost of using vehicles for logistics typically includes expenses such as vehicle purchase or lease, insurance, maintenance, driver's salary, and fuel. The total travel duration is minimized since it is highly correlated to the total distance traveled and total fuel spent.

3.3.2 A two-index compact formulation for 2E-MVRP-SS with pickups

The decisions to be optimized are the routes for LEFVs, the best times to visit satellites for transfers, the best satellite assignments for the transfers, and optimal routes for vessels to serve the transfer tasks on time at the scheduled satellites. The x_{ij} variable gives the sequence of the pickup operations in which customers are assigned to a LEFV. ϕ_i determines the transshipment operation right after the pickup operation at node i to unload collected items to a vessel before serving the next pickup at node j. Similarly, y_{ij} represents the sequence of transshipment operations assigned to a vessel. If there exists a transfer decision provided by $\phi_i = 1$, then v_{ip} decides whether the satellite p is assigned to the transfer task i.

The synchronization is ensured based on transfer task and satellite assignments, meaning that there is a transfer task at satellite p for the LEFV serving customer i and visiting the satellite after the service. v_{ip} allows us to create a time interval for the transfer task ϕ_i regarding the earliest arrival time to satellite p, and the latest time to leave the satellite for the next customer considering its time window since h_i gives the service start time at customer i. For temporal synchronization, the start time of transfer operation i, u_i must fall within this time interval, and vehicles at different levels should wait for each other. For spatial synchronization, we adjust f^s_{ij}, the total travel time on the streets between nodes i and j, if a LEFV serves customers i and j consecutively. If there is no transfer decision after customer i (i.e., $\phi_i = 0$) then $f^s_{ij} = t_{ij}$. Otherwise, if $\phi_i = 1$, the LEFV should visit the satellite assigned to the transfer before going to the next customer j. Then, the travel time needs to incorporate that, i.e., $f^s_{ij} = t_{ip} + t_{pj}$, if the transfer is assigned to the satellite p. The same logic is used for deciding the travel time at water level, f^w_{ij}, if a vessel serves the transfer task i and j consecutively. Without taking explicit satellite assignments into account, the two-index routing formulation for water level allows us to reduce the number of binary variables required to

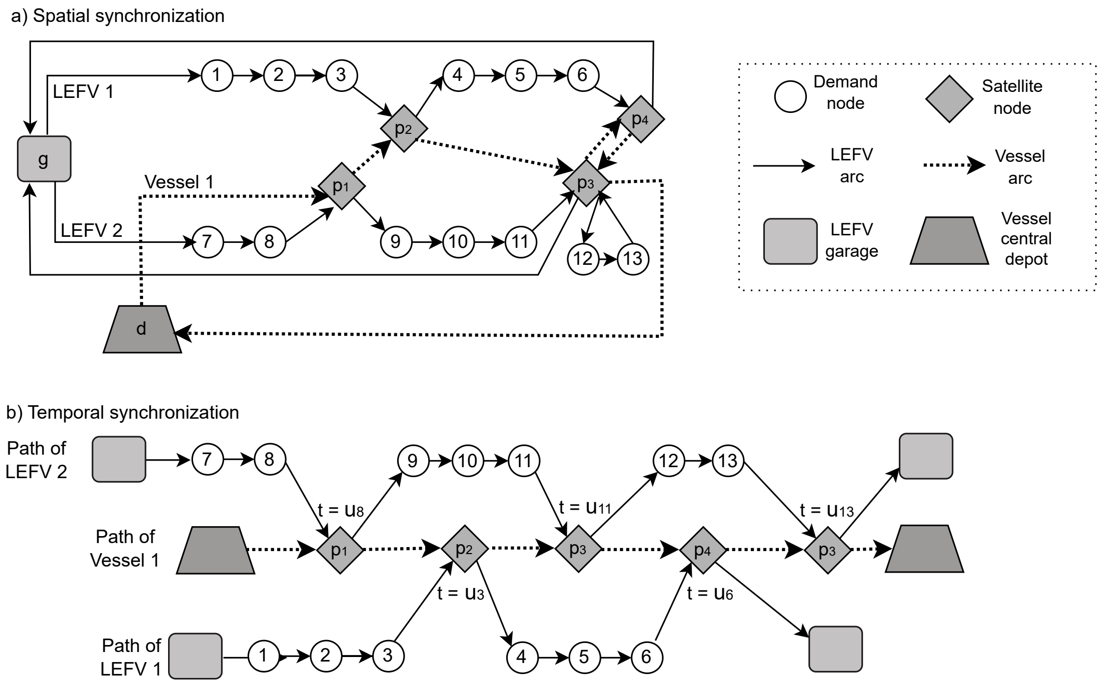


Figure 3.1: Example of a small network and feasible scheduling for the proposed IWLT system, where LEFVs collect goods at the customer level and visit satellites to transship all the goods onto a vessel. A satellite can be visited several times by the same or different vehicles, but at most, a vessel and a LEFV perform a transfer operation at a time considering unitary transshipment. This lets vehicles have cycles in space (a) if necessary or efficient while temporal synchronization (b) guarantees that there is no cycle in the temporal-spatial graph of all operations. For a transfer decision after node i, spatial synchronization is ensured by assigning it to a satellite p in reach, v_{ip}. Furthermore, the temporal synchronization is ensured by the transshipment start time on a vessel, u_i, without violating the time constraints of upstream or downstream operations of the vehicles interacting. Schedules of LEFVs: $\{x : g \to 1 \to 2 \to 3 \to 4 \to 5 \to 6 \to g,\}, \{x : g \to 7 \to 8 \to 9 \to 10 \to 11 \to 12 \to 13 \to g\}, \{\phi : 8, 3, 11, 6, 13\}$. *Schedules of satellites:* $\{v : 8 \to p_1,\ 3 \to p_2,\ 11 \to p_3,\ 6 \to p_4,\ 13 \to p_3\}$. *Schedule of the vessel:* $\{\ y : d \to 8 \to 3 \to 11 \to 6 \to 13 \to d\ \}$

represent each copy of a satellite for each customer node, allowing LEFVs to utilize a satellite more than once (Karademir et al. 2022a). Figure 3.1 represents an IWLT network for pickups, multi-trips by LEFVs, and transfers at satellites executed in synchronization by vessels and LEFVs. All sets, parameters, and decision variables are presented in Table 3.1.

$$\min \quad \overbrace{\sum_{i\in C}\beta_s x_{gi} + \sum_{i,j\in C_s} c^s f^s_{ij}}^{\text{Street Level Cost: } z^s(x,v)} + \overbrace{\sum_{i\in C}\beta_w y_{di} + \sum_{i,j\in C_w} c^w f^w_{ij}}^{\text{Water Level Cost: } z^w(x,v,y)} \tag{3.1}$$

subject to

<u>*Street Level Routing Problem*</u>

$$\sum_{j\in C_s} x_{ij} = \sum_{j\in C_s} x_{ji} = 1 \qquad \forall i\in C \tag{3.2}$$

$$\sum_{i\in C} x_{gi} = \sum_{i\in C} x_{ig} \le K_s \tag{3.3}$$

$$\phi_i \ge x_{ig} \qquad \forall i\in C \tag{3.4}$$

$$m_j - m_i \ge q_j - Q_s(1 - x_{ij} + \phi_i) \qquad \forall i,j\in C, i\ne j \tag{3.5}$$

$$h_i + \tau_i + f^s_{ij} + U\phi_i \le h_j + M^s_{ij}(1 - x_{ij}) \qquad \forall i\in C, j\in C_s, i\ne j \tag{3.6}$$

$$f^s_{ij} \ge t_{ij}x_{ij} + \min_{p\in P}\{t_{ip} + t_{pj} - t_{ij}\}(x_{ij} + \phi_i - 1) \qquad \forall i,j\in C_s, i\ne j \tag{3.7}$$

$$x_{ij}\in\{0,1\} \qquad \forall i,j\in C_s, i\ne j \tag{3.8}$$

$$\phi_i\in\{0,1\} \qquad \forall i\in C \tag{3.9}$$

<u>*Synchronization Problem*</u>

$$\sum_{p\in P} v_{ip} = \phi_i \qquad \forall i\in C \tag{3.10}$$

$$u_i \ge h_i + \tau_i + \sum_{p\in P} t_{ip}v_{ip} \qquad \forall i\in C \tag{3.11}$$

$$u_i + \sum_{p\in P}(U + t_{pj})v_{ip} \le h_j + M^s_{ij}(1 - x_{ij}) \qquad \forall i\in C, j\in C_s, i\ne j \tag{3.12}$$

$$a_d + \sum_{p\in P} t_{dp}v_{ip} \le u_i \le b_d - \sum_{p\in P}(U + t_{pd})v_{ip} \qquad \forall i\in C \tag{3.13}$$

$$f^s_{ij} \ge \sum_{p\in P}(t_{ip} + t_{pj})(x_{ij} + v_{ip} - 1) \qquad \forall i\in C, j\in C_s, i\ne j \tag{3.14}$$

$$v_{ip}\in\{0,1\} \qquad \forall i\in C, p\in P \tag{3.15}$$

<u>*Water Level Routing Problem*</u>

$$\sum_{j\in C_w} y_{ji} = \sum_{j\in C_w} y_{ij} = \sum_{p\in P} v_{ip} \qquad \forall i\in C \tag{3.16}$$

$$\sum_{i\in C} y_{di} = \sum_{i\in C} y_{id} \le K_w \tag{3.17}$$

$$m_i \le l_i \le Q_w \qquad \forall i\in C \tag{3.18}$$

$$l_j - l_i \ge m_j - Q_w(1 - y_{ij}) \qquad \forall i,j\in C, i\ne j \tag{3.19}$$

$$u_i + U + f^w_{ij} \le u_j + M^w_{ij}(1 - y_{ij}) \qquad \forall i,j\in C, i\ne j \tag{3.20}$$

$$f^w_{di} \ge \sum_{p\in P} t_{dp}(y_{di} + v_{ip} - 1) \qquad \forall i\in C \tag{3.21}$$

$$f^w_{id} \ge \sum_{p\in P} t_{pd}(y_{id} + v_{ip} - 1) \qquad \forall i\in C \tag{3.22}$$

$$f^w_{ij} \ge t_{pr}(y_{ij} + v_{ip} + v_{jr} - 2) \qquad \forall i,j\in C, i\ne j, p,r\in P \tag{3.23}$$

$$f^w_{ij} \ge 0 \qquad \forall i,j\in C_w, i\ne j \tag{3.24}$$

$$y_{ij}\in\{0,1\} \qquad \forall i,j\in C_w, i\ne j \tag{3.25}$$

The objective function (3.1) minimizes the total logistics cost of both levels, $z^s(x,v)$ for the street level and $z^w(x,v,y)$ for the water level, by minimizing the fixed cost of the vehicles used and total traveling cost at both levels.

Constraints (3.2) – (3.9) are related to the *street level routing problem*, formulated as a multi-depot vehicle routing problem with multi-trips and time windows where trips can visit any satellite to transfer and empty the load. Constraints (3.2) ensure that each customer is served exactly once by a LEFV while the constraint (3.3) indicates that the number of leaving and returning LEFVs must be equal and should not exceed the available fleet size of LEFVs. Constraints (3.4) impose a final transfer task for each LEFV to deliver the collected goods in the last trip to a vessel before returning to the garage. Constraints (3.5) are the capacity constraints considering direct flows and transfer decisions for load replenishment between customers i and j. Constraints (3.6) schedule the service start times of the customers assigned to a LEFV. If there exists any transfer task between nodes, the arrival time to the next node is delayed at least by the sum of the realized travel time and the duration of a transfer operation. Constraints (3.7) guarantee that the travel time realized from i to j must be positive if a LEFV is visiting i and j subsequently and also define a lower bound on the travel if any transfer exists immediately after node i, assuming the closest satellite is visited. Lastly, constraints (3.8)–(3.9) are the variable domains for arc travel duration, routing LEFVs, and transfer task assignment.

Constraints (3.10) – (3.15) are related to the *synchronization problem* of the operations at both levels, where the satellite assignments are optimized based on the trade-off between the cost of street and water levels. Constraints (3.10) assign a single satellite to a transfer task if it exists. Constraints (3.11) ensure that the transfer operation cannot start before the LEFV arrives at the assigned satellite, while constraints (3.12) guarantee that LEFV cannot leave the satellite until the transfer operation is completed by delaying the arrival to the next node regarding the start time of the transfer. Besides temporal bounds imposed by LEFVs, constraints (3.13) ensure that the service start time for the transfer tasks should also respect the time window of the vessels, i.e., their daily operational hours. Constraints (3.14) update the travel time needed to visit the assigned satellite in between i and j, if there is any. Satellite assignment decisions are binary as given by constraints (3.15).

Constraints (3.16) – (3.25) are related to the *water level routing problem* where all the scheduled transfer tasks should be assigned to the vessels and served to ensure load and temporal synchronization. Constraints (3.16) ensure that if there is a transfer task scheduled immediately after serving customer i, then the task should be served exactly once by a vessel. The constraint (3.17) limits the number of vessels used up to the fleet size. Constraints (3.18) ensure that the required capacity of a transfer task should be at least equal to the load of the LEFV after the last customer it served.

It eliminates partially transshipped loads to the vessels. However, the model is free to add more transfers if it is more efficient to split a transfer into two or more vessels to increase the vessels' capacity utilization. Constraints (3.19) guarantee that the capacity of each vessel is not exceeded at any point. Constraints (3.20) schedule the service start times of the transfer tasks assigned to a vessel and ensure that the delay between two subsequent tasks of a vessel must be as small as the sum of the required duration of a transfer task and the travel time that it should incur based on the satellite assignments of the tasks. Constraints (3.21)–(3.23) are the water level cost components to accurately calculate the realized travel time to serve the scheduled transfer tasks if there are any. They also ensure that there is sufficient time for vessels to be at the scheduled satellites for space synchronization. Constraints (3.24) – (3.25) are the domain of flow variables over water.

Notice that if there is no transfer task scheduled after a customer node i, then all constraints (3.10) – (3.25) related to synchronization and water level become redundant. For the majority of the cases in the optimal solution, the number of scheduled transfer tasks is much lower than the number of customers, and most of the constraints are redundant. Fewer transfer tasks reduce travel costs at both levels since the transfer tasks generated by the street level represent the problem to be solved by the water level. The only exception occurs if more transfers allow for further cost reduction by distributing demand more efficiently at the water level. Therefore, it is not necessarily true that global optimality is achieved at the minimum feasible number of transfers.

3.3.3 Modeling unitary transshipment capacity

In this study, satellites are public spaces without any necessity for infrastructures as opposed to typical operational hubs of different multi-modal systems where goods can be sorted and stored. However, the real-time capacities of the satellites must be taken into account, considering the limited spaces for multiple vehicles to park or maneuver, the lifting capacities (e.g., cranes, rollers), and the labor available for the vehicles. To address the synchronization issues in real-time capacities, it is assumed that at most one transfer task can be executed at a satellite at a time, meaning that any two scheduled transfer tasks cannot temporally overlap. It also means that a vessel cannot serve multiple LEFVs at the same time.

Let r_{ij} be the time difference between the service start time of the transfer tasks requested immediately after collecting node i and j. If they are allocated to the same satellite p, we guarantee that they are at least U units of time apart such that one is completed before the other begins by adding constraints:

$$|u_i - u_j| \geq U(v_{ip} + v_{jp} - 1) \qquad i, j \in C, i \neq j, p \in P, \tag{3.26}$$

which can be linearized as:

$$u_i - u_j \leq r_{ij} \qquad i, j \in C, i < j \tag{3.27}$$
$$u_j - u_i \leq r_{ij} \qquad i, j \in C, i < j \tag{3.28}$$
$$r_{ij} = r_{ji} \qquad i, j \in C, i \neq j \tag{3.29}$$
$$r_{ij} \geq U(v_{ip} + v_{jp} - 1) \qquad i, j \in C, i < j, p \in P. \tag{3.30}$$

The capacity of the satellites can be increased to multiple transfers at a satellite. If there exists space and resources to execute more than a single transfer at a satellite at any point in time, a copy of the satellite can be added to the problem.

3.3.4 A compact formulation for 2E-MVRP-SS with deliveries

In the 2E-MVRP-SS with pickups (Section 3.3.2), LEFVs collect goods at customer locations and deliver them to vessels operating on inland waterways for the last mile to a central depot. In contrast, the 2E-MVRP-SS with deliveries considers the reverse flow: Vessels transport goods from a central depot to satellites in order to transfer them to several LEFVs that perform the last mile to the customers. Both problems ensure satellite synchronization, where the different-echelon vehicles responsible for a transfer must be present at the selected satellite to realize the transfer operation. These vehicles may arrive earlier than the other but are strictly forbidden to leave before the transfer operation ends, which implies synchronization in time, space, and cargo flow. Therefore, the only difference between pickup and delivery problems lies in the direction of the transfers at the satellites. Performing deliveries requires loading packages to be delivered to the customers from vessels to LEFVs at the beginning of each trip, whereas performing pickups involves transferring collected items from LEFVs to vessels at the end of each trip.

The notation, sets, and parameters described in Section 3.3.2 are also valid for the delivery problem, but the following modifications apply:

- $\phi_i = 1$ if there is a transfer task immediately *before* serving customer i and 0 otherwise.
- m_i represents the total load on the LEFV immediately *after* visiting customer node i to deliver q_i, which is now bounded as $0 \leq m_i \leq Q_s - q_i$.

Additionally, modeling deliveries requires modifying the constraints related to load synchronization on both levels for forward flows. To do so, the constraints (3.5) and (3.18) are replaced with:

$$m_i \geq m_j + q_j - Q_s(1 - x_{ij} + \phi_j), \qquad \forall i, j \in C, i \neq j \tag{3.31}$$
$$l_j \geq m_j + q_j, \qquad \forall j \in C \tag{3.32}$$

For temporal synchronization, the constraints (3.6), (3.11) and (3.12) are replaced with:

$$h_i + \tau_i + f^s_{ij} + U\phi_j \leq h_j + M^s_{ij}(1 - x_{ij}), \qquad \forall i, j \in C, i \neq j \tag{3.33}$$

$$u_j \geq h_i + \tau_i + \sum_{p \in S} t_{ip} v_{jp} - M^s_{ij}(1 - x_{ij}), \qquad \forall i, j \in C, i \neq j \tag{3.34}$$

$$u_j + \sum_{p \in S} (U + t_{pj}) v_{jp} \leq h_j, \qquad \forall j \in C \tag{3.35}$$

To ensure that LEFVs are loaded with delivery packages at a satellite before visiting any customer, the constraints (3.4) are replaced with:

$$\phi_i \geq x_{gi}, \qquad \forall i \in C \tag{3.36}$$

Lastly, the cost definitions for street level considering transfer task assignments by constraints (3.7) and (3.14) are replaced with:

$$f^s_{ij} \geq t_{ij} x_{ij} + \min_{p \in P} \{t_{ip} + t_{pj} - t_{ij}\}(1 - x_{ij} + \phi_j), \qquad \forall i, j \in C_s, i \neq j \tag{3.37}$$

$$f^s_{ij} \geq \sum_{p \in S} (t_{ip} + t_{pj})(x_{ij} + v_{jp} - 1), \qquad \forall i \in C, j \in C_s, i \neq j \tag{3.38}$$

3.3.5 Different variants through modular formulation

Ultimately, the proposed linear model for the synchronized two-echelon problem can be used for different variants considering different applications affecting the operations at one or both levels or transfers at the satellites. Thanks to our modular formulation, which is composed of three explicit problems, namely, the routing problems of street and water levels and the synchronization problem at the satellites, any change in the operations can be reflected in the related sub-module in the integrated problem. For example, a service type change from pickups to deliveries given in this section only affects the flow of the goods at the street level and the start of the transfers at the satellites since each transfer is performed just before a trip to load necessary cargo on LEFVs. Another application might consider an electric 2E-VRP with charging options at the satellites (Breunig et al. 2019). Table 3.2 provides an overview of potential variants that our formulation can handle upon necessary adaptations. Moreover, the proposed formulation can be extended to other transportation modes without losing its generality, e.g., vans-bikes, vans-trucks, bikes-trams. Vehicles operating on these modes, e.g., vans, trucks, trams, etc., can act as vessels, and the transshipment operations can be executed at the satellites, e.g., parking lots for trucks and vans and tram stations for trams. However, the changes related to the synchronization problem must be reflected accordingly, considering the available satellites to perform transfers such as trucks, tram stations, warehouses, etc.

3.4 A logic-based Benders'decomposition approach

Benders Decomposition (BD) was proposed by Benders (1962) for tackling large-scale optimization problems, where the complexity tends to increase exponentially with the size of the problem. The essential idea is to decompose the problems into a master problem having the complicating variables and a linear subproblem by fixing those variables. The master problem is solved iteratively by generating feasibility and optimality cuts using duality information of fixed variables on the subproblem. The main drawback of BD is the limitation of having a linear problem (LP) structure for subproblems. Hooker & Ottosson (2003) proposes LBBD and generalizes the convergence mechanism of the classical BD to a wider variety of problems that can be decomposed into easier subproblems in the form of not only an LP but also a mixed integer problem (MIP) or constraint programming (CP). LBBD uses a more general inference dual to generate cuts derived from logical deductions.

Table 3.2: Formulation modifications for different 2E-MVRP variants with satellite synchronization.

Use case (Variant)	Street level	Synchronization	Water level
Unlimited satellite capacity, e.g., Marques et al. (2020)	MVRP	Remove upper(lower) bound on transfer end(start) time for pickup (delivery)	LRP
Limited satellite capacity & dedicated customers, e.g., Li et al. (2018)	MVRP	Add flow balance constraints to ensure transfer task sequences do not exceed capacity at any time	VRP
Limited satellite capacity & re-charging at the satellites, e.g., Breunig et al. (2019)	e-MVRP	Delay transfer operations for charging decisions and limit the maximum amount of goods assigned to the satellites	LRP
Limited satellite capacity & simultaneous pickup-delivery, e.g., Dumez et al. (2023)	MVRPSPD	Track the satellites' used capacity and delay vehicle departures if exceeded	LRPSPD

Notes: VRP: Vehicle routing problem, MVRP: Multi-trip VRP, LRP: Location routing problem, e-MVRP: Electric MVRP, MVRPSPD: MVRP with simultaneous pickup and delivery, LRPSPD: LRP with simultaneous pickup and delivery.

$$\mathbb{J} = min\ \{\ z(x,v,y)\ |\ Constraints(3.2)-(3.25),\ x\in D_x,\ v\in D_v,\ y\in D_y\} \tag{3.39}$$

$$\mathbb{M} = min\{\ z(x,\phi)\ |\ Constraints(3.2)-(3.9),\ OPT(x,\phi),\ FEAS(x,\phi),\ x\in D_x,\ \phi\in D_\phi\} \tag{3.40}$$

$$\mathbb{S} = \mathbb{J}(\bar{x},\bar{\phi}) = min\{\ z(\bar{x},\bar{\phi},v,y)\ |\ Constraints(3.6)_{\bar{x},\bar{\phi}}\ |\ Constraints(3.10)-(3.25),\ \ v\in D_v,\ y\in D_y\} \tag{3.41}$$

The 2E-MVRP-SS is formulated in the form of $\mathbb{J}$ by (3.39) in terms of feasible regions provided in the MILP formulation in Section 3.3.2 and complicating binary variables, namely x for routing LEFVs, ϕ for transfers, v for satellite assignments of the transfers, and y for routing vessels. Constraints for the synchronization problem define the feasible region of the transfers considering all possible satellite assignments. Constraints for the water level routing problem represent the feasible region of the vessel routing problem to serve these transfers, respecting temporal, spatial, and load synchronization requirements.

The complexity of the problem increases quadratically to construct the synchronization and water level problems' regions. However, all the constraints and complicating variables related to these problems are redundant except the binding constraints defined by the optimal solution (if it exists). To reduce the complexity and have a tractable algorithm, we propose decomposing the problem $\mathbb{J}$ into a master problem and a subproblem. The master problem, $\mathbb{M}$ by (3.40), is to solve the street level problem over the region provided by constraints set defined by considering x and ϕ decisions. To ensure feasibility and the optimality of the street level decisions, logical Benders cuts are added to the problem derived from the solution of the subproblem $\mathbb{S}$ by (3.41), which solves the 2E-MVRP-SS for a given feasible solution to the master problem.

3.4.1 Master problem ($\mathbb{M}$)

The master problem $\mathbb{M}$ is a relaxed street level problem for all feasible x and ϕ decisions constrained by (3.2) – (3.9). The actual cost of street level movements depends on the total travel time adjusted by satellite assignments for transfer tasks, $z^s(x,v)$ to achieve global optimality. $\mathbb{M}$ relaxes these assignments into $z^s(x,\phi)$ by assuming that transfers are assigned to the closest satellite and served on time upon the arrivals of LEFVs by (3.7). It implies no waiting time for LEFVs in the best-case scenario under unlimited resources at satellites. Accordingly, the total traveling cost at the street level is formulated by (3.42) and (3.43) to bound the travel cost of the routing decisions, x, without and with satellite visit, ϕ. On the other hand, the best feasible water level cost is the fleet cost of having the minimum number of vessels to store all the demand, $K^l_w = \lceil \frac{\sum_{i\in C} q_i}{Q_w} \rceil$, and traveling cost of those vessels to the closest satellite from the central depot. Therefore, the lowest bound on the cost of water level movements to serve a given set of transfers is formulated by (3.44). With these assumptions, $\mathbb{M}$ does not eliminate any feasible solution to the 2E-MVRP-SS, and reformulates the objective of the synchronized two-echelon problem by decomposing the cost function into a linear part, denoted as f_- by (3.45), and a nonlinear part, denoted as f_+ by (3.46). The objective, $z_{\mathbb{M}}$, is to minimize the integrated cost based on routing and transfer decisions by (3.47) without losing the generality. It reduces the problem to a multi-depot MVRPTW (MDMVRPTW), where street vehicles visit any of the satellites as many times as needed for capacity replenishment.

$$\psi_{ij} \geq c^s t_{ij}(x_{ij} - \phi_i), \qquad \forall i\in C, j\in C_s, i\neq j \tag{3.42}$$

$$\varepsilon_{ij} \geq c^s \min_{p\in P}\{t_{ip}+t_{pj}\}(x_{ij}+\phi_i-1), \qquad \forall i\in C, j\in C_s, i\neq j \tag{3.43}$$

$$z^w \geq K^l_w \left(\beta_w + \min_{p\in P}\{t_{dp}+t_{pd}\}\right) \tag{3.44}$$

$$f_- \geq \sum_{i\in C}(\beta_s + c^s t_{gi})x_{gi} + \sum_{i\in C, j\in C_s} \psi_{ij} \tag{3.45}$$

$$f_+ \geq z^w + \sum_{i\in C, j\in C_s} \varepsilon_{ij} \tag{3.46}$$

$$z_{\mathbb{M}} \geq f_{-} + f_{+} \tag{3.47}$$

$$\psi_{ij}, \varepsilon_{ij}, f_{-}, f_{+} \geq 0 \qquad \forall i, j \in C_s, i \neq j \tag{3.48}$$

$$\textit{Logical Benders cuts} \tag{3.49}$$

$\mathbb{M}$ provides feasible solutions with lower bounds. A feasible solution, $\{\bar{x}, \bar{\phi}\}$, is fed to the subproblem representing the variables for the used arcs and transfer points only. The solution is checked against feasibility and optimality by solving the related $\mathbb{S}(\bar{x}, \bar{\phi})$ to optimize the costs over a two-echelon synchronized setting. The proof of optimality or infeasibility is added to $\mathbb{M}$ before accepting a solution as the incumbent solution via logic-based Benders cuts (3.49) deducted from the corresponding subproblem provided in Section 3.4.2. These cuts improve the bound on the nonlinear part of the cost, f_{+}, due to the interdependence problem in the two-echelon problems.

3.4.2 Subproblem ($\mathbb{S}$)

The synchronization and optimization subproblem, $\mathbb{S}$, is solved for a given feasible solution with $\{\bar{x}, \bar{\phi}\}$ to optimize transfer-satellite assignments (v) and routing of vessels (y) to serve the transfers in the set of $\bar{\phi}$ in synchronization with LEFVs considering the routing decisions in $\bar{x}$. A feasible schedule for LEFVs defines the temporal precedence relationships between the operations, the subproblem defines the satellite visits on the arcs with transfer decisions.

The subproblem $\mathbb{S}(\bar{x}, \bar{\phi})$ is relatively easier to solve since the constraints related to the synchronization and water level problems are constructed only for the given set of transshipment decisions on the chosen arcs, provided Fig. 3.2. It is formulated as a MILP to minimize the total cost with respect to complicating satellite assignments and water level routing decisions. The problem is to locate all the transshipment operations given on the selected arcs, by (3.53) and route the vessels by complying the temporal precedence constraints on all arcs, without (E_{-}) and with (E_{+}) transshipment, by (3.51) and (3.52). $\mathbb{S}$ is used as a proof of infeasibility as well as optimality by using the feasible solutions that provide better or at least as good lower bounds as $\mathbb{M}$ at linear relaxation.

$$\mathbb{S}(\bar{x}, \bar{\phi}) : \min \; z(E_{-}, E_{+}) \tag{3.50}$$

s.t.

$$h_i + \tau_i + t_{ij} \leq h_j \qquad \forall (i,j) \in E_{-} \tag{3.51}$$

$$h_i + \tau_i + t_{ij} + \varepsilon_{ij} + U \leq h_j + M^s_{ij}(1 - \sum_{p \in P} v_{ip}) \qquad \forall (i,j) \in E_{+} \tag{3.52}$$

$$\sum_{p \in P} v_{ip} = 1 \qquad \forall (i,j) \in E_{+} \tag{3.53}$$

$$\textit{Constraints } (3.11) - -(3.13) \qquad \forall (i,j) \in E_{+} \tag{3.54}$$

$$\varepsilon_{ij} \geq \sum_{p \in P} \{t_{ip} + t_{pj}\} v_{ip} \qquad \forall (i,j) \in E_{+} \tag{3.55}$$

$$\textit{Constraints } (3.15) - (3.25) \& (3.44) \tag{3.56}$$

$$z^{UB} \geq z^s_{\mathbb{S}} \geq \sum_{x_{gi} \in E_{-}} (\beta_s + c^s t_{gi}) + \sum_{(i,j) \in E_{-}} c^s t_{ij} + \sum_{(i,j) \in E_{+}} c^s \varepsilon_{ij} + z^w(s) \tag{3.57}$$

$$f_{+} \geq \sum_{(i,j) \in E_{+}} c^s \varepsilon_{ij} + z^w \tag{3.58}$$

Figure 3.2: The subproblem for a given $\mathbb{M}$ feasible solution, $\{\bar{x}, \bar{\phi}\} := E_{-} \cup E_{+}$. E_{-} is the set of (i,j) pairs representing the consecutive customer visits from i to j without a transfer in between, where $x_{ij} = 1$ and $\phi_i = 0$ in the solution (fixed cost of the solution). E_{+} is the set of (i,j) pairs with a transfer, where $x_{ij} = 1$ and $\phi_i = 1$ (variable cost of the solution).

3.4.3 Branch and check: a generalization of LBBD

Both classical BD and LBBD approaches first solve the master problem to optimality and then solve the subproblem(s) using the fixed master-optimal solution. In this study, the master problem is formulated as MDMVRPTW with the assumption of the best satellite assignment for LEFVs. The subproblem is defined as an assignment and scheduling optimization problem.

The master problem relaxes all the resource constraints and provides solutions that are feasible on the demand side, ensuring a feasible service by the LEFVs. On the other hand, the subproblem evaluates the feasibility of the supply side by the vessels and the cost of the proposed solutions for global optimality. However, it does not necessarily match with the minimum feasible cost schedule for $\mathbb{M}$. Optimizing $\mathbb{M}$ at each iteration improves the lower bound but prolongs improving the upper bound by discarding intermediate solutions (Fragkogios et al. 2024). However, these discarded solutions may be revisited in subsequent iterations if optimality is not achieved.

The multi-trip VRP is challenging to solve, considering the timing aspects of the trips when scheduling the vehicles in the existence of time windows (Pan et al. 2021). The state-of-the-art model for the single depot MVRPTW literature solves problems up to 50 nodes by using column generation, column enumeration, and cutting plane for single depot case (Paradiso et al. 2020). Similarly, Huang et al. (2021) propose a column generation method for MVRPTW with a limited number of transshipment operations at the depot at a time. They show that resource capacity at the depots complicates the problem further by limiting the scale of the problems to 50 customers to provide feasible solutions. Considering the complexity of the master problem, we propose a branch and check (B&C) method, a generalization of LBBD Thorsteinsson (2001), to solve $\mathbb{M}$ with the use of subproblems until a predefined termination criterion. As a single search tree, it incorporates solving subproblems into a branch and bound (B&B) process at every feasible solution as a proof of feasibility to cut off infeasible or sub-optimal solution, instead of solving $\mathbb{M}$ to optimality at once. B&C is also referred to as branch-and-Benders-cut (B&BC) (Rahmaniani et al. 2017).

Geoffrion (1972) shows that using the optimal multiplier values corresponding to various trials ensures termination in a finite number of steps if a positive optimality gap is allowed, *epsilon*-optimality. Instead of using a predefined gap, we add optimality cuts to improve the lower bound of $\mathbb{M}$ up to one of the corresponding relaxed subproblems. The method terminates if the lower bounds of the best-known solution and $\mathbb{M}$ are equal, the time limit is achieved, or the problem is infeasible. The lower bounds are derived from the Lagrangian dual of the synchronized two-echelon problem, improving the bounds provided by linear relaxation of $\mathbb{M}$. Frangioni (2005) reminds the effective use of a continuous relaxation for Lagrangian approaches within algorithms by using the dual values of the "easy" satellite assignment constraints by (3.10) in the form of $Ex = b$. The proposed B&C aims at finding feasible solutions faster to maintain improved upper bounds in a single B&B tree and exponentially converges to the optimality if the duality gap is zero. Otherwise, it terminates earlier with a positive gap. While the joint MILP depends on continuous relaxations, $\mathbb{M}$ exploits the Lagrangian relaxations for feasible street level solutions. The flow chart for the proposed LBBD is given in Fig. 3.3.

Benders feasibility cuts

A feasible solution to $\mathbb{M}$ is considered infeasible for $\mathbb{S}$ due to two reasons. Firstly, it might be infeasible under available temporal capacities at the satellites limited to unitary transshipments. $\mathbb{M}$ relaxes this limitation, assuming each transfer is served upon arrivals of LEFVs. Scheduling the transfers at each satellite might cause waiting times for LEFVs, and the delay might lead to temporal infeasibility. Secondly, a given solution with a promising relaxed objective value might not yield a better solution than the incumbent solution found up to that point. The model needs to cut off the solution. If any of the two cases occur, (3.59) is added to $\mathbb{M}$ implying a change in the κ^{th} master feasible solution $E^{\kappa} := E_{-} \cup E_{+}$. This should be at least a single change in excluded routing decisions or the removal of at least one transfer decision included in the current solution.

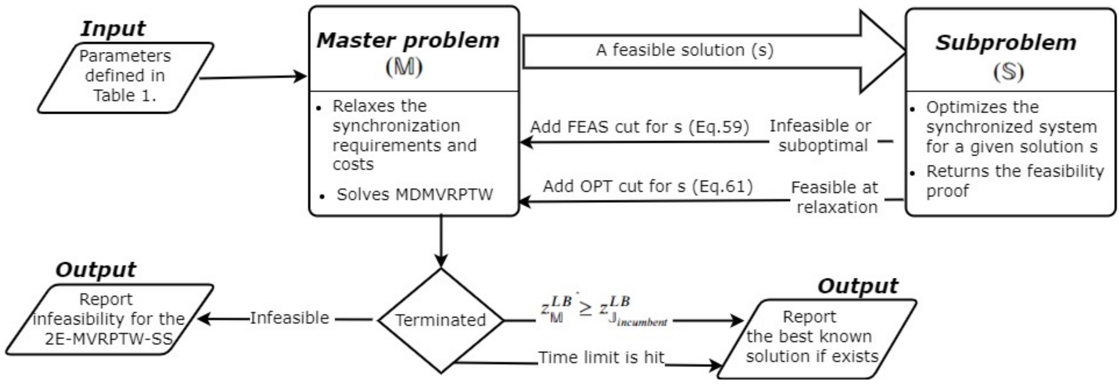


Figure 3.3: The flowchart for the proposed LBBD proposed as B&C. $z^{LB}_{\mathbb{M}}$ and $z^{LB}_{\mathbb{J}_{incumbent}}$ are the best lower bounds of the master problem and the synchronized two-echelon problem respectively.

$$FEAS(E^{\kappa}): \sum_{(i,j)\notin E^{\kappa}} x_{ij} + \sum_{i\notin\overline{\phi}} \phi_i + \sum_{(i,j)\in\overline{\phi}} (1-\phi_i) \geq 1 \tag{3.59}$$

Theorem 3.1 *The cut proposed in* (3.59) *must remove the current solution from the master problem space.*

Proof. The combinatorial cut given by (3.59) eliminates a single unique solution by enforcing the master problem to make at least one change in the solution, i.e., either the routing or the transfer set should change. It discards the current solution without providing any bound information or search direction. It acts as naive feasibility cuts. If the subproblem is a linear optimization problem, then this cut is sufficient for the optimality convergence (Ahat et al. 2018). For nonlinear subproblems, it provides *no-good* optimality cut that might or might not improve the lower bound (Martínez et al. 2022). This cut is used as a feasibility cut for an infeasible solution and as an optimality cut for a sub-optimal solution. Cutting off a sub-optimal solution using a "naive cut" might not improve the lower bound but reduces the burden on the solver compared to using dual information for each feasible solution.

The proposed Lagrangian bounding approach

In classical BD, a master feasible solution improves the upper and lower bounds using the duality of the convex subproblems. However, the strong duality is not applicable to solving the 2E-MVRP-SS due to the non-convex nature of the underlying subproblems. Therefore, a combinatorial logical cut must be derived to provide a valid lower bound if applicable. Otherwise, it should not remove any globally optimal solution.

Suppose $\mathbb{S}$ provides a feasible solution to the synchronized two-echelon problem fixed at a master feasible solution, E^{κ}. $\mathbb{S}$ only includes the complicating decisions set by E^{κ} and excludes the decisions not in E^{κ}. The relaxed solution $\mathbb{S}$ can still be used to obtain Lagrangian multipliers for the decisions in E^{κ}_{+} constrained to the routing decisions in E^{κ}.

Dual inference using Lagrangian optimization

The street level and water level problems regarding the transfer decisions in a feasible solution are connected via the synchronization problem formulated linearly in Section 3.3.2. It is clear that $\mathbb{S}$ is equivalent to $\mathbb{J}$ for any given solution. Satellite-transfer assignment constraints (3.53) enforce space synchronization for transfers to achieve global optimality that minimizes the total logistic costs at both levels. If they are relaxed in $\mathbb{S}$, it solves the synchronized two-echelon problem by allocating the transfers to the satellites while solving a minimum cost flow problem for feasible allocations. Additionally, the cost of water level routing built by (3.22)–(3.24) provides equal or improved bounds on the integrated cost, considering the quadratic assignment problem of the transfer decisions. If any of them is removed, it simply removes the related arc from the solution by breaking binding temporal constraints on the interacting vehicles. There is no reason to assign transfers to satellites and to vessels or assign any cost on both levels. The optimal dual values of these constraints, λ^{κ}_{ij} for each decision in E^{κ}_{+} where $x_{i,j} = 1$ and $\phi_i = 1$, provided by the subproblem relaxation give us the maximum improvements in the relaxed objective if both are removed from the solution (Fisher 2004). Therefore at the optimal solution, the Lagrangian relaxation of $\mathbb{J}$ with respect to the complicating satellite assignment constraints can be written as:

$$z^*_{\mathbb{J}} = z^*_{\mathbb{S}} \geq z^*_{\mathbb{M}} \geq f^*_{-} + f^*_{+} + \sum_{(i,j)\in E^*_{+}} \lambda^*_{ij}(x_{ij} + \phi_i - 2) \tag{3.60}$$

Equivalently, it can be written for the feasible relaxation of the subproblem corresponding to the solution E^{κ} as follows:

$$z_{\mathbb{M}} \geq \sum_{(g,i)\in E^{\kappa}_{-}} (\beta_s + c^s t_{gi}) x_{gi} + \sum_{(i,j)\in E^{\kappa}_{-}} \psi_{ij} + f_{+}^{E^{\kappa}_{0}} + \sum_{(i,j)\in E^{\kappa}_{+}} \lambda^{\kappa_0}_{ij}(x_{ij} + \phi_i - 2) \tag{3.61}$$

Theorem 3.2 *The cut proposed in Eq. (3.61) provides improved bounds for the synchronized two-echelon problem compared to the bounds from continuous relaxation of* $\mathbb{M}$.

Proof. The complicating constraints for the synchronized problem are the satellite assignments, which are relaxed in $\mathbb{M}$ altogether with the constraints in the synchronization and water level problems. The lower bound provided by the relaxation of $\mathbb{S}$ for a feasible solution might be good for the feasible solutions that also exclude the same decisions. Exclusion is a decision given by the B&B process to improve the lower or upper bound for $\mathbb{M}$. It might not necessarily be the best decision for optimality. When this is the case, $\mathbb{M}$ should search for removing at least one decision included in the current solution to achieve a different feasible solution. Otherwise, it should not affect the global lower bound. The lower bound provided by $\mathbb{S}$ is valid for a unique solution and does not affect the lower bound for globally feasible solutions by providing a feasible relaxation to the synchronized two-echelon problem.

Eq. (3.61) does not provide a better lower bound than the global lower bound if excluded decisions for any feasible solution to $\mathbb{M}$ differ by at least one. When this is not the case, it is a valid cut because the only possibility for a different feasible solution is to have the same routing and change transfer decisions in the current solution. The linear part ensures a lower bound based on shadow prices of the decisions on the arcs with transshipment.

Solution time accelerating strategies

To accelerate the LBBD method, $\mathbb{M}$ is first solved to obtain initial solutions without checking the feasibility. Then, these solutions are tested using $\mathbb{S}$ to provide an upper bound for the model. In this way, expensive subproblems are eliminated for the solutions in the beginning. Additionally, the subproblems are solved with a time limit to minimize the time to achieve optimality for intermediate solutions. However, the relaxations of the subproblems are solved optimally to obtain dual values and the integrated lower bound of the solutions. A master feasible solution might be feasible for the subproblem relaxation. However, it might not improve the incumbent solution by yielding a sub-optimal solution for the synchronized two-echelon problem. In the case of sub-optimal solutions during B&C, optimality cuts by (3.61) are added to the $\mathbb{M}$ as lazy constraints for the master feasible solutions, providing a feasible subproblem relaxation to improve the lower bound. However, feasibility cut by (3.59) is also added to the model to cut off the solution.

3.5 Computational results

In this section, we introduce the data set used in the experimental study and present the results. The problems are solved by a commercial solver, Gurobi 9.12. The master problems are solved using lazy callbacks for each feasible solution, as documented in the Gurobi manual (Gurobi Optimization 2021). The test are conducted using 4 CPUs on Intel(R) Xeon(R) Gold 5218 with 2.30 GHz clock speed. For the solution methods, the time limit is 4 hours (14400 s) regarding the extent and the scale of the problems solved in this study. Furthermore, the time limit to optimize the subproblems is set to 50 seconds for the instances up to 30 demand nodes, while it is set as 100 seconds for the instances with 100 nodes. The same time limits are used for initial solution generation at the beginning of the proposed LBBD approach.

3.5.1 Test instances

Grangier et al. (2016) introduce and solve the 2E-MVRP-SS with no storage option using a customized ALNS by rescheduling operations after an insertion to prevent time window violations, with linear complexity in the size of the route. The linearity depends on the assumption that many transshipment operations can be handled at the satellites at any time and these operations happen instantly, without causing delays due to the loading/unloading of the goods. However, it removes the resource synchronization problem at the satellites and only accounts for the delays in visiting the satellites. The 2E-MVRP-SS with unitary transshipment is proposed to schedule transshipment operations to the available satellites with no storage, ensuring that the real-time capacities are not violated. Since it has not been studied in the literature, we first describe the test instances used in the experiments.

Network: The instances are generated by modifying Solomon's (1987) VRPTW instances for the geographical configuration of the demand network. Solomon class "2" instances are considered with relatively wider time windows and long scheduling horizons to let LEFVs have multi-trips.

To generate problems of varying sizes, we utilize the initial $|C|$ nodes from the given Solomon instances. For each size, three types of demand distribution are considered. The "C" type comprises 8 instances where customers are concentrated in clusters, while the "R" type consists of 11 instances with customers randomly located throughout the area. As a mix of R and C, the third type "RC" includes 8 instances where customers are either clustered or randomly positioned.

To ensure the feasibility of the instances for 2E-MVRP-SS with unitary transshipment, the time windows for satellites and the central depot are the same as the garage defining the working hours of all the vehicles and set to the latest possible return time from any customer in the demand set. The return time assumes the latest possible service start time at a customer and the furthest satellite to visit to perform the last transshipment before vessels return to the depot. This limits the feasible number of transshipment operations in time at the satellites after the daily customer service is completed. It prevents SL vehicles from queuing at the cheapest satellites and waiting long enough for the vessels to minimize the SL logistics costs.

For the water level network, the satellites and the vessel central depot are located outside the city, while the general practice is to locate them in urban areas. Keeping the transfer operations away from the public is primarily motivated by our previous study on waste collection (Karademir et al. 2022b). This assumption reduces the concerns and related costs about inconveniences caused by transfer operations, such as noise, congestion, and reduced mobility due to the lack of space in the city.

In total, 4 satellites and a vessel central depot, d, are located for all problems tested in this study ranging from 10 to 100 customer nodes for different scenarios. The satellites are positioned at the midpoint of every side of the map that covers all of the demand nodes. The assumed locations of the satellites are depicted in Figure 3.4 in Section 3.5.4 for different demand distributions. We further examine this assumption by using several rules based on the proximity to the centroid of the demand network.

Vehicles: To better observe multiple trips and transfer tasks, the capacity of a LEFV is set to 50 units, and the capacity of a vessel is set to 250 units. The distance and travel duration along any arc are defined to be equal to the Euclidean distance between the nodes on that arc. For all computations, the fleet size of each level is assumed to be unlimited to observe at least a feasible solution. Lastly, U is assumed to be twice the average service duration of the customers, rounded up.

Objective: We use a lexicographic objective to prioritize the fleet size over the travel cost, meaning that any solution with fewer vehicles is superior to any other with more vehicles at any level. However, the model is highly dependent on the relative costs of the levels to minimize the total cost on one level further over the cost of the other level. Estimating the fixed cost of using vehicles for logistics and determining the optimal number of vehicles for a single-echelon VRP can be challenging. The larger the fixed cost, the less the model focuses on improving the travel cost. It might lead to early termination due to the smaller gaps considering large fixed cost values for the vehicles. The smaller the fixed cost, the more the model works on improving the travel cost. However, the minimum travel cost does not always guarantee the minimum number of vehicles. Therefore, it is important to choose the parameters wisely to reflect the priorities of the stakeholders. To reduce the effect of the cost parameters on the experiments, we consider a reference value for each cost parameter. Then, the parameters are multiplied by the importance ratio defined by the user based on the purpose of the experiments.

For the travel costs on both networks, we assume $\underline{c} = 1$, implying that navigating on the streets per unit of time is equal to the one on the waterways. For the fixed costs, the maximum travel cost of serving a customer requires a visit to the customer by a LEFV and another visit to a satellite by the LEFV and a vessel for transferring the collected items. In other words, a customer service costs two vehicles in a two-echelon setting. The maximum value guarantees that fewer vehicles are preferred over travel costs since the smallest fleet does not necessarily always achieve the smallest travel costs.

$$\underline{\beta}(c^s, c^w) = \max_{i \in C,\, p \in S} \{c^s(t_{gi} + t_{ip} + t_{pg}) + c^w(t_{dp} + t_{pd})\} \tag{3.62}$$

Since the fixed cost is the worst possible route for a LEFV and a vessel to serve, it is always larger or equal to the serving in an existing route if possible. The fixed costs of the vehicles help the model decide whether it is cheaper to serve a customer or a transfer in an existing route or use a new vehicle to serve it.

For all experiments, the reference values are calculated for each instance. Then, the user chooses a *water level significance (WLS or* α*)*, the relative importance of water level logistic costs compared to the street level cost. The values for the water level are updated as the multiplication of the reference values, $\left[c^s, c^w, \beta_s, \beta_w\right] = \left[1, \alpha, \underline{\beta}(1,\alpha), \alpha\underline{\beta}(1,\alpha)\right]$. The instances and models can be accessed online for future uses of the problems discussed and solved in this chapter. [2]

3.5.2 Performance of the proposed methods

This study proposes two models to solve 2E-MVRP-SS with unitary transshipments: the joint MILP described in Section 3.3.2 and the LBBD method outlined in Section 3.4.3. Table 3.3 provides an overview of the proposed methods for analyzing the value of using a decomposed approach for highly complicated and integrated problems. We conduct tests on various problem sizes for each instance, considering 10, 20, or 30 demand nodes ($|C|$) and 4 satellites ($|P|$). *WLS* is set as 1:10 for the cost parameters, prioritizing the minimization of street-level logistic costs due to congestion-related issues addressed by the 2E-MVRP-SS in this study. First, the results for the joint MILP are presented. Then, the results for LBBD are provided, with the percent improvement of the solution quality compared to the joint MILP. Lastly, we provide averages across all instances within the same size for both methods.

The first set of instances with 10 demand nodes is easily solved by both methods. This confirms that the proposed LBBD can find optimal solutions for all instances with different time window structures, geographical distributions, and cargo loads at the demand nodes. When the size of the demand network increases from 10 to 20, both methods face difficulties in solving the problems due to the complexity of the joint MILP and the inherent weaknesses of the underlying MDVRPTW, i.e., the master problem. However, LBBD manages to provide near-optimal solutions, improving the best-known solutions by 0.5% on average. The maximum optimality gap, 5.3%, is for the instance $R205$, a randomized network with tight time windows, where the Lagrangian bound is weaker for the global optimality. The performance of LBBD becomes particularly evident when analyzing the last set of instances, which consists of 30 demand

[2] https://github.com/cigdemkarademir/2echelon-synchronization

Table 3.3: Comparative results on test instances.

Size	$\lvert C\rvert = 10, \lvert P\rvert = 4$						$\lvert C\rvert = 20, \lvert P\rvert = 4$						$\lvert C\rvert = 30, \lvert P\rvert = 4$					
Method	Joint MILP			LBBD			Joint MILP			LBBD			Joint MILP			LBBD		
Instance	BK	Gap %	Inc. Time(s)	BK	Imp. %	Inc. Time(s)	BK	Gap %	Inc. Time(s)	BK	Imp. %	Inc. Time(s)	BK	Gap %	Inc. Time(s)	BK	Imp. %	Inc. Time(s)
C201	365.5	0	0	365.5	0.0	1	697.7	0	4	697.7	0.0	2	1011.9	0	1313	1012.5	0.1	113
C202	327.5	0	18	327.5	0.0	12	678.7	22	1690	678.7	0.0	241	876.4	32	9620	**854.9**	-2.4	4235
C203	327.5	0	19	327.5	0.0	14	682.7	54	8395	**676.3**	-0.9	1649	1047.2	52	10406	**843.6**	-19.4	6006
C204	304.3	0	78	304.3	0.0	2	683.5	57	2261	**668.1**	-2.3	380	902.9	62	11985	**810.8**	-10.2	2663
C205	365.5	0	1	365.5	0.0	1	685.2	0	69	685.2	0.0	99	869.6	10	4735	869.6	0.0	194
C206	365.5	0	2	365.5	0.0	9	680.8	0	137	680.8	0.0	133	853.7	10	4212	**847.5**	-0.7	3081
C207	365.5	0	1	365.5	0.0	0	681.8	23	1258	**678.8**	-0.4	428	836.9	35	7128	843.3	0.8	687
C208	358.4	0	6	358.4	0.0	2	678.1	0	2457	680.3	0.3	14	845.5	42	5856	**835.7**	-1.2	324
R201	420.1	0	0	420.1	0.0	0	821.7	0	102	821.7	0.0	50	1048.8	2	6757	1048.8	0.0	143
R202	387.8	0	22	387.8	0.0	11	757.0	19	11478	**756.7**	0.0	243	1046.8	49	13800	**1003.0**	-4.2	5179
R203	387.8	0	23	387.8	0.0	12	638.4	37	12783	**635.8**	-0.4	1710	999.9	54	10185	**919.8**	-8.0	6090
R204	351.4	0	61	351.4	0.0	1	605.7	42	5713	605.7	0.0	3036	929.3	55	9735	**851.1**	-8.4	2015
R205	376.4	0	2	376.4	0.0	1	642.2	0	1990	676.3	5.3	529	1017.6	40	6300	**968.5**	-4.8	2401
R206	327.6	0	32	327.6	0.0	1	612.9	31	7405	**603.8**	-1.5	517	950.1	50	9933	**914.0**	-3.8	6695
R207	327.6	0	31	327.6	0.0	1	601.7	36	8972	605.4	0.6	2747	969.9	55	8144	**914.5**	-5.7	6204
R208	327.6	0	54	327.6	0.0	1	549.9	37	11009	549.9	0.0	809	931.2	56	8706	**884.6**	-5.0	3532
R209	362.1	0	4	362.1	0.0	1	626.3	6	10974	626.3	0.0	99	1071.7	53	7514	**933.9**	-12.9	4303
R210	353.4	0	9	353.4	0.0	7	647.1	11	3954	**632.8**	-2.2	3158	1024.6	36	3302	**937.3**	-8.5	2760
R211	344.5	0	15	344.5	0.0	2	669.1	48	10782	**584.4**	-12.7	1316	964.9	57	13067	**900.3**	-6.7	1618
RC201	392.8	0	1	392.8	0.0	0	981.2	0	27	981.2	0.0	168	1712.7	11	2321	**1665.5**	-2.8	1896
RC202	356.5	0	55	356.5	0.0	8	906.4	44	5928	906.4	0.0	751	1641.9	60	10662	**1413.4**	-13.9	1984
RC203	356.5	0	51	356.5	0.0	7	754.3	56	8413	767.6	1.8	2947	1589.6	70	3490	**1379.3**	-13.2	4536
RC204	320.2	0	86	320.2	0.0	1	642.4	50	10375	642.4	0.0	3763	1336.6	71	13249	**1273.9**	-4.7	1927
RC205	440.6	0	71	440.6	0.0	24	935.5	15	1098	938.4	0.3	570	1639.7	39	3705	**1597.7**	-2.6	2571
RC206	363.1	0	5	363.1	0.0	1	885.2	28	1149	885.2	0.0	837	1395.6	26	13448	**1384.6**	-0.8	442
RC207	364.4	0	4	364.4	0.0	1	885.0	26	4242	888.7	0.4	13	1705.9	64	4718	**1602.3**	-6.1	12293
RC208	318.7	0	210	318.7	0.0	2	881.6	65	4166	**858.7**	-2.6	1478	1353.9	71	8681	**1293.0**	-4.5	6252
Averages	*357.7*	*0.0*	*31.9*	*357.7*	*0.0*	*4.5*	*722.7*	*26.2*	*5067.8*	*719.0*	*-0.5*	*1025.3*	*1132.4*	*43.0*	*7887.8*	*1066.8*	*-5.5*	*3338.6*
Run time (s)			*197*			*11*			*10554*			*9192*			*13346*			*13365*
Initial solution				*357.8*						*747.7*						*1197.0*		

BK: The best-known solutions to the methods, *Inc. Time*: The time it takes to find the best-known solution, *Gap%*: The percent gap reported by the solver for the joint method, *Imp.%*: The percent improvement of the *BK* of LBBD compared to the *BK* of the joint MILP. The time limit is 14400 secs for both models.

nodes. LBBD provides an improved solution for 23 out of 27 instances, with improvement ranging from 0.7% to 19.4%, while the joint method only improves two of them, *C*201 and *C*207. To maintain the best feasible lower bound, the LBBD ignores the solutions that do not improve the global lower bound but still can improve the upper bound. On average, it takes less than half the time compared to the joint model to achieve a 5.5% improvement for all problems.

Initial solutions for 10-node problems are the optimal solutions for MDMVRPTW, the minimum cost schedules for the SL problem. However, for instances *R*202 and *R*203, it does not guarantee global optimality. Furthermore, the initial solutions provide feasible solutions within a 0.2%, 3.4%, and 5.7% gap compared to the joint MILP for the instances with 10, 20, and 30 demand nodes, respectively. Using the subproblems for checking up on the feasibility of the SL solutions indicates the potential of the proposed decomposition approach to provide better upper bounds within shorter times. These solutions are further improved by the LBBD using the Lagrangian lower bounds and consecutively analyzing more solutions to the SL problem toward the global optimality.

The proposed LBBD method offers an effective approach for tackling complex mixed integer combinatorial problems. It leverages existing knowledge to solve simpler problems at the master and subproblem levels.

3.5.3 Impact of cost coefficients

In designing an IWLT system, a system designer must assess the feasibility and cost-effectiveness of intermodal transportation, which involves transferring goods from roads to waterways. Therefore, in this section, we analyze the relative importance of logistics costs on the water level and street level.

To reflect the implications of multi-level hierarchical objectives in synchronized environments, an analysis of the relative importance of different levels' logistics costs is conducted from a methodological perspective. Different scenarios are created by adjusting the cost ratio between water level (WL) and street level (SL) cost parameters, which is referred to as *WLS* in Section 3.5.1. The scenarios include:

i. SL costs are significantly higher than WL costs (WLS = 1:10).

ii. SL costs are five times higher than WL costs (WLS = 1:5).

iii. A balanced scenario where WL and SL costs are equal (WLS = 1:1).

iv. WL costs are significantly higher than SL costs (WLS = 10:1).

Considering significant changes in the cost scenarios, the proposed methods are tested on instances with 10, 20, and 50 demand nodes for convergence and solution quality. The objective is twofold: to analyze the trade-offs associated with IWLT systems and to verify the LBBD method under the laid out experimental setting in Section 3.5.1. Hence, we present the average results of the methods in Table 3.4, first for the overall solution quality and then for each objective component, including the number of used satellites in the solutions.

The results of 10-node scenarios verify that the LBBD method converges to solutions within 1% of the optimal values found by the joint MILP across various cost configurations. For problems with 20 and 50 nodes, the LBBD method provides better solutions on average and reaches those solutions much faster than the joint MILP. LBBD is especially superior for the problems with 50 nodes, improving the total cost by 4.9% on average and achieving better metrics on both levels regarding the total travel and fleets. The results of the scenario with 20 nodes and WLS set to 1:5 indicate that the multiple solutions with the same objective value result in different schedules. Regarding fleet size minimization, LBBD can reduce street vehicles more than the joint model when WL significance increases. Across all scenarios, the decomposed model achieves the lower bounds for the vessels in terms of cargo load, while the joint MILP struggles with fleet optimization on both levels when the size increases to 50 nodes.

The master problem in LBBD is intentionally formulated in a simplified way to reduce the complexity of optimizing street-level operations to improve city logistics while seeking global optimality. It ignores the water level and synchronization problems, focusing solely on spatial synchronization costs for a given

Table 3.4: Performance with respect to cost parameters and problem scale, $|P| = 4$.

						Average travel distance			Fleets		Used
$\|C\|$	WLS	Method	BK	Inc. time	Gap/Imp.%	Total	Streets	Waterways	SL	WL	satellites
10	1:10	Joint MILP	357.7	31.9	0.0	381.9	207.9	174.1	1.00	1.00	2.8
		LBBD	357.7	4.5	0.0	381.9	207.9	174.1	1.00	1.00	2.8
	1:5	Joint MILP	403.5	40.7	0.0	364.3	210.9	153.4	1.00	1.00	2.3
		LBBD	403.5	7.1	0.0	364.3	210.9	153.4	1.00	1.00	2.3
	1:1	Joint MILP	851.5	205.0	0.0	334.1	247.4	86.7	1.00	1.00	1.0
		LBBD	854.5	19.2	0.4	337.1	247.7	89.4	1.00	1.00	1.0
	10:1	Joint MILP	19,330.8	101.4	0.0	343.8	262.7	81.0	1.00	1.00	1.0
		LBBD	19,337.4	29.4	0.0	346.8	265.3	81.4	1.00	1.00	1.0
20	1:10	Joint MILP	722.7	5,067.8	26.2	785.8	404.9	380.8	1.59	2.00	3.8
		LBBD	719.0	1,025.7	-0.5	786.8	401.9	385.0	1.59	2.00	3.9
	1:5	Joint MILP	833.0	5,910.1	26.6	773.6	407.8	365.8	1.59	2.00	3.6
		LBBD	833.0	2,218.0	0.0	782.0	397.9	384.1	1.63	2.00	3.6
	1:1	Joint MILP	1,961.4	7,031.2	22.5	717.2	448.1	269.1	1.63	2.00	2.3
		LBBD	1,939.8	2,741.4	-1.1	723.6	447.6	276.0	1.56	2.00	2.3
	10:1	Joint MILP	51,167.3	6,819.3	5.0	781.1	538.6	242.4	1.68	2.00	1.6
		LBBD	50,903.9	3,198.9	-0.5	734.8	485.0	249.7	1.56	2.00	1.6
50	1:10	Joint MILP	1,989.3	12,007.9	58.0	2,017.3	1,117.4	899.9	3.81	3.89	4.0
		LBBD	1,941.8	5,107.3	-2.4	1,951.0	1,099.4	851.6	3.70	3.59	4.0
	1:5	Joint MILP	2,361.9	12,404.6	57.1	2,051.6	1,165.4	886.1	4.04	3.85	4.0
		LBBD	2,250.5	4,867.4	-4.7	1,924.2	1,101.4	822.8	3.89	3.59	3.9
	1:1	Joint MILP	5,477.0	12,269.1	45.2	2,096.5	1,312.9	783.7	4.26	3.63	3.5
		LBBD	5,021.8	5,615.6	-8.3	1,918.1	1,173.1	745.0	3.70	3.59	3.7
	10:1	Joint MILP	124,438.2	13,248.9	12.5	2,436.7	1,703.7	733.0	5.04	3.59	3.1
		LBBD	119,488.7	8,436.3	-4.0	2,089.9	1,428.7	661.2	3.67	3.59	2.8

BK: The best-known solutions to the methods, *Inc. Time*: The time it takes to find the best-known solution, *Gap/Imp.%*: The percent gap reported by the solver for the joint method/The percent improvement for the *BK* of LBBD compared to the *BK* of the joint MILP. The time limit is 4*h* for both models. 27 instances in the test data are averaged for each scenario.

solution. Consequently, the convergence requires LBBD to explore all feasible routes for street-level operations while considering only the cheapest spatial synchronization. In contrast, the joint model can utilize the relationships between transfers and satellite assignments to aid in proving optimality. Nonetheless, LBBD remains a stronger method for finding feasible solutions within shorter computational times compared to the joint model.

Among all the analyzed scenarios, the balanced scenario with equal costs, WLS = 1:1, achieves the minimum average travel distance in total. The balanced scenario provides a lower bound on the cost of the IWLT system where fleets are first minimized, then the travel cost. This indicates that generating cost scenarios based on *WLS* can minimize a lexicographic objective of an IWLT system if the relative cost parameters are available. The LSPs can use it as a guide to prioritize different components of the objective. If the objective is to improve the logistics costs on the streets, they can reduce the *WLS* value, meaning that WL costs are less significant than SL costs. Conversely, they can increase *WLS* value to prioritize the logistics cost over waterways for further reduction up to its lower bound.

The value of the *WLS* parameter further highlights the significance of integrated modeling for achieving global optimality. Traditional approaches often involve separate optimization problems that oversimplify the limitations of upstream or downstream processes. In the balanced scenario, as expected, the street or waterway distances are not minimized to their best possible values. Better solutions occur in different scenarios when the model significantly favors one component over the other. Disregarding the integration costs and solving problems independently at each level can result in asynchronous schedules for upstream or downstream operations.

Another observation is that significantly expensive WL operations lead the solution to locate the minimum number of vessels across all scenarios at the satellites without any visit or with very few visits between satellites. It converges to a two-echelon location routing problem (2E-LRP) where the most important decisions are to locate the satellites to visit. The average number of satellites used in the WLS = 10:1 scenario is 1.0, 1.6, and 2.8 for the problems with 10, 20, and 50 nodes, respectively, choosing the same or as few satellites as possible for all transshipment operations compared to the number of the vessels used in the solutions. When SL is expensive, it uses almost all available satellites to further reduce the cost on the streets. These observations suggest the need for improvement in the relaxed cost formulation of the master problem considering explicit satellite assignments, particularly regarding spatial synchronization when the cost parameters prioritize the water level problem. Therefore, it is important to design the solution methods regarding the cost parameters and their effect on the system to understand the economic benefits of the IWLT systems better.

3.5.4 Impact of satellite locations

In this study, we assume that satellites are positioned on the outskirts of cities to minimize infrastructure investments and inconveniences associated with transfer operations. According to Crainic et al. (2010), the maximum benefits of two-echelon systems are achieved when the satellites are situated between the central depot and the customers. Increasing the proximity of satellites to customers reduces the distances traveled to visit the satellites. However, it is still challenging to define closeness in highly integrated and synchronized systems.

To analyze the extent of the benefits of the proposed IWLT system, we test the satellite locations by using different proximity values and *k-means* clustering. Proximity values indicate the distance between the satellites and the edges of the service area, as shown in Figure 3.4. The values allow us to proportionally move the satellites along the radius toward the center and analyze the savings associated with locating transshipment operations closer to the city center, where the garage is generally located. We use the k-means algorithm to minimize the sum of distances between demand nodes and satellites by locating the satellites at the centroids of 4 clusters. The use of k-means is to assess the economic gains associated with placing satellites closer to the demand points without considering the cost of the satellites, inconveniences related to transshipment operations, or the feasibility of reaching the waterways. The instances are solved by the LBBD method based on its performance on the cost analysis.

Figure 3.4 presents a summary of the results obtained from the satellite location scenarios, provided with the percentage increase in the total distance costs compared to the base scenario, where proximity equals 0. The results are categorized based on the demand distribution types to analyze the effectiveness of location policies and verify the LBBD method considering different service networks. For each scenario, the LBBD method achieves the lower bound on the required number of vessels, which are 4, 3, and 4 for C, R, and RC type problems, respectively. Overall, the k-means algorithm for satellite locations outperforms proximity-based locations by minimizing the travel time between satellite and customer visits on the streets. It reduces the total travel time more than any proximity value, achieving 21.3, 15.5, and 5.2% improvements on average for C, R, and RC type problems, respectively. On the other hand, the integrated systems, regardless of the demand distribution, work better when satellites are located at the outer rings instead of the inner rings. On average, across all problems, total travel time increased by 15.3, 6.6, 6.8, 14.0, and 21.2% for proximity values 0 to 0.4 compared to k-means. With the same number of vessels at the lower bounds, k-means achieves the best average street-level fleet at 3.61, but fleet requirements vary with travel time (3.76, 3.64, 3.87, 3.97, 4.39) for proximity-based locations. Among them, the proximity scenario with a value of 0.1 optimizes the problems better on average in terms of fleet size and overall travel time compared to k-means, likely due to its geographical superiority in capturing the spatial demand centroids for the problems solved in this study.

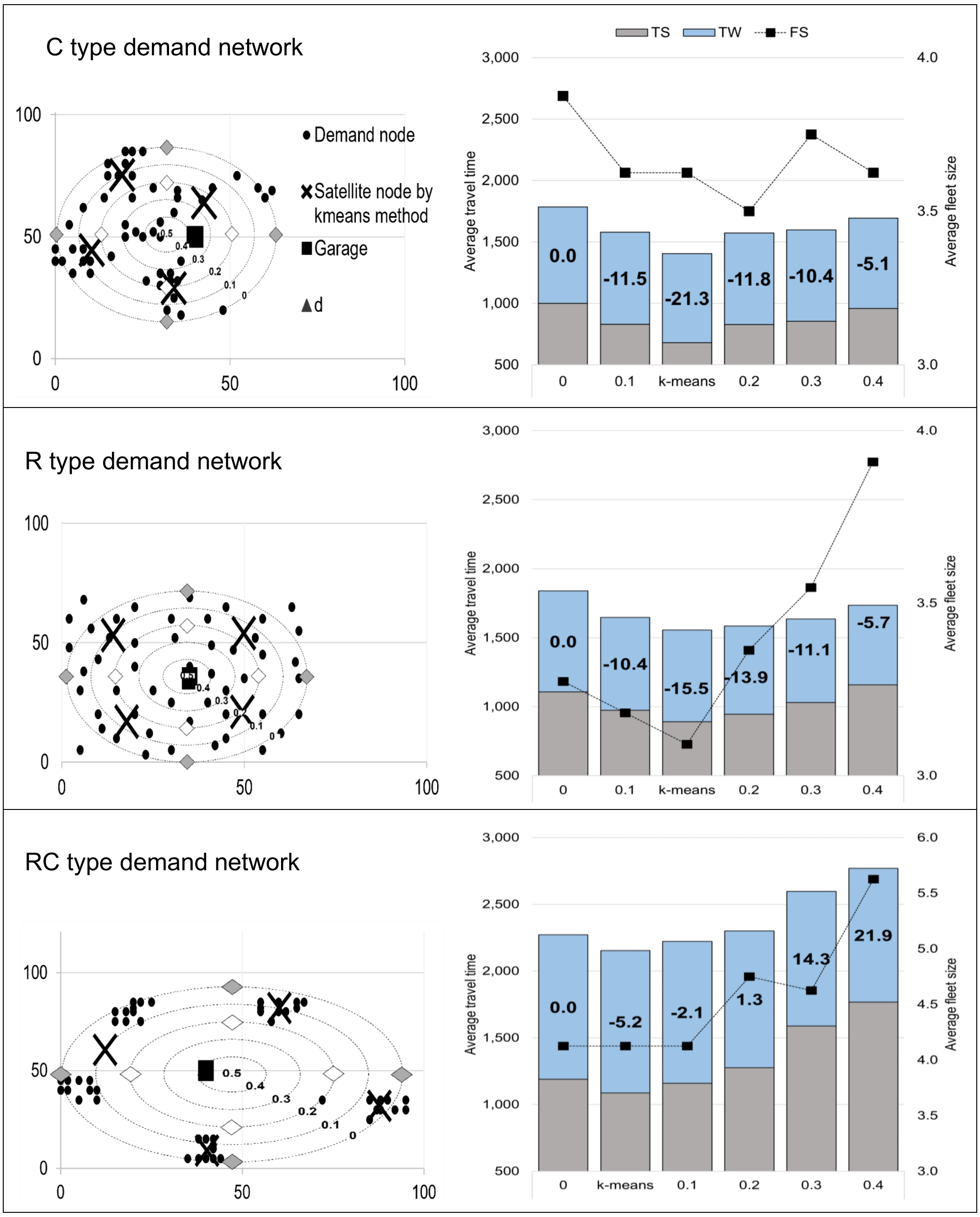


Figure 3.4: *Comparison of different satellite locations across clustered (C), random (R), and random clustered (RC) customer distributions with 50 customers and 4 satellites (|C|=50, |P|=4). For each type, on the left, the satellite location scenarios with different proximity values are illustrated as diamonds, and k-means centers are shown as crosses. On the right, the results are ordered by the proximity values, and the k-means scenario is placed at the intersection of two consecutive proximity scenarios closest in total costs for each distribution type. The percentage savings are reported for each scenario in terms of total travel time with respect to the base scenario, shown as gray diamonds for the demand network of each type on the left. The time limit is 4h for both models. 8, 11, and 8 instances in the test data are averaged for C, R, and RC type distribution scenarios, respectively. WLS = 1:10.*

The costs of the proximity measures are proportional to the distances between the corresponding located satellites and k-means centers. For C type problems, these centers lie between 0.1 and 0.3, where the best SL travel is achieved by the k-means method, and the best fleet is achieved by the proximity value at 0.2. It also represents the closest scenario with respect to the k-means centers by locating the satellites in the middle ranges of these centers. The presence of randomness in the locations of demand nodes complicates the problem of locating satellites. Ignoring the temporal distance between demand points in the existence of time windows and synchronization might lead to several visits to the satellites at different points of the day.

For R type problems, where there are no clear centers in the demand network, the savings become marginally proportional to the savings in the SL distances. However, these changes affect the fleet size requirements by delaying the arrival time at the customers with time windows. On the other hand, RC type problems present the demand networks where randomly distributed clusters exist. It becomes more significant to locate the satellites closer to k-means centers, lying between proximity values at 0 and 0.1. These proximity scenarios contain the k-means centers and differ slightly in total distances. However, centralizing the satellites at 0.4 proximity value for these problems only deteriorates the logistics costs without improving the trip lengths.

3.5.5 Service design alternatives

This section presents and evaluates various design alternatives that have been considered in the literature and in practice. The aim is to obtain managerial insights for the possible implementation of IWLT systems for city logistics.

Alternative systems

Alternative systems are first classified according to the service network design of interest, analyzing systems with or without an integrated synchronized fleet as a secondary echelon. Next, we evaluate the impact of adopting new technologies in city logistics in comparison to the trucks primarily used by LSPs. For a fair comparison, we do not allow multiple trips for large vehicles (e.g., trucks) in the proposed alternative systems either, as the multi-trip aspect of the vessels is left out of the scope of this study for the sake of simplicity.

Single-echelon systems: City freight vehicles are the sole resource of these services, operating between pickup demand points in cities and transferring freight goods at a central depot. The proposed model is modified to change the service network to a single echelon by locating satellites at the central depot. We assess two vehicle type choices operating on the roads regarding their sizes and fuel types.

- *Only trucks:* Most of the current practices rely on large fossil-fueled vehicles, but LSPs now need to explore other options to comply with regulations. Therefore, one might consider the system with heavy trucks as a benchmark to analyze the trade-offs between current practices and alternatives.

  Only trucks system assumes the fleet is composed of cargo trucks as the SL freighters have limited access in cities due to the restrictions. Trucks serve many customers in a single trip and are not allowed to perform multiple trips. To prevent multiple trips, the number of vehicles on the street is limited to the number of transfers.

- *Only LEFVs:* New technologies are promising to be viable and cost-efficient vehicles for LSPs to reach customers in the existence of restrictions. Therefore, one might consider the system with LEFVs to analyze the effect of new technologies with limited capacities.

  Only LEFVs system assumes the fleet is composed of LEFVs that are five times lighter than trucks in size. They can perform multiple trips but need to visit the central depot whenever necessary.

Two-echelon systems: LEFVs and vessels constitute the primary and secondary resources of the services. Together, they perform the first and last mile of the logistics service, respectively within a synchronized IWLT system. We evaluate two vehicle type choices operating on inland waterways in

Table 3.5: Service design alternatives.

Service design	Single-echelon systems		Synchronized two-echelon systems	
Alternative system	Only trucks	Only LEFVs	IWLT-Stationary	IWLT-Flexible
SL freighters (capacity)	Trucks (250)	LEFVs (50)	LEFVs (50)	LEFVS (50)
WL freighters (capacity)	-	-	Barges (250)	Vessels (250)
Sailing between satellites	-	-	✗	✓
Location of satellites	Central depot (d)	Central depot (d)	proximity = 0.1	proximity = 0.1
Optimization problem	VRP	MVRP	2E-LRP-SS	2E-MVRP-SS

terms of their operational costs for achieving spatial synchronization. The proposed two-echelon systems can also be applicable to other modes of transport for the integration of transshipment activities with existing transportation services. This could be achieved by adjusting the locations and time intervals of satellites to accommodate different types of vehicles, such as trams, trucks, or trains. While the number of satellites increases the complexity of the joint MILP, it only affects the subproblem of the proposed LBBD.

- *IWLT-Stationary:* Traveling over waterways between satellites might be expensive, inefficiently slow, or restricted due to network capacity or safety reasons during the day. Then, one might consider a stationary vessel system that uses satellites as fixed depots and vessels as temporary safe storage spaces.

  The IWLT-Stationary system assumes that vessels are delivered to the best possible satellites before the operations and located there until the end of operations. We consider barges as the vessel type that can act well as storage spaces and be moved efficiently by tugboats. The problem minimizes the number of satellites used at least once for transshipment operations.

  The proposed model is modified to prevent any movements between satellites other than moving the barges to the satellites by only letting positive f^s_{ij} from/to the central depot. Due to the capacity limitations requiring unitary transshipment at the satellites, we also set the fleet size to the lower bound to contain all the cargo load. In the cases of a limited number of satellites compared to demand, multiple barges might be necessary at the satellites to handle the workload.

- *IWLT-Flexible:* The more flexible the water level transportation operates, the more an IWLT system addresses the issues related to congested cities. Traveling over waterways might become easy and cheap enough thanks to the advancements in autonomous sailing and the high level of water network accessibility in populated cities such as Amsterdam, Brussels, New York, etc. (Janjevic & Ndiaye 2014). Then, one might consider a flexible vessel system operating over water between satellites as a viable alternative to reduce the global cost of the system.

  The *IWLT-Flexible* system assumes that vessels are large electric vehicles that can visit any satellite at any time, as proposed in this study. Vessels act as mobile depots in contrast to the stationary system and sail between satellites.

Modeling and testing the alternative systems

The proposed methods can solve all the alternative systems by changing the service network and limitations accordingly. In each alternative scenario, all vehicles respect the latest return time defined in Section 3.5.1. For single-echelon networks, the transshipment operations are performed at the central depot by trucks or LEFVs only. Therefore, satellites are located at the central depot, where non-overlapping transshipment operations are executed for U units of time. However, there is no prioritization problem at the satellites due to the unitary transshipment if the number of satellites is more than or equal to the fleet size. Therefore, we model *Only trucks* and *Only LEFVs* systems as a VRP and MVRP, respectively, for the single echelon systems. For the two-echelon networks, it eliminates any movement between the satellites for the *IWLT-Stationary* case. Synchronized unitary transshipment operations ensure that the barges will be replaced when needed and the goods are stored on the barges one by one. Therefore, we model *IWLT-Stationary* and *IWLT-Flexible* systems as multi-trip 2E-LRP-SS and 2E-MVRP-SS for the two-echelon systems. Overall, these methods enable the evaluation of different design alternatives and assist decision-makers in optimizing service network design and operations with multiple objectives in mind.

Test instances consist of different numbers of demand nodes, ranging from 10 to 50, and 4 satellites are located at the 0.1 proximity value for two-echelon systems and at the depot for single-echelon systems. We assume that the larger vehicles (trucks, barges, sailing vessels) are five times bigger in storage capacity than LEFVs. Furthermore, WLS is set to 1:10 for the two-echelon systems to minimize the SL costs as much as possible. Table 3.5 summarizes the settings for the proposed alternative systems.

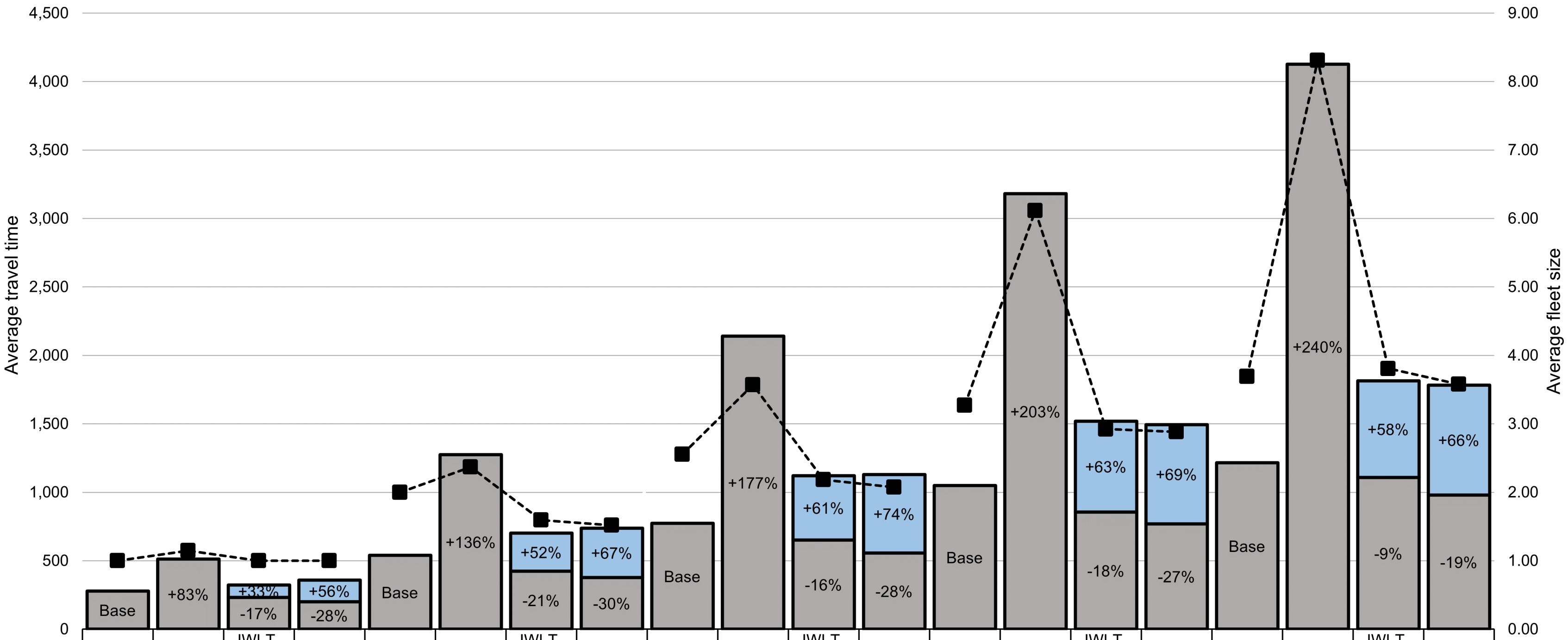
Based on the performances of the methods discussed in Section 3.5.2 and the verification of the proposed LBBD on changing cost parameters, the alternatives are successively solved using the proposed LBBD as outlined for two-echelon systems. For single-echelon systems, spatial synchronization is included at the master level, precisely considering the depot for satellite assignments. Hence, the cost of the master problem is always the same as the subproblem for a given solution, if feasible. Infeasibility occurs due to the ignored synchronization constraints of the transfers at the satellites located at the depot. To address this, the subproblem is employed only to assess the feasibility of transfers at the depot and eliminate infeasible solutions accordingly.

Evaluation of the alternative systems

For the LSPs, the first goal of assessing different alternative designs is to switch from large trucks to economically viable lighter vehicles. Therefore, the *Only trucks* system is compared to the three alternatives as the base scenario. The average results on the test instances are presented in Figure 3.5. The data table in the figure provides the detailed costs on the streets for all alternatives and on the waterways if applicable. Additionally, we provide increases or reductions in traveled time on both levels as a percentage change compared to the base scenario. The values for the water level of the two-echelon systems represent the relative ratio of the traveled time on waterways to the traveled time on the streets of the base scenario, providing the extra logistics needed to be performed on the waterways.

Electrified fleets offer several advantages, including low operating, environmental, maintenance, and repair costs, excluding battery change. However, the high investment costs associated with acquiring electric vehicles hinder service providers from adopting these promising alternatives (Carrese et al. 2021), hence, they prioritize smaller and cheaper fleets. On a positive note, policymakers have been actively working on subsidies for electric vehicles in commercial applications. Besides promoting emission-free cities, the policies also favor fewer vehicles in urban areas. Comparing different scenarios, the *Only LEFVs* benchmark requires a larger fleet of vehicles on the streets in all instances. In contrast, the two-echelon systems achieve the same service level with fewer vehicles. Additionally, the *IWLT-Flexible* system further reduces the number of LEFVs needed. Furthermore, overall for each size, the *Only LEFVs* systems cause increases in total travel time by approximately 4 times of the two-echelon systems. The integration allows LSPs to initially invest less in new vehicle technologies and support these vehicles with more conventional larger vehicles in less restricted zones.

The results presented in Figure 3.5 highlight the significant advantages of IWLT systems in terms of



	Only trucks	Only LEFVs	IWLT-Stationary	IWLT-Flexible	Only trucks	Only LEFVs	IWLT-Stationary	IWLT-Flexible	Only trucks	Only LEFVs	IWLT-Stationary	IWLT-Flexible	Only trucks	Only LEFVs	IWLT-Stationary	IWLT-Flexible	Only trucks	Only LEFVs	IWLT-Stationary	IWLT-Flexible
	Single echelon		Two-echelon		Single echelon		Two-echelon		Single echelon		Two-echelon		Single echelon		Two-echelon		Single echelon		Two-echelon	
	|C| = 10				|C| = 20				|C| = 30				|C| = 40				|C| = 50			
TW			92	156			278	359			468	573			664	723			707	803
TS	279	512	232	202	539	1,274	423	379	774	2,140	652	556	1,049	3,181	856	770	1,215	4,127	1,108	981
FW			1.00	1.00			2.00	2.00			2.56	2.56			3.27	3.27			3.58	3.58
FS	1.00	1.15	1.00	1.00	2.00	2.37	1.59	1.52	2.56	3.57	2.19	2.07	3.27	6.12	2.92	2.88	3.69	8.31	3.81	3.58

Figure 3.5: Comparison of benchmark systems. For the number of customers $|C|$ ranging from 10 to 50, the "Only LEFVs," "IWLT-Stationary," and "IWLT-Flexible" systems are compared with the baseline "Only trucks." The on-street movement was reduced across all two-echelon scenarios at the expense of increased total travel duration over the two levels. The time limit is 4h for both models. 27 instances in the test data are averaged for each alternative system, up to 30 demand nodes. 26 instances are averaged for the scenarios with 40 and 50 demand nodes, where the instance RC205 becomes infeasible for single echelon systems under the test settings.

total traveled time on the streets. When considering the system where only LEFVs are utilized without integration, the total traveled time on the streets increases by 83, 136, 177, 203, and 240% for varying problem sizes. In contrast, two-echelon benchmarks enable LEFVs to focus on providing the primary service in cities while vessels are responsible for capacity replenishment. The *IWLT-Stationary* system achieves reductions of 17, 21, 16, 18, and 9% in the traveled time on the streets, while the *IWLT-Flexible* system enables even greater reductions of 28, 30, 28, 27, and 19%, respectively. By reducing vehicle kilometers driven, we can alleviate traffic congestion through a mode shift from roads to waterways. This not only leads to cost savings but also enhances road safety and improves overall transportation efficiency.

While IWLT systems offer benefits such as fewer LEFVs and reduced vehicle kilometers on the streets, they require the coordination and deployment of vessels to support the replenishment and supply of LEFVs. This introduces additional logistical complexities and costs associated with managing vessel operations. However, IWLT can mitigate some of these challenges. I.e., *IWLT-Stationary* systems simplify the logistical aspects of strategically locating barges at optimal satellites at the expense of flexibility. On the other hand,*IWLT-Flexible* systems allow vessels to dynamically navigate between any pair of satellites for adaptable supply chain operations at the expense of employing a flexible and reliable vessel fleet. As expected, due to the consolidation opportunity of using trucks, moving from larger vehicles to lighter electric vehicles increases the total traveled time for the alternative benchmarks. However, the increase is more than double for *Only LEFVs* systems on average. For *IWLT-Stationary* systems, total travel time, as a sum of both levels, are 16, 30, 45, 45, and 49% more, whereas *IWLT-Flexible* systems require 28, 37, 26, 42, and 48% more in total compared to the base system. The increase in flexible systems compared to the stationary system is mainly intended by the objective function to reduce street movements further. Moreover, decreasing vehicle kilometers not only contributes to more economical freight transportation but also helps to address environmental concerns related to emissions per kilometer.

The summarized indicators suggest that IWLT systems can be a viable option in designing city logistics transportation systems to meet the increasing demand under different limitations in terms of access, fuel, and size of the vehicles in urban areas. While the integration reduces the costs of the transition with the help of coordination and synchronization, the flexibility in navigation over waterways improves the overall costs more compared to the dedication of the barges. LSPs can further improve the logistics costs of the IWLT systems by locating satellites within the service region using more customized clustering approaches. *IWLT-Flexible* systems can achieve more by letting vessels perform multiple trips on water level, considering their flexibility in navigating, which is not included in this chapter.

3.5.6 Results on large-scale instances

Up to now, several analyses have been provided regarding the proposed methods as well as design choices on the instances with up to 50 demand nodes. In this section, we evaluate the proposed models on large-scale instances to show their applicability to real-life problems where the real-time capacities of the satellites are limiting the feasibility and the cost of the system.

The average results are summarized in Table 3.6. The column ”zIP” presents the average of the best-known solutions to the methods for the solution quality. For travel time, the averages are shown as the travel time of the best-known solutions of the methods at both levels, SL and WL, respectively. The average fleets are provided for SL and WL, along with the fleet size deviation of vessels from the lower bound based on the total cargo load. Lastly, we report the average numbers of transshipment operations per LEFV, vessel, and satellite. To compare the models, the average percentage savings are calculated for the LBBD model with respect to the joint MILP. Increasing the scale increases the number of minimum transfers to schedule at available satellites. These values are 37.0, 30.9, and 33.3 for the C, R, and RC type problems, respectively. For LBBD, the master problem is to find at least 30 trips, and the subproblem is to schedule transshipment operations for these trips at the resource-constrained satellites.

Both models can provide feasible solutions to the problems, while LBBD provides significant savings compared to the joint MILP, namely an improvement of 10.6% is achieved in the objective on average across all instances. Even though the subproblems become larger, LBBD optimizes the WL fleet size closer to the lower bound in terms of cargo load. Besides, it provides better upper bounds for the other

Table 3.6: Comparison of the proposed models on large-scale instances. $|C|$ = 100, and $|P|$ = 4.

Type	Method	zIP	Travel time Total	Travel time SL	Travel time WL	Fleets SL	Fleets WL	Fleets Deviation from vessel LB	Transshipment operations Transshipment per LEFV	Transshipment operations Transshipment per vessel	Transshipment operations Transshipment per satellite
C	Joint MILP	4,271.3	4,723.6	2,212.4	2,511.2	8.00	8.75	0.75	5.3	4.8	10.6
	LBBD	3,857.2	4,039.6	1,958.5	2,081.1	7.50	8.00	0.00	5.5	5.2	10.3
	Savings(%)	9.7	14.5	11.5	17.1	6.25	8.57				
R	Joint MILP	4,158.9	4,443.4	2,182.8	2,260.6	9.27	9.55	3.55	4.3	4.1	9.9
	LBBD	3,720.9	3,415.3	1,997.7	1,417.6	8.64	6.09	0.09	4.4	6.2	9.5
	Savings(%)	10.5	23.1	8.5	37.3	6.86	36.19				
RC	Joint MILP	5,432.5	5,452.9	2,840.2	2,612.7	9.50	9.25	2.25	4.8	4.9	11.4
	LBBD	4,810.6	4,451.6	1,525.1	1,970.6	8.75	7.88	0.88	5.0	5.6	11.0
	Savings(%)	11.4	18.4	46.3	24.6	7.89	14.86				
Average savings(%)		10.6	18.7	22.1	26.3	7.0	19.9				

Time limit is 4h for both models. WLS = 1:10, and the proximity = 0.1. 8, 11, and 8 instances in the test data are averaged for C, R, and RC type distribution scenarios, respectively. The average gaps are 60.1, 74.6, and 77.0% respectively for C, R, and RC type problems, reported by Gurobi solver for the Joint MILP.

objectives by reducing the SL fleet more and improving the total travel time by 18.7%. Additionally, the average savings in travel time for WL are significantly larger than those for SL, especially when randomization exists in the demand distribution by scheduling transshipment efficiently for WL services. Lastly, it improves the utilization of the resources allocated to the transshipment operations. It reduces the number of transfers with smaller fleets leading to more trips served by LEFVs and vessels on average while reducing the time spent at each satellite.

3.6 Conclusions

This study focuses on two-echelon synchronized logistic problems for integrated water- and land-based transportation systems. We have proposed two models, the joint model and the LBBD model, for solving the 2E-MVRP-SS, a novel rich variant of a two-echelon vehicle routing problem arising in city logistics. The models' performances are compared using instances of varying sizes. For smaller instances, the joint model obtains the best-known solution, indicating optimal or near-optimal performance. However, as the demand network size increases, the LBBD model outperforms the joint model across almost all instances. It finds improved solutions for a larger number of instances, suggesting its effectiveness in exploring the solution space. Additionally, on average, the LBBD model reduces the computational time required to find the best-known solution, indicating improved efficiency compared to the joint model.

Besides comparing the two models, we analyze the impact of cost parameters and the locations of satellites on the performance of the proposed IWLT system. Cost analysis involves adjusting the cost ratio between water level and street level cost parameters to create different scenarios. For different cost scenarios, on average, LBBD succeeds in finding better solutions compared to the joint model in less computational time. For satellite locations, we have explored proximity-based and clustering-based approaches, finding that the k-means algorithm provides the most savings in total traveled distances for clustered demand networks but offers limited improvements for randomized networks. Further benefits can be achieved by considering both spatial and temporal distances in satellite location decisions, particularly in scenarios with randomness in demand geographical distribution.

Additionally, different system alternatives are evaluated in the context of LSPs and their goal to transition from large trucks to economically viable lighter vehicles in urban areas. Comparisons are made between the *Only trucks* system and three alternatives, showing that IWLT systems significantly reduce total travel distances compared to the system without any integration. We have shown that flexible IWLT systems achieve even greater reductions in street travel distances ranging from 20% to 30% on average, providing cost savings, improved road safety, and transportation efficiency. Although IWLT systems introduce additional complexities and costs related to vessel operations, they offer viable solutions for urban logistics transportation under various limitations. Moreover, experiments on the large-scale instances show that the proposed LBBD can improve the costs by 10.6% while providing substantial reductions in fleet size by 7.0% and 19.9% for the SL and WL, respectively, as well as a reduction of 18.7% in total travel time on both networks.

In this study, we have proposed novel formulations for 2E-MVRP-SS with unitary transshipment capacities and demonstrated that the proposed LBBD method is an effective approach for solving such complex mixed integer combinatorial problems. It leverages existing knowledge to solve complicated problems iteratively in simple forms. The simple and compact formulation of the system can be used to consider different real-life settings such as service type, storage options at the satellites, and vehicle charging considerations. Further research can be devoted to enhancing the relaxed cost formulation of the master problem to potentially address the computational time issue and improve the performance of the LBBD model in scenarios where water level operations are of greater importance.

The outcomes also indicate that LBBD has the potential to facilitate the development of further heuristics, enabling better resolutions for large-scale instances. Instead of using a single search tree in B&B, future studies can exploit the underlying decomposition structures to develop metaheuristics to explore the solutions using diversification strategies. Similarly, the underlying Lagrangian bounding framework can provide the basis for designing subgradient optimization methods.

Recent studies take into account the minimization of total waiting times for the customers or the satellites (Sluijk et al. 2023). Anderluh et al. (2017) suggest a method to decrease long waiting times by imposing bounds on the waiting time at any satellite specific to vehicle types. We allow vehicles to wait at no cost, thereby enabling the evaluation of services with minimal fleets and vehicle kilometers. Inconveniences related to parking the vehicles at the satellites or customers can be overcome by dedicating areas by the service designers. However, to fully understand the impact of the waiting times, further work is needed to collect and incorporate the cost parameters for unit waiting times on both networks regarding city regulations and also vehicle types (i.e., bikes, barges).

In this chapter, we address **SQ2** by providing tractable MILP models for optimizing the synchronized two-echelon routing problems, specifically an integrated and a decomposition-based formulation. The decomposition-based formulation demonstrates superior robustness for large-scale instances with up to 100 demand nodes. However, solving the underlying problems for real-life applications requires further investigation. Moreover, the proposed decomposition-based formulation offers promising avenues for modeling uncertainty in synchronized two-echelon systems, an area currently lacking in literature regarding operational delays.

Based on the performance of the decomposition method in improving the solution quality, we develop a decomposition-based metaheuristic in Chapter 4. Based on the performance of the decomposition method in reducing the complexity of the synchronized two-echelon problems, we develop a two-stage stochastic optimization model in Chapter 5.

Chapter 4

Scaling up the solution methods for real-life applications

This chapter evaluates different aspects of IWLT systems for large-scale, real-life problems. This assessment provides insights into the costs and societal impacts of various IWLT systems, comparing those with storage options to those with flexibility options. Flexibility is defined as the synchronization of vehicles to eliminate the need for storage investments. Therefore, this chapter tackles **SQ3**. The decomposition formulation developed in Chapter 3 is here enhanced to work for large-scale instances up to serving 700 customers on average and consequently scheduling more than 1000 operations across both echelons.

Efficiently operating IWLT systems involves minimizing operational costs and considering the computational costs required to determine optimal operations. This introduces a critical trade-off between solution quality and computational time. Faster decision-making enables systems to respond more effectively to changes in the system, but it often comes at the expense of optimality gaps. This chapter aims to design a metaheuristic to handle various routing problems and ultimately analyze the efficiency of the IWLT systems.

We propose an iterative tabu search mechanism to tackle the complexity of the multi-trip aspect of LEFVs systems and the synchronization requirements of IWLT systems. First, we greedily explore the solution space for the street vehicles using ALNS followed by a local search by allowing infeasible solutions. Then, promising solutions are optimized further for the feasibility and cost efficiency of the synchronized two-echelon system using commercial solvers. Systems with or without storage are tested on a case study in Amsterdam to assess the costs associated with the integrated waterborne transport systems in terms of efficiency of the integration, urban space use, and the potential to reduce negative externalities of urban freight transportation.

This chapter is organized as follows. Section 4.1 introduces the research background. Section 4.2 presents a literature review of related works. Section 4.3 describes the optimization problems, while Section 4.4 presents our approach. Section 4.5 discusses the computational experiments on problems in the literature and on our real-life case study. Finally, Section 4.6 concludes the chapter. Parts of this chapter will be submitted to a journal. [1]

[1] Karademir, C., Beirigo B. A., & Atasoy, B. Optimizing city logistics: Decision-making and synchronization in urban space competition, to be submitted to a journal (2025).

Notation used in this chapter

Parameters and sets of the problem

- C: Set of customers.
- C^2: Set of arcs in the SE, including the garage for SEVs, $C \cup g$.
- P: Set of available satellites.
- β^1, β^2, c^t: Vehicle use costs for FE and SE, and cost of a transshipment operation at satellites.
- c^1, c^2: Unit travel cost for FE and SE, respectively.
- $z^1(x_{ij}, v_{pj})$: Cost of FE to serve the given schedule optimally.
- s_i: Service time at customer i.
- q_i: Load requirement of customer i.
- $[a_i, b_i]$: Time windows for customer i.
- $Q^1 \& Q^2$: Capacity of FEVs and SEVs.
- U: Constant transshipment duration.
- T^1, T^2: Linearization constants for temporal connectivity constraints on FE and SE, respectively.
- t_{ij}^2, t_{ij}^1: Shortest travel time between node i and node j on the SE and FE, respectively, considering different speeds.
- $p(j)$: The assigned satellite for the transshipment before serving customer node j.
- $\overline{m(j)}$: The assigned volume of the customers in the trip.

Decision Variables

- Decisions in the SE:
  - x_{ij}: Binary variable indicating if arc (i, j) is used by a SEV.
  - f_{ij}: Travel time on arc (i, j).
  - v_{pi}: Binary variable indicating if the transshipment operation after customer i is assigned to satellite p.
  - m_i: Load on the SEV at the arrival before serving node i.
  - h_i: Arrival time at node i.
- Decisions in the FE:
  - y_{ij}: Binary variable indicating if transshipment operations $(i \& j)$ are assigned to a FEV consecutively.
  - l_i: Load carried on FEV when arriving for transshipment i.
  - u_i: Transshipment start time for the transshipment i.

Parameters and sets of the proposed methodology

- R: SE schedules consisting of the arcs traveled.
- O: Transshipment operations, specifying the locations, loads, and feasible time intervals.

- O_w: Transshipment operations and the central warehouse, $\{O \cup w\}$.
- $\mathcal{N}$: Set of solutions found within a neighborhood.
- $\mathcal{N}_{INIT}$: Set of solutions found after initialization.
- $\mathcal{N}_{ALNS}$: Set of solutions found after adaptive large neighborhood search
- $\mathcal{N}_{LS}$: Set of solutions found after local search
- T: Tabu list, consisting of infeasible (individual) routes with respect to multi-trip aspect, list of r.
- $storage$: Indicator of storage option at the satellites.
- m_{start}: The number of start in the initialization heuristics
- max_{ITS}^{iters}: The maximum number of iterations in the proposed iterated tabu search (ITS)
- max_{LS}^{iters}: The maximum number of iterations in the proposed local search (LS)
- max_{LS}^{reps}: The maximum number of replications in the proposed LS
- max_{ALNS}^{iters}: The maximum number of iterations in proposed adaptive Adaptive Large Neighborhood Search (ALNS)
- S_I, S_W, S_R, S_N, S_A: Scores of the operators used in MLD for roulette selection types (identical and weighted), removal types (route and node), and additional removal of a neighbor size of A% of the remaining nodes, respectively.

a) Autonomous air \land vehicles (AVs)

b) Electrified conventional vehicles (EVs) with two to four wheels

Figure 4.1: Emerging vehicle technologies in freight transport.

4.1 Introduction

Urban freight logistics faces an unprecedented challenge: balancing the escalating demands of growing populations with the imperative to reduce congestion and emissions (Crainic et al. 2021b). In this context, the integration of underutilized inland waterways presents a promising avenue for sustainable and efficient city logistics, especially considering the regulations limiting the reach of freight vehicles in cities (Mommens & Macharis 2012). However, the cost efficiency of a multimodal system largely depends on strategic decisions, such as the selection of optimal locations for transshipment facilities, also known as satellites, where goods are transferred from the water network to the road network or vice versa. These facilities provide limited resources shared by vehicles on both networks such as space, storage, equipment, and time. The integrated planning of resources under such realistic settings requires innovative mathematical and computational solution approaches.

Multi-echelon supply chains are commonly used in multimodal city logistics to transport goods from origin to destination via indirect shipping from one level of the distribution network to another. Larger vehicles are more efficient in terms of cost per shipped quantity, whereas smaller vehicles are more desirable in city centers, as they emit less noise and require smaller parking spots (Romeijn et al. 2007). These systems involve the optimization of interacting fleets at two levels and offer more flexibility in modeling complex and real-world challenges in supply chain management. In the recent decade, these distribution systems have grown in popularity in city logistics, which can be attributed to the increasing pressure on logistics service providers (LSPs) to adapt their services to new regulations targeting emission-free cities (Alarcón et al. 2023).

LSPs are exploring multimodal transportation systems using new emerging technologies (see Figure 4.1). While these technologies may have limited capacity on their own, they can be efficiently used in combination with conventional vehicles by incorporating these vehicles into the multi-echelon transport chain (Yu et al. 2020). However, the existing applications of freight transport often overlook the broader spatial and systemic dimensions of urban freight transportation (Fried et al. 2024), specifically regarding the design of the satellites where transshipment operations are located in urban areas. The planning of efficient freight transportation is a complex tactical challenge, particularly in metropolitan cities where carriers must navigate a competitive environment while meeting customer demands for reliable, high-quality, and low-cost services. Service Network Design Problem (SNDP), which involves selecting and scheduling services, routing freight, and specification of terminal operations, is central to this tactical planning, and mathematical programming models offer valuable tools for optimizing these complex systems (Wieberneit 2008, Crainic 2000).

To measure the impact of the service network design on the benefits of multimodal city logistics, we study different variants to model the limited resources at the satellites. Asynchronous (`Asynch`) systems refer to applications where satellites have sufficient resources to store and process transfers, such as warehouses or distribution centers. In such systems, the fleets can operate asynchronously, assuming that the goods are delivered to the satellites by the first echelon vehicles before the delivery service starts on the second echelon. Instead of investing in resources at the satellites, public places can also be utilized as transshipment points, such as parking spots and public transportation stops, among others. These systems are referred to as synchronized (`Synch`) systems for applications where satellites have no storage resources and require fleets to be present at the satellites during the transfers. This introduces additional synchronization costs for the interacting vehicles, imposing spatio-temporal synchronization and leading to more travel or waiting time for the vehicles. Incorporating this complexity into decision-making allows us to assess two edge cases in the two-echelon literature: storage options at the satellites and synchronized delivery coordination across both echelons.

While multimodal transport systems present significant opportunities for enhancing urban logistics, their effectiveness is often compromised by the challenges of synchronizing transshipment operations — particularly in resource-constrained urban environments. To evaluate the advantages of Integrated Water- and Land-based Transportation (IWLT) systems and to contextualize this study within practical urban dynamics, we apply the aforementioned system models to Amsterdam, the capital of the Netherlands, a city where inland waterways constitute a significant 25% of its land area. Due to their large logistics flows, the municipality of Amsterdam has prioritized innovative waterborne solutions for logistics activities in the construction and hospitality sectors, ensuring efficient use of space and time with minimal footprint (Gemeente Amsterdam 2024).

We model daily operational routing problems as multi-trip two-echelon vehicle routing problems (2E-MVRP) with or without temporal synchronization based on the storage options. On the first echelon, vessels transport the goods to the satellites to supply Light Electric Freight Vehicles (LEFVs) on the second echelon to meet the demand in the city. An iterated tabu search mechanism is proposed to handle different variants of synchronized two-echelon routing problems. The purpose is to address the gap in designing synchronized two-echelon distribution systems under realistic resource capacity settings and the gap in assessing the cost for different stakeholders in IWLT systems considering a large-scale real-life application. Such decisions require an inclusive cost analysis for stakeholders to enhance the city logistics.

Therefore, the contributions of this chapter can be summarized as follows:

- A multi-purpose solver for large-scale synchronized two-echelon routing problems.
- Assessment of storage option and temporal synchronization.
- Insights into service network design problems in real-life applications

The proposed two-echelon system can also be adapted to other multimodal settings that integrate emerging autonomous vehicle technologies, such as drones and robots. These vehicles offer higher speeds but smaller cargo capacities, making them particularly effective for reaching remote or congested urban areas that are difficult to access by conventional vehicles. Autonomy requires us to standardize the trips and associated handling and delivery processes during transshipment or service operations. In general practice, such technologies are often dedicated to specific trucks or warehouses, where synchronization in terms of cargo load, time, and space is less complex to achieve (Morim et al. 2024). In contrast, the vehicles in this study are not restricted to specific satellites; they are free to visit any satellite at any time, provided it improves the global system cost.

4.2 Related work

City logistics is a complex environment that necessitates consideration of various stakeholders to integrate waterborne transportation systems under realistic settings. A holistic approach to cost-benefit analysis is needed, encompassing the perspectives of all stakeholders (e.g., shippers, carriers, customers, and the public). This will enable informed decision-making and facilitate the adoption of IWLT systems (Bilegan et al. 2022). However, it requires understanding the intricate relationship between service network design and the overall performance of IWLT systems. This includes evaluating the trade-offs between different design choices and their impact on key performance indicators, considering space and resource use associated with the scheduling operations at the transshipment points.

Addressing the challenges of limited resources at transshipment points requires innovative solutions for optimizing resource allocation, scheduling, and synchronization. Many studies assume unlimited resources at these places, ignoring the practical constraints of time, space, and labor. Furthermore, they mainly concentrate on the tactical and operational level of Two-echelon Vehicle Routing Problem (2E-VRP), neglecting the strategic aspects of network design, such as satellite location decisions within Two-echelon Location Routing Problem (2E-LRP) and their impact on fleet composition. For optimizing a 2E-LRP, one must solve several 2E-VRP for potential network designs differing in the number of and locations of satellites.

Case studies have provided valuable insights into the potential benefits and challenges of IWLT systems (CCNR 2022). These include unused waterborne transport capacity, reduced cost, and carbon emissions per vehicle kilometer (Durajczyk & Drop 2021). While the applicability of research findings to real-world scenarios is crucial for strategic decision-making, the focus on last-mile operations can lead to inaccurate cost estimations and sub-optimal policy recommendations regarding capacity planning and space use (Holguín-Veras et al. 2020). Such an analysis should also consider the specific context of different cities, like Amsterdam, where the municipality has prioritized water transport and logistics hubs as key solutions for sustainable city logistics (Gemeente Amsterdam 2024).

The performance of the existing heuristics for 2E-VRP varies significantly depending on problem settings, highlighting the need for tailored solution approaches customized for specific cases and assumptions (Sluijk et al. 2023). This raises concerns about the practicality and feasibility of these insights in real-life settings. The complexity of 2E-VRP further increases when considering multi-trip scenarios and temporal synchronization constraints (Drexl 2012). Various solution approaches have been proposed for multi-trip 2E-VRP, including an Adaptive Large Neighborhood Search (ALNS) (Grangier et al. 2016), a Greedy Randomized Adaptive Search Procedure (GRASP) (Anderluh et al. 2017), and a Large Neighborhood Search (LNS) (Anderluh et al. 2020). The heuristic approaches have shown promising results in handling the complexities of multi-trip operations to address the challenges of real-time capacities with limited storage (Li et al. 2018) and synchronization between different vehicle types (Li et al. 2021a).

Metaheuristics can tackle large-scale 2E-VRP instances (Li et al. 2021a), but the complex time-space network of interdependent operations poses computational challenges in the case of resource synchronization at the satellites. However, much of the existing literature focuses on solving routing problems within a predefined service network, where satellite locations are determined manually without a thorough assessment of network size and overall cost. Decomposition techniques and analytical optimization algorithms offer promising avenues for addressing these challenges by simplifying location-routing problems and reducing computation time (Hemmelmayr et al. 2012, Winkenbach et al. 2016). These techniques break down the problem into smaller, more manageable sub-problems for independent or iterative solving. This approach allows for the design of solutions that effectively balance computational time and solution quality (Karademir et al. 2025).

In this chapter, we tackle large-scale SNDP within integrated transportation systems that bridge the gap between theoretical models and practical implementation. By studying the optimal service network design, businesses can create robust and efficient two-echelon distribution systems that meet customer needs and drive profitability within increasing urban space competition Romeijn et al. (2007). The problems are modeled as synchronized two-echelon routing problems to model IWLT systems differing in storage dedication and vehicle composition. The feasibility of the systems is maintained using a decomposition framework spanning potential on-street routes, and the overall logistics cost is improved for 2E-MVRP using an iterated search mechanism. The performance is compared to the state-of-art method in the literature (Grangier et al. 2016) for the problems with 100 demand nodes. Then, several design scenarios are tested on the case study of up to 700 demand nodes to provide a comprehensive understanding of the impact of service network configurations. The associated trade-offs for IWLT systems are summarized in terms of the extent of the costs and benefits and the development of robust solution approaches that address the complexities of real-world city logistics operations.

4.3 A decomposition-based problem formulation for 2E-MVRP

We use the formulations provided in Karademir et al. (2025), which shows us that the decomposition method can provide better resolution and quality for large-scale problems. While we provide the decomposed formulation for this study, the second echelon problem can be extended to include all the variables in domain sets of the water level problem associated with every feasible transshipment operation.

In the multimodal system, at the second echelon, there exists a fleet of identical LEFVs with a capacity of Q^1 units to deliver the goods to the customers in the city. All LEFVs are located at a main garage, g, in the city. They start and end their journeys at the garage while visiting a set of customer nodes, C, and one or more satellites in between to transfer the goods. Each customer node $i \in C$ requires q_i units of goods to be delivered up by a single LEFV and associated with a service duration of s_i within a time window of $[a_i, b_i]$. t^2_{ij} denotes the shortest travel time between nodes i and j. LEFVs should replenish the goods via transfer operations at a predefined set of satellites P over multiple times, where vessels deliver the goods between the central warehouse and satellites. A transfer operation for unloading and loading goods requires U time units.

4.3.1 Variants: storage and synchronization options at the satellites

This chapter aims to evaluate the performance of IWLT systems with synchronization under various resources at the satellites considering storage and network design scenarios. We define the following synchronization settings in space and time based on the resources provided at the transshipment facilities, which can be characterized as:

- Asynchronous `(Asynch)` systems rely on the dedicated storage capacities available at the satellites. While the storage option reduces fleet costs by eliminating the temporal dependency, it brings inventory investment and management challenges.

- Synchronized `(Synch)` systems rely on the efficient coordination and integration of vehicle capacities that are synchronized at the satellites. While synchronization reduces the cost of storage investments, it introduces synchronization costs to ensure spatio-temporal dependency.

The multi-trip two-echelon problem, 2E-MVRP, of `Asynch` and `Synch` systems is decomposed into solving VRPs on both echelons connected with satellite synchronization. It solves a multi-trip VRP for the second echelon (SE) for routing LEFVs on the urban streets. Then, it solves the corresponding capacitated VRP for the first echelon (FE) by considering the synchronization setting. We refer to Section 3.3.4 for the formulations and the notations used in this section to model 2E-MVRP-SS for delivery services.

4.3.2 The second echelon (SE)

The street-level routing problem on the second echelon is the same for `Asynch` and `Synch` cases and consists of a multi-depot MVRP for scheduling on-street vehicles. Therefore, the SE problem ($MILP_{MVRP}$) is formulated as follows:

$$\min \quad \overbrace{\beta^2 \sum_{i \in C} x_{di} + c^2 \sum_{i,j \in C^2} f_{ij}}^{z^2(x_{ij}, v_{pj})} + \overbrace{c^t \sum_{i \in C} \sum_{p \in S} v_{ip}}^{Satellite\ use\ cost} + z^1(x_{ij}, v_{pj}) \tag{4.1}$$

subject to

$$\sum_{j \in C^2} x_{ij} = 1 \qquad \forall i \in C \tag{4.2}$$

$$\sum_{j \in C^2} x_{ji} = 1 \qquad \forall i \in C \tag{4.3}$$

$$\sum_{i \in C} x_{di} = \sum_{i \in C} x_{id} \tag{4.4}$$

$$m_j \geq m_i - q_i - Q^2(1 - x_{ij} + \sum_{p \in S} v_{pj}) \qquad \forall i, j \in C, i \neq j \tag{4.5}$$

$$x_{di} \leq \sum_{p \in S} v_{pi} \leq 1 \qquad \forall i \in C \tag{4.6}$$

$$a_i \leq h_i \leq b_i \qquad \forall i \in C \tag{4.7}$$

$$h_i + s_i + f_{ij} + U v_{pj} \leq h_j + T^2(1 - x_{ij}) \qquad \forall i \in C, \forall j \in C^2, i \neq j \tag{4.8}$$

$$f_{ij} \geq (t^2_{ip} + t^2_{pj})(x_{ij} + v_{pj} - 1) \qquad \forall i \in C, \forall j \in C^2, i \neq j, p \in S \tag{4.9}$$

$$f_{ij} \geq t^2_{ij} x_{ij} \qquad \forall i, j \in C^2, i \neq j \tag{4.10}$$

$$z^1(x_{ij}, v_{pj}) \geq 0 \qquad \forall i \in C \tag{4.11}$$

$$m_i \geq 0 \qquad \forall i \in C \tag{4.12}$$

$$x_{ij} \in \{0, 1\} \qquad \forall i, j \in C^2, i \neq j \tag{4.13}$$

$$v_{pi} \in \{0, 1\} \qquad \forall i \in C, \forall p \in S \tag{4.14}$$

The objective function by 4.1 aims at minimizing the number of transshipment operations besides minimizing the total logistics costs, including vehicle, fuel, and satellite usage costs. The motivation is to reduce the nuisances associated with these operations in cities. Equations 4.2–4.4 are customer-vehicle assignment constraints while equations 4.5–4.6 are load synchronization constraints. Equations 4.7–4.10 are temporal synchronization constraints. Lastly, equations 4.12–4.14 define mixed integer decision variables. Binary x_{ij} decisions are the arc decisions between customer nodes i and j, indicating the order of customer service operations on a vehicle. The binary v_{pi} variable decides the transshipment operation at satellite p on the vehicle serving node i.

The SE problem can be decomposed with respect to routes, allowing us to independently optimize their transfer decisions and satellite assignments to the closest ones. To optimize a given set of routes of the on-street vehicles (R) in terms of multi-trips, it can be solved for each route r in R by fixing the arc decisions in r. If feasible, the optimal transfer tasks (O) are the set of the minimum cost transfer-satellite assignments of each route.

4.3.3 The first echelon (FE)

Within the decomposition framework proposed in this study, two independent VRPs are solved for the `Asynch` systems, while `Synch` systems require us to solve a VRP and a dependent operations' scheduling problem. Therefore, the FE problem is formulated as a capacitated VRP for `Asynch` systems to serve transfer tasks at given satellites and volumes. These tasks are further constrained by the time windows for `Synch` systems to ensure temporal connectivity with the on-street routes.

For each on-street vehicle used in R, there exists a route r denoting the order of the nodes visited by the vehicle. For each transfer decision made for each route r, $v_{pj} = 1$, there exists a transfer task j required before serving customer j at the satellite $p(j)$ with a load of $\overline{m_j}$. In the first echelon, the problem is to minimize the cost of serving each task $j \in O$ while maintaining the feasibility of each route $r \in R$.

Asynchronous *(2E-MVRP)*

It is assumed that all the goods are delivered to satellites for the assigned tasks the day before, as satellites have storage options. Since there is no concern about the feasibility of the on-street routes in terms of the timing of the tasks, it is a basic capacitated VRP. It ensures load and space synchronization for the transfer tasks but requires storage and a reliable supply system on the first echelon. Therefore, FE problem for `Asynch` systems ($MILP_{CVRP}^{storage=1}$) is formulated as follows:

$$\min \quad z^1(x_{ij}, v_{pj}) = z^1(O_w) = \beta^1 \sum_{i \in O} y_{wi} + c^1 \sum_{i,j \in O_w} t^1_{p(i)p(j)} y_{ij} \tag{4.15}$$

subject to

$$\sum_{j \in O_w} y_{ij} = 1 \qquad \forall i \in O \tag{4.16}$$

$$\sum_{j \in O_w} y_{ji} = 1 \qquad \forall i \in O \tag{4.17}$$

$$\sum_{i \in O} y_{wi} = \sum_{i \in O} y_{iw} \tag{4.18}$$

$$l_j \geq l_i - \overline{m_i} - Q^1(1 - y_{ij}) \qquad \forall (i,j) \in O, i \neq j \tag{4.19}$$

$$u_i + U + t^1_{p(i)p(j)} \leq u_j + T^1(1 - y_{ij}) \qquad \forall i \in O, j \in O_w, i \neq j \tag{4.20}$$

$$\overline{m_i} \leq l_i \leq Q^1 \qquad \forall i \in O \tag{4.21}$$

$$y_{ij} \in \{0,1\} \qquad \forall i,j \in O_w, i \neq j \tag{4.22}$$

The objective by constraints 4.15 minimizes the vehicle usage and fuel costs. Eq. by 4.16–4.18 are assignment constraints. Constraints 4.19 and 4.20 ensure synchronization of the operations on vehicles in load and time, respectively. Constraints 4.21–4.22 are domain variables. Split demand is not allowed by constraints 4.21, meaning that FEVs deliver total transshipment volume to reduce the visits to the satellites. Please note that the model is independent of R in time but dependent on O decisions of R in load and space.

Synchronized *(2E-MVRP-SS)*

In case of any storage option at the satellites (with or without), the goods must be brought to the satellites before the second echelon vehicles collect them for distribution. Arriving late is not acceptable.

$$u_j + U + t^2_{p(j)j)} \leq h_j \qquad \forall j \in O, \forall (i,j) \in r \tag{4.23}$$

If there is no storage, then the first echelon vehicles wait for the respective second echelon vehicles to meet at the satellites. Leaving early or late is not acceptable.

$$h_i + s_i + t^2_{ip(j))} \leq u_j \qquad \forall j \in O, \forall (i,j) \in r \tag{4.24}$$

Furthermore, the following temporal limitations are added to maintain the feasibility of the on-street routes.

$$h_i + s_i + t^2_{ij} \leq h_j \qquad \forall r \in R, \forall (i,j) \in r, \forall j \notin O \tag{4.25}$$

$$h_i + s_i + U + t^2_{ip(j)} + t^2_{p(j)j} \leq h_j \qquad \forall r \in R, \forall (i,j) \in r, \forall j \in O \tag{4.26}$$

Please note that on both variants, `Asynch` and `Synch` cases, the FEVs execute the transshipment one by one, in contrast to multiple transshipments occurring at the same time (Grangier et al. 2016).

4.4 An iterated tabu search mechanism

To solve two-echelon problems with different synchronization settings, we propose an Iterated Tabu Search (ITS) that minimizes the logistics costs on both echelons. ITS is a metaheuristic algorithm that integrates tabu search with iterated local search to solve combinatorial optimization problems efficiently.

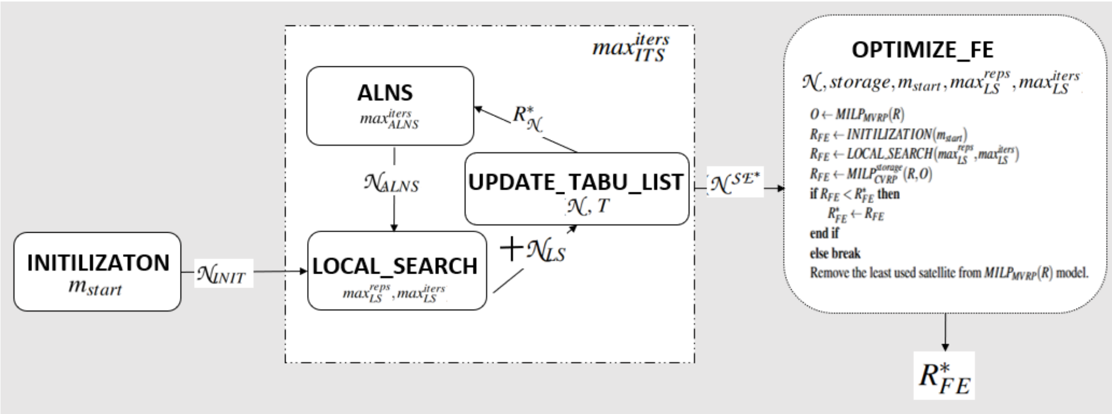


Figure 4.2: The flowchart of the proposed ITS within the decomposition method.

Tabu search is recognized for its adaptive memory mechanism, preventing revisiting previously explored solutions, while an iterated local search aims to intensify the search around local optima. It can handle different variants of routing problems by iterating between diversification and intensification (Cordeau & Maischberger 2012). The diversification mechanism is based on constraint relaxations and tabu solutions.

Let T be the tabu list for the street routes that are neither wanted to be revisited nor allowed to be constructed during the search. It is the sequences of the nodes that cannot be visited in time by a vehicle when transshipment decisions are considered. It also proves the infeasibility of any route r partially including this sequence in that order, as no insertion would be feasible. It represents the irreducible infeasible set in terms of r. Therefore, if there exists a non-dominating sequence, it is removed from T during ITS. It improves the efficiency of the proposed tabu search by reducing the size of T. The general outline of the proposed ITS is as follows:

- Initialization provides $\mathcal{N}_{INIT}$: Feasible initial solutions found by a greedy insertion heuristic, respecting T and relaxing multi trips.
- ALNS provides $\mathcal{N}_{ALNS}$: Feasible solutions found in the large neighborhood search, respecting T and relaxing multi trips.
- Local search provides $\mathcal{N}_{LS}$: Feasible solutions found in the local search, respecting T and relaxing multi trips.
- Tabu list update call restricts the search space further for the next iterations: T extended by any infeasible route $r \in \mathcal{N}$ regarding multi trips, verified by the model in Section 4.3.2.

Due to the complexity of optimizing each on-street solution regarding the two-echelon setting, we employ neighborhood search mechanisms that work on the relaxation of the temporal synchronization constraints. The relaxation considers the minimum satellite transshipment allocations, assuming that SEVs can visit the closest satellites on the way up to the minimum number of transshipment operations in cargo load. Finally, promising schedules for SEVs are optimized within a two-echelon setting as a post-process to ensure global feasibility and optimality, rather than optimizing each solution immediately after its construction during the search process.

The flowchart of the proposed ITS method is provided in Figure 4.2 and iterated by the pseudo-code in Algorithm 4.1, detailing the iterations and each function used at each level of the scheduling. This algorithm employs an iterative framework to solve intricate logistics optimization problems within 2E-MVRP-SS. It relies on several key parameters to guide its search: m_{start} dictates the number of initial solutions generated, promoting diversity from the outset. max_{ITS}^{iters}, max_{LS}^{reps}, max_{LS}^{iters}, and max_{ALNS}^{iters} control the iterations for the main search loop, local search refinement, and the ALNS respectively, influencing the balance between exploration and exploitation.

Algorithm 4.1 ITS($storage$, m_{start}, max^{iters}_{ITS}, max^{reps}_{LS}, max^{iters}_{LS}, max^{iters}_{ALNS})

$R^* \leftarrow inf$: *best objective value*
$T \leftarrow \{\}$: *empty tabu list*
$\mathcal{N}_{INIT} \leftarrow$ INITIALIZATION(m_{start}, T) ▷ Section 4.4.2
$\mathcal{N}_{LS} \leftarrow$ LOCAL_SEARCH$(R^*_{\mathcal{N}_{INIT}}, max^{reps}_{LS}, max^{iters}_{LS})$ ▷ Section 4.4.4
$R^* \leftarrow$ UPDATE_TABU_ LIST$(\mathcal{N}_{INIT} \cup \mathcal{N}_{LS}, T)$ ▷ Section 4.4.5
$k \leftarrow 1$
while $k \leq max^{iters}_{ITS}$ **do**
  $SAA^k \leftarrow \frac{SAA}{k}$, $S_I{}^k \leftarrow \frac{S_I}{k}$, $S^k_R \leftarrow \frac{S_R}{k}$, $max^{iters}{}^k_{LS} \leftarrow k(max^{iters}_{LS})$ ▷ Tuning diversification
  $\mathcal{N}^k_{ALNS} \leftarrow$ ALNS$(R^*, max^{iters}_{ALNS})$ ▷ Section 4.4.3
  $\mathcal{N}^k_{LS} \leftarrow$ LOCAL_SEARCH$(R^*_{\mathcal{N}^k_{ALNS}}, max^{reps}_{LS}, max^{iters}_{LS})$ ▷ Section 4.4.4
  $R_{new} \leftarrow$ UPDATE_TABU_ LIST$(\mathcal{N}^k_{ALNS} \cup \mathcal{N}^k_{LS}, T)$ ▷ Section 4.4.5
  if $R_{new} < R^*$ **then**
    $R^* \leftarrow R^{new}$
  end if
  $k \leftarrow k+1.$
end while
$R^*_{two-echelon} \leftarrow$ OPTIMIZE_FE$(\mathcal{N}^{\mathcal{SE}^*}, storage, m_{start}, max^{reps}_{LS}, max^{iters}_{LS})$ ▷ Section 4.4.6
return $R^*_{two-echelon}$

The algorithm proceeds in distinct stages. First, it creates multiple initial solutions and applies local search to quickly improve the cheapest solution. This sets the stage for the core iterative phase, where ALNS strategically modifies solutions to escape local optima, followed by further local search refinement. The proposed combination iterates between exploration and exploitation by reducing the importance of diversification strategies in ALNS by reducing initial score values S_I and S_R, and SAA percentage. Furthermore, it is doubled by increasing the intensification strategies in local search (increasing max^{iters}_{LS}). This is crucial for finding the best solutions in a vast and intricate landscape of possibilities. A tabu list mechanism, managed through the Update Tabu List subprocedure, prevents revisiting previous solutions, ensuring continuous progress. Finally, the algorithm focuses on optimizing "two-echelon subproblems", further evaluating the solutions within the integrated logistics system by incorporating the cost of the relevant FE routing problems. This structured approach, with its interplay of parameters and subprocedures, provides a robust framework for tackling challenging logistics optimization problems.

4.4.1 Relaxation of SE problem

To allow infeasible solutions during the tabu search algorithm, we relax the temporal feasibility constraints of street solutions. These are as follows:

- The order sequence in the route does not violate the time windows of the customers if transshipment operations are not considered.
- The route does not violate the maximum route duration if it has enough slack time to compensate for the time delay of the minimum satellite visits.

While the condition on time window for the customers is trivial, finding the route duration takes time for the minimum feasible transshipment decisions and is mostly redundant for intermediate solutions. The minimum transshipment duration is the total time to process the minimum number of transshipments of a given route. The minimum travel time delay considers locating the transshipment operations only spatially, to reduce the computational burden, on the arcs in the route except the returning arc to the garage. It finds the minimum extra travel time for transshipment operations on these arcs. Then, these delays are sorted in increasing order to get the sum up to the minimum number of transshipment operations. The relaxation assumes that there might be a feasible allocation to locate these operations feasible in cargo load and time. For the relaxed cost, the minimum delays are added to the total travel time of the solution.

4.4.2 Initialization

At the beginning of each iteration in ITS, a greedy multi-start heuristic is utilized to generate the initial solution(s) up to m_{start}. To initiate each starting solution, a route r is assigned to a different seed customer node that results in the minimum relaxed cost, assuming the transshipment takes place at the closest satellite. Next, the remaining customers are inserted into this starting solution based on the best relaxed insertion cost. The constructed solution R_0 is then optimized using the multi-trip SE problem defined in Section 4.3.2. Any infeasible route within R_0 is subsequently added to T. In the next iteration of construction, T is respected so that it does not produce visited infeasible solutions. The initialization process terminates when the maximum iteration is reached. The solution with the smallest objective is then selected as the starting solution for the proposed ITS.

Algorithm 4.2 INITIALIZATION(m_{start}, T)

Select m_{start} lowest-cost seeds.
$k \leftarrow 1$ and $\mathcal{N}_{INIT} \leftarrow \{\}$.
while $k \leq m_{start}$ **do**
  Seed new solution, R_k^0.
  $R_k^0 \leftarrow$ Insert remaining customers.
  If not found before, **then** $\mathcal{N}_{INIT} \leftarrow \mathcal{N}_{INIT} \cup R_k^0$.
  UPDATE_TABU_LIST($\mathcal{N}_{INIT}$, T).
  $k \leftarrow k+1$.
end while
return $\mathcal{N}_{INIT}$

4.4.3 Adaptive large neighborhood search (ALNS)

The proposed ALNS uses a multi-level destroy (MLD) operator that randomizes several decisions to populate the destroy operators to change the direction of the search, the primary objective component, and the size of the neighborhood. T is respected during any repair operations in the ALNS search considering relaxed insertion costs. Therefore, in each iteration of ITS, this search mechanism aims at changing the sequences of the routes to eliminate undesired routes and end up at different solutions. The sequence of route changes with any move feasible, insertion or swap, and within-route or between routes.

Algorithm 4.3 ALNS(R, max_{ALNS}^{iters})

$k \leftarrow 1$ and $\mathcal{N}_{ALNS} \leftarrow \{R\}$.
while $k \leq max_{ALNS}^{iters}$ **do**
  Apply an MLD operator to R.
  Apply the repair operator, obtain R_{new}.
  Update the scores of the MLD operators for each level.
  Use SAA with the aspiration criterion on SE fleet size.
  If accepted, **then** $R \leftarrow R_{new}$
  If not found before, **then** $\mathcal{N}_{ALNS} \leftarrow \mathcal{N}_{ALNS} \cup R_{new}$.
  $k \leftarrow k+1$.
end while
return $\mathcal{N}_{ALNS}$.

Destroy operators

The proposed MLD first randomly chooses a roulette wheel selection type, identical or weighted. Then, it flips the second coin to decide either a route or a node to remove. If the roulette wheel selection type is identical, all routes and nodes have an equal probability of removal. The identical selection type acts as a diversification strategy in contrast to the weighted one, where routes or nodes are removed based on their cost in the current solution for intensification purposes. In the third step, to enhance the feasibility of accommodating the removed nodes, a set of additional nodes is removed. It chooses a percentage of nodes to remove randomly. Node removal follows the same procedure for the identical selection type. For the weighted case, the algorithm removes a set of nodes based on their proximity to the initially removed nodes. This aims to create a cluster of nearby nodes for potential route additions during the repair phase. The second stage of MLD (route or node removal) provides the initial seed node(s). Each remaining node in the partial solution has the weight of being removed, calculated as the Euclidean distance between the node in consideration and the nodes already removed up to that point. The MLD process can be summarized in three levels:

- Removal Strategy: Choose either weighted or identical roulette wheel selection.
- Seed Node(s): Remove either a single node or all nodes in a route, based on the chosen removal strategy.
- Making Room: Remove *A%* of the remaining nodes using the selected removal strategy.

Figure 4.3 shows the outline of the hierarchical destroy operator. Each operator attribute is assigned a score (S), which is dynamically adjusted throughout the iterations based on its contribution to solution improvement. Initial score values can also be set to give a warm-up for the search algorithm before jumping to the costly solutions. Assigning higher initial scores to the weighted selection type can promote faster intensification early in the search. Similarly, prioritizing route removal over node removal through higher initial scores can enhance fleet optimization early on.

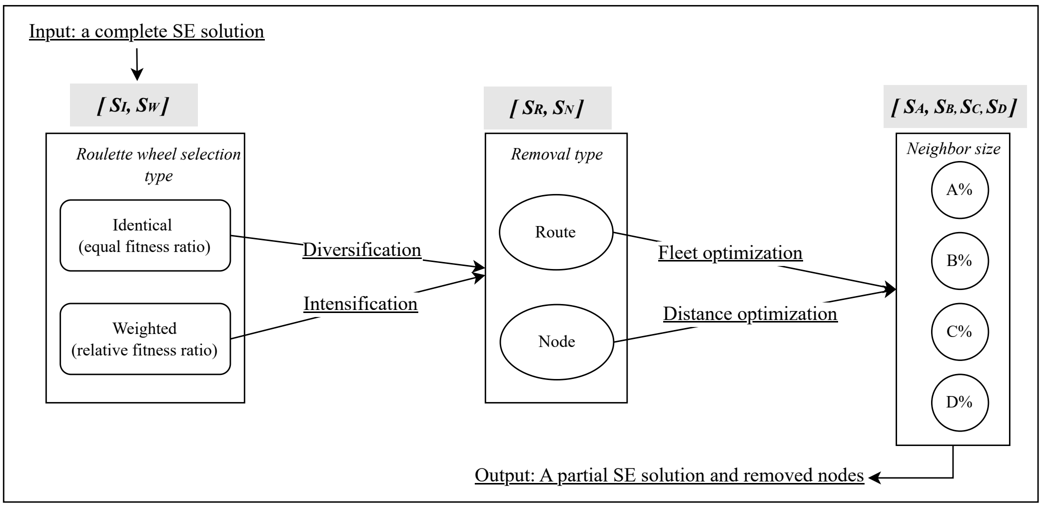


Figure 4.3: The proposed MLD mechanism, where score values are initialized at the beginning of ALNS and updated in each iteration based on the performance in improving or restoring the feasibility. The destroy operators employed here involve route (R) or node (N) removals from the current solution, combined with considering A% of the remaining nodes from various neighbor size options. These combinations are further diversified by randomizing the removals with either identical (I) or weighted (W) roulette wheel selection probabilities.

Repair operators

The destroy operator generates a partial solution and a set of nodes for re-insertion. During the repair phase, these removed nodes are inserted sequentially, in the order they were removed, at their best possible insertion point. Initially, the MLD either removes a node or all nodes of a route to potentially improve the objective, and it first evaluates these removed nodes within the partial solution. Subsequently, a set of additional nodes is removed to enhance the likelihood of the initially removed nodes being re-inserted. Consequently, the removal order is maintained to increase the probability of route elimination or cost reduction. This approach also accelerates the repair operators by simplifying node selection, as insertion options are evaluated only once per node. However, this method potentially sacrifices optimality by not considering the simultaneous evaluation of multiple node insertions.

Algorithm 4.4 Repair(R, *unserved_list*)

Allocate orders in the *unserved_list* to the closest satellites.
Add assigned satellites to $satellite\_list$
Initialize *pool* with the orders assigned to the most loaded satellite and remove it from $satellite\_list$.
while $pool\_not\_empty$ **do**
  Remove the first node, n_0, from the $pool$.
  Insert n_0 at its best position in the R.
  if $total\_load\_pool$ is less than a $trip\_load$ and $satellite\_list\_not\_empty$ **then**
    Update the *pool* with the orders of closest satellite in $satellite\_list$ to n_0.
    Remove the selected satellite from $satellite\_list$.
  end if
end while
return R

Acceptance

In ALNS, a simulated annealing acceptance criterion is used. The temperature is fixed in each iteration at a percentage of the total travel cost of the starting solution, denoted as *SAA*. The aspiration criterion is improving the best-known fleet size on the streets. Based on the performance of the constructed solution, the score values of the destroy operators are updated. While the acceptance only affects the direction of the search, any solution found is stored for further post-optimization employed after ALNS within ITS.

4.4.4 Local search

Customer relocation and route segment crossover moves, illustrated by Tarantilis et al. (2008), are used as neighborhood structures in local improvement heuristics. In the customer relocation, a randomly selected demand node is removed and inserted into its best in a randomly selected route if improving. In the route crossover, two randomly selected routes exchange their initial segments at randomly selected positions. Within the local search algorithm, first relocation and then crossover moves are both executed up to max_{LS}^{iters} times. This is repeated for max_{LS}^{reps} iterations if any neighborhood provides improvements. Otherwise, it terminates. The local search is used to improve the initial solution and the best-known solution provided by ALNS.

4.4.5 Updating tabu list

Updating the tabu list is restoring the feasibility of the search. For any solution found for the SE, the routes are first optimized considering multi-trips to the satellites individually by the model in Section 4.3.2. For feasible multi-trip solutions, the resulting subproblem is given O and R to the two-echelon problem.

Algorithm 4.5 LOCAL_SEARCH($R, max_{LS}^{reps}, max_{LS}^{iters}$)

$reps \leftarrow 1$, $k \leftarrow 1$, and $\mathcal{N}_{LS} \leftarrow \{R\}$.
while $reps \leq max_{LS}^{reps}$ **do**
  while $k \leq max_{LS}^{iters}$ **do**
    Randomly choose a node to remove.
    Randomly choose a route to insert.
    Perform the best relocation move, (R_k), if improving.
    If not found before, **then** $\mathcal{N}_{LS} \leftarrow \mathcal{N}_{LS} \cup R_k$.
    $k \leftarrow k+1$.
  end while
  while $k \leq max_{LS}^{iters}$ **do**
    Randomly choose two routes.
    Randomly choose two points for crossover.
    Perform the crossover, (R_k), if improving.
    If not found before, **then** $\mathcal{N}_{LS} \leftarrow \mathcal{N}_{LS} \cup R_k$.
    $k \leftarrow k+1$.
  end while
  if not improved, **then break**.
  else $reps \leftarrow reps+1$.
end while
return $\mathcal{N}_{LS}$.

Algorithm 4.6 UPDATE_TABU_LIST($\mathcal{N}$, T)

$R^*_{\mathcal{N}} \leftarrow inf$
for all $R \in \mathcal{N}$ **do**
  for all $r \in R$ **do**
    if $r \notin T$ **then**
      Verify multi-trip feasibility by model 4.3.2 for r.
      if r is infeasible **then**
        Extend T for r.
      end if
    end if
  end for
end for
Remove the solutions from $\mathcal{N}$ if more SEVs are used than the best-known global SEV fleet size.
Sort the solutions in $\mathcal{N}$ by objective function value.
for all $R \in \mathcal{N}$ **do**
  $unserved\_list \leftarrow \emptyset$
  for all $r \in R$ **do**
    if $r \in T$ **then**
      Remove infeasible nodes from r and add them to $unserved\_list$.
    end if
  end for
  $R_{new} \leftarrow$ REPAIR*$(R, unserved\_list)$
  if $R_{new} < R^*_{\mathcal{N}}$ **then**
    $R^*_{\mathcal{N}} \leftarrow R^{new}$
  end if
end for
return $R^*_{\mathcal{N}}$

To ensure the feasibility and efficiency of the algorithm, a post-repair procedure is applied to the promising infeasible solutions, indicated as *Repair∗*. It differs from the repair operations used in initialization, ALNS, and *LS* procedures, which ignore the multi-trip aspect and evaluate feasibility for uncapacitated VRPs. The solutions with promising fleet sizes and at least an infeasible route are evaluated further locally before discarding them. However, this intermediate step increases the solution time on average.

A matheuristic is used to decide the set of nodes to be removed from an infeasible route to ensure multi-trip feasibility. This matheuristic combines a first-fit bin packing approach with the verification model presented in Section 4.3.2. Routes in a feasible solution (relaxed for multi-trips and provided within different neighborhoods) are tested for feasibility one by one in the given order of the customer operations' sequence.

For the feasibility check using the proposed matheuristic, the route starts with the first node as a single trip, connecting it to the closest available satellite. The next customer node is added to the trip if it fits in terms of load; otherwise, a new trip is created and assigned to the closest satellite. If the route is feasible, the process moves to the next customer. If it fails, the infeasibility is verified by the MILP, considering optimal trip assignments beyond the initial first-fit bin packing approach. If a feasible trip schedule exists for the route, trip assignments are updated to the optimal schedule, ensuring the route's feasibility itself before evaluating the next customer insertion. If it is mathematically infeasible, the customer node in consideration is removed from the route and added to the *unserved_list* to be inserted into the partial solution after restoring feasibility for all routes.

When repairing the partial solution for the removed nodes, the proposed matheuristic evaluates the feasibility and cost to ensure that the final solution guarantees multi-trip feasibility. This is a heuristic as it only considers whether to remove the next customer or not, without considering early decisions.

4.4.6 Optimizing FE problems

Compared to the SE problem, the FE problem is relatively easier considering the number of transshipment operations, constituting VRP for FE. In many methods, the FE routing problem is solved using exact methods, while the others use simple heuristics like best insertion, nearest neighbor, random insertion, or Clarke & Wright savings algorithm (Sluijk et al. 2023).

Algorithm 4.7 OPTIMIZE_FE($\mathcal{N}, storage, m_{start}, max_{LS}^{reps}, max_{LS}^{iters}$)

```
R*_FE ← inf
for all R ∈ N do
    while True do
        O ← MILP_MVRP(R)
        R_FE ← INITILIZATION(m_start)
        R_FE ← LOCAL_SEARCH(max_LS^reps, max_LS^iters)
        R_FE ← MILP_CVRP^storage(R, O)
        if R_FE < R*_FE then
            R*_FE ← R_FE
        end if
        else break
        Remove the least used satellite from MILP_MVRP(R) model.
    end while
end for
return R*_FE.
```

For optimizing the global costs, the greedy initialization heuristic in Section 4.4.2 constructs the initial solutions for the resulting FE problem, and local search in Section 4.4.4 is used to improve the cheapest initial solution. These two sub-procedures optimize FE routes for serving transshipment tasks with or without time windows at the assigned satellites, defined by the storage option. Then, the best solution is fed to the model 4.3.3 as a starting solution for further optimization within the given synchronization setting if possible.

To further improve consolidation at satellites and move towards global optimality, a problem-specific satellite removal operator is designed and applied to each multi-trip feasible solution. It removes all the unused satellites and the least used satellite from available satellites, and checks feasibility using the matheuristics explained above. If it is feasible and improving, then the best-known solution is updated. The satellite removal operator is called until the solution is infeasible for the reduced satellite set or does not improve anymore.

4.5 Computational experiments

In this section, we introduce the data sets used in the experimental study and present the results. The proposed ITS is implemented in Python language. Subproblems for updating the tabu list in the trip assignment of SE vehicles and routing of FE vehicles are solved by a commercial solver, Gurobi 9.12. The tests are conducted using 16 CPUs on Intel(R) Xeon(R) Gold 5218 with 2.30 GHz clock speed.

4.5.1 Parameter setting

The parameter settings of the proposed ITS are the same for both problems: `Asynch` and `Synch` systems. The time limits for solving the subproblems differ, considering the scale of the problems. The following parameter values are used based on their performances in extensive numerical experiments. The number of iterations used within ALNS and *LS* is varied to evaluate the solution evolution and computational time.

- m_{start}: 5
- max_{ITS}^{iters}: 5
- max_{LS}^{reps}: 5
- max_{LS}^{iters}: {0, 500}
- max_{ALNS}^{iters}: {0, 500, 1000}
- *SAA*: Initialized at 5% of the starting solution.
- Initial scores for the destroy operators in MLD:
  - Roulette wheel selection types (S_I, S_W): 10 and 1 for identical or weighted types, respectively.
  - Removal types (S_R, S_N): 10 and 1 for route and node removal, respectively.
  - Neighbor sizes ($S_5, S_{10}, S_{25}, S_{35}$): 1 for all 5, 10, 25, and 35%.
- The scores are increased by 1 if improving, 0.1 if the same, and 0 if deteriorating.
- For benchmark problems with 100 customer nodes, subproblem time limits are set to 10 seconds for solving MVRPs of the SE and 100 seconds for solving the VRP of FE. For the case study with 700 customers, these limits are increased to 100 seconds and 1000 seconds, respectively.
- The unit cost of traveling on each echelon is set to 1 while vehicle use cost for each echelon is set to shift durations of the data sets.

4.5.2 Experiments on benchmark instances

This section evaluates our algorithm's performance against the state-of-the-art method proposed by Grangier et al. (2016), which utilizes an ALNS approach. They employ a hierarchical optimization strategy, prioritizing the minimization of fleet size on FE, followed by the SE, and finally, the total routing cost. The benchmark instances are derived from the well-known Solomon instances (Solomon 1987), consisting of 8 satellites with no storage and 100 delivery nodes. For a fair comparison to the real-life problems studied in this chapter, we selected clustered-type instances (C-type). These instances are characterized by closer demand locations, long vehicle working hours, and high demand volumes, resulting in fewer customer visits per trip on the SE. These C-type instances, which include varying customer time windows, are known for their complexity. Marques et al. (2022) demonstrate that finding feasible solutions for these instances can be particularly challenging in scenarios without storage.

It is important to note that the ALNS method by Grangier et al. (2016) assumes zero lead time for transshipment operations, allowing the authors to develop a linear time feasibility check algorithm. This assumption, however, underestimates the actual vehicle times in the system. To evaluate the differences between our ITS and the state-of-the-art method, we provide percentage deviations for each travel time component relative to relevant best-known solutions (denoted as BK^*).

The performance and limitations of the proposed decomposition-based approach

This section evaluates the proposed decomposition-based modeling approach by comparing it against the integrated approach employed in the ALNS method by Grangier et al. (2016), where insertions are assessed by considering the cost and feasibility of two-echelon problems. In our proposed approach, SE optimization is performed initially, followed by a global optimization step that incorporates FE optimization. As there is no transshipment handling costs in the benchmark instances, the satellite use cost c^t is set to 0. Table 4.1 summarizes the results obtained from the following solution methods:

- INITIALIZATION($m_{start} = 5$): The proposed multi-start heuristic is used to generate up to 5 initial solutions for SE optimization. These solutions are subsequently refined by FE optimization to achieve global optimality.
- $\text{MILP}_{MVRP}^{10mins}$: The proposed MILP formulation for the SE problem is optimized using a commercial solver with a time limit of 10 minutes. The best resulting SE solution is then refined by FE optimization for global optimality.
- $\text{MILP}_{MVRP}^{60mins}$: The proposed MILP formulation for the SE problem is optimized using a commercial solver with a time limit of one hour (60 minutes). The best resulting SE solution is then refined by FE optimization for global optimality.

The proposed initialization uses a greedy heuristic to construct the solution in less than a minute. It provides starting solutions that are, on average, 32.8% worse than the best-known solutions reported by Grangier et al. (2016). It tends to utilize more SEVs than the best-known solutions, with SE travel time (ST) deviating sharply by 47.4%, while FEVs consistently remain at their lower bound across all instances. In contrast, MILP methods improve with extended runtime: the 10-minute variant reduces total travel time (TT) deviation to 9.6%, while the 1-hour variant achieves near-baseline SE performance (-0.8% ST deviation). This suggests that the two-echelon systems can be further improved in favor of SE logistics costs at the expense of more travel time on FE.

Both MILP methods underperform on the FE, exhibiting 20–24% higher FE travel times (FT) than the benchmarks. Despite this, the 1-hour MILP still indicates potential for overall objective improvement. It suggests that an initial focus on SE optimization can be beneficial for global fleet optimization, and evaluating multiple solutions before discarding them has the potential to reduce the total travel time within the system. Furthermore, the consistent increase in the number of transshipments across all tested methods compared to the best-known solutions indicates a potential for increased operational complexity. This suggests using penalty costs on the number of transshipment operations to improve the consolidation for vehicles even increasing total travel times.

Table 4.1: The performance of the proposed decomposition modeling framework, iterating first solving routing problem on SE (formulation in Section 4.3.2) and then optimizing the related routing problem on FE (see formulation in Section 4.3.3.

		nSEVs	nFEVs	TT	ST	FT	NT	TT dev %	ST dev%	FT dev%
	c201	3	2	1389.4	837.8	551.6	14.0			
	c202	3	2	1305.0	848.9	456.1	15.0			
BK^*	c203	3	2	1272.4	816.3	456.1	14.0			
	c204	3	2	1237.7	781.6	456.1	14.0			
Grangier et al. (2016)	c205	3	2	1312.4	856.3	456.1	15.0			
Approximately	c206	3	2	1312.7	856.6	456.1	14.0			
50 mins	c207	3	2	1280.4	824.3	456.1	14.0			
	c208	3	2	1278.5	822.4	456.1	14.0			
	Avrg	*3*	*2*	*1298.6*	*830.5*	*468.0*	*14.3*			
	c201	4	2	1537.8	1009.8	528.0	16.0	10.7	20.5	-4.3
	c202	4	2	1535.8	1079.7	456.1	17.0	17.7	27.2	0.0
	c203	4	2	1585.6	1114.9	470.7	15.0	24.6	36.6	3.2
INITIALIZATION(5)	c204	4	2	2086.6	1585.0	501.6	17.0	68.6	102.8	10.0
Less than	c205	4	2	1813.2	1342.5	470.7	18.0	38.2	56.8	3.2
a minute	c206	4	2	1641.9	1171.2	470.7	16.0	25.1	36.7	3.2
	c207	4	2	1757.3	1154.1	603.2	16.0	37.2	40.0	32.3
	c208	4	2	1793.9	1302.4	491.5	16.0	40.3	58.4	7.8
	Avrg	*4*	*2*	*1719.0*	*1220.0*	*499.1*	*16.4*	32.8	47.4	6.9
	c201	3	2	1414.4	812.8	601.6	16.0	1.8	-3.0	9.1
	c202	3	2	1416.9	815.3	601.6	16.0	8.6	-4.0	31.9
	c203	3	2	1462.1	810.5	651.6	16.0	14.9	-0.7	42.9
$\text{MILP}_{MVRP}^{10mins}$	c204	4	2	1520.2	954.1	566.1	15.0	22.8	22.1	24.1
Time limit	c205	3	2	1408.7	804.2	604.5	15.0	7.3	-6.1	32.5
10 minutes	c206	3	2	1405.4	803.8	601.6	15.0	7.1	-6.2	31.9
	c207	4	2	1372.6	859.2	513.4	15.0	7.2	4.2	12.6
	c208	4	2	1371.5	880.0	491.5	15.0	7.3	7.0	7.8
	Avrg	*3.375*	*2*	*1421.5*	*842.5*	*579.0*	*15.4*	9.6	1.7	24.1
	c201	3	2	1414.4	812.8	601.6	16.0	1.8	-3.0	9.1
	c202	3	2	1393.8	792.2	601.6	16.0	6.8	-6.7	31.9
	c203	3	2	1387.9	786.3	601.6	15.0	9.1	-3.7	31.9
$\text{MILP}_{MVRP}^{60mins}$	c204	3	2	1405.1	878.2	526.9	14.0	13.5	12.4	15.5
Time limit	c205	3	2	1408.7	804.2	604.5	15.0	7.3	-6.1	32.5
An hour	c206	3	2	1405.4	803.8	601.6	15.0	7.1	-6.2	31.9
	c207	4	2	1294.3	838.2	456.1	15.0	1.1	1.7	0.0
	c208	4	2	1355.7	864.2	491.5	15.0	6.0	5.1	7.8
	Avrg	*3.25*	*2*	*1383.2*	*822.5*	*560.7*	*15.1*	6.6	-0.8	20.1

The table presents the following metrics: the number of vehicles on the SE ($nSEVs$) and FE ($nFEVs$), the total travel time (TT), the travel time on the SE (ST) and FE (FT), and the number of transshipment operations (NT). Notably, the minimum number of transshipment operations regarding the capacity of a SEV and total volume to deliver is 11 for all instances. Percentage deviations from BK^* are provided.

The proposed decomposition-based approach presents both notable potentials and inherent challenges in tackling two-echelon vehicle routing problems. Its primary potential lies in its ability to break down a complex, large-scale problem into more manageable subproblems (SE and FE optimization), potentially leveraging specialized solvers and heuristics for each echelon. This modularity could lead to more efficient optimization of individual echelons, as evidenced by the 1-hour MILP achieving near-optimal SE performance. The persistent FE inefficiencies observed in the MILP-based decomposition highlight the difficulty in capturing the interdependencies between the echelons, suggesting a need for sophisticated mechanisms to ensure that optimizing the SE does not come at a substantial cost to the FE.

The performance of the proposed ITS

Table 4.2 summarizes the results obtained from our algorithm, using various parameter settings, and compares them to the best-known solutions. Within the proposed ITS, ALNS aims to improve the fleet size and total travel costs on SE. In the first experiment, we solve the problems using only ALNS without applying *LS*, indicated as 0 and 500 iterations for these modules, respectively. It is shown that it can reduce the number of vehicles on SE to the best-known fleet size and improve the total travel time. However, the percentage deviation of total travel time is 10.6%, indicating the need for improving SE routes locally. When *LS* is applied to the intermediate solutions, it rearranges the routes to improve the total travel time. *LS* works around the incumbent solution, and the neighborhoods are limited. On the other hand, *ALNS* works globally and enables us to explore many directions by multiple magnitudes defined by destroy operators. When the number of iterations in ALNS is increased further and combined with *LS*, indicated as 500 and 1000, the proposed algorithm can provide solutions within 2.3%.

Table 4.2: Performance of the proposed ITS on benchmark instances, consisting of 100 delivery nodes and 8 satellites.

ITS settings	Ins	nSEVs - nFEVs	TT	ST	FT	NT	TT dev%	ST dev%	FT dev%	Run time (mins)
INITIALIZATION	c201	3 - 2	1414.4	812.8	601.6	16.0	1.8	-3.0	9.1	6.0
($m_{start} = 5$)	c202	3 - 2	1447.9	881.7	566.2	15.0	11.0	3.9	24.1	21.6
	c203	3 - 2	1394.8	828.6	566.2	14.0	9.6	1.5	24.1	23.2
LS	c204	3 - 2	1357.0	851.9	505.1	15.0	9.6	9.0	10.7	30.0
($max_{LS}^{reps}, max_{LS}^{iters} = 0$)	c205	3 - 2	1400.8	834.6	566.2	16.0	6.7	-2.5	24.1	15.2
	c206	3 - 2	1596.3	944.7	651.6	15.0	21.6	10.3	42.9	15.5
ALNS	c207	3 - 2	1426.0	859.8	566.2	16.0	11.4	4.3	24.1	17.7
($max_{ALNS}^{iters} = 500$)	c208	3 - 2	1444.0	877.8	566.2	17.0	12.9	6.7	24.1	16.9
	Avg	*3 - 2*	*1435.2*	*861.5*	*573.7*	*15.5*	*10.6*	*3.8*	*22.9*	*18.3*
INITIALIZATION	c201	3 - 2	1390.5	838.9	551.6	13.0	0.1	0.1	0.0	37.4
($m_{start} = 5$)	c202	3 - 2	1328.3	823.2	505.1	13.0	1.8	-3.0	10.7	45.3
	c203	3 - 2	1339.4	834.3	505.1	13.0	5.3	2.2	10.7	54.5
LS	c204	3 - 2	1265.0	794.3	470.7	13.0	2.2	1.6	3.2	70.3
($max_{LS}^{reps} = 5, max_{LS}^{iters} = 500$)	c205	3 - 2	1311.3	806.2	505.1	12.0	-0.1	-5.9	10.7	40.0
	c206	3 - 2	1331.0	860.3	470.7	13.0	1.4	0.4	3.2	39.6
ALNS	c207	3 - 2	1350.0	893.9	456.1	13.0	5.4	8.4	0.0	48.1
($max_{ALNS}^{iters} = 1000$)	c208	3 - 2	1312.5	856.4	456.1	14.0	2.7	4.1	0.0	58.6
	Avg	*3 - 2*	*1328.5*	*838.4*	*490.1*	*13.0*	*2.3*	*1.0*	*4.8*	*49.2*
No tabu search	c201	3 - 2	1419.7	853.5	566.2	13.0	2.2	1.9	2.6	0.0
INITIALIZATION	c202	3 - 2	1374.8	823.2	551.6	13.0	5.3	-3.0	20.9	28.3
($m_{start} = 5$)	c203	3 - 2	1425.5	873.9	551.6	13.0	12.0	7.1	20.9	32.5
	c204	3 - 2	1482.9	927.8	555.1	13.0	19.8	18.7	21.7	49.3
LS	c205	3 - 2	1461.4	909.8	551.6	12.0	11.4	6.2	20.9	56.1
($max_{LS}^{reps} = 5, max_{LS}^{iters} = 500$)	c206	3 - 2	1448.5	913.8	534.7	13.0	10.3	6.7	17.2	41.7
	c207	3 - 2	1414.6	893.9	520.7	13.0	10.5	8.4	14.2	39.5
ALNS	c208	3 - 2	1484.4	856.4	628.0	14.0	16.1	4.1	37.7	45.4
($max_{ALNS}^{iters} = 1000$)	*Avg*	*3 - 2*	*1439.0*	*881.5*	*557.4*	*13.0*	*11.0*	*6.3*	*19.5*	*32.3*

The table presents the following metrics: the number of vehicles on the SE ($nSEVs$) and FE ($nFEVs$), the total travel time (TT), the travel time on the SE (ST) and FE (FT), and the number of transshipment operations (NT). Notably, the minimum number of transshipment operations regarding the capacity of a SEV and total volume to deliver is 11 for all instances. Percentage deviations from BK^* are provided.

To evaluate the tabu search mechanism on escaping local optima, we compare the solutions of the proposed method without a tabu list, indicated as solutions without tabu search, and 500 iterations in LS and 1000 iterations in ALNS. While tabu search increases solution time, it improves the solutions by providing a larger set of feasible solutions to optimize further. Furthermore, this study aims to minimize the number of transshipment operations at the satellites, in addition to logistics costs, using a multi-objective function for the SE problem described in Section 4.3.2. ITS solutions produced by combining

ALNS, LS, and tabu search require fewer transshipments than the best-known solutions but with increased travel distance on both echelons. Fewer transshipment operations translate to reduced handling operations, congestion, and emissions at the urban satellites.

Results on benchmark instances demonstrate that the proposed ITS is competitive, producing solutions with a maximum gap of 5.4% from the best-known solutions for challenging problems with time windows. The ITS utilizes a greedy search algorithm enhanced by tabu search. This enables us to reduce redundancy in computations by preventing the algorithm from revisiting infeasible solutions, thus mitigating the risk of local optima inherent in a greedy search.

The performance of the proposed MLD

In this section, we test the proposed ALNS concerning its hierarchical structure, where levels dictate the search directions and the search space size in each iteration. We consider c201 and c208 instances from the benchmark set, representing the tightest and loosest time window settings for delivery nodes, respectively. The destroy operators employed here involve route (R) or node (N) removals from the current solution, combined with considering A% of the remaining nodes from various neighbor size options. These combinations are further diversified by randomizing the removals with either identical (I) or weighted (W) roulette wheel selection probabilities. For experiments assessing the impact of levels in the proposed MLD operators, as depicted in Figure 4.3, we test the following scenarios for the ALNS subprocedure within the proposed ITS.

- 1-level: In total, 16 independent destroy operators are generated to represent all the destroy operators considered in the proposed 3-level MLD. These operators are combinations of ({W, I} x {R, N} x {A%: 5%, 10%, 25%, and 35%}). The score values are updated for a destroy operator in each ALNS iteration.

- 2-level MLD: In total, 4 destroy operators are generated to represent all the destroy operators considered in a 2-level MLD.. These operators are combinations of ({W, I} x {R, N}x {A%: 5%}) settings. The score values are updated for two destroy operators in each ALNS iteration.

- 3-level MLD: In total, 16 destroy operators are generated as proposed. These operators are combinations of ({W, I} x {R, N} x {A%: 5%, 10%, 25%, and 35%}). The score values are updated for three destroy operators in each ALNS iteration.

Table 4.3: The performance of the proposed MLD within ALNS method.

	Tight TWs (c201)						Loose TWs (c208)					
Methods	nSEVs	nFEVs	TT	ST	FT	NT	nSEVs	nFEVs	TT	ST	FT	NT
BK^*	3	2	1389.4	837.8	551.6	14	3	2	1278.5	822.4	456.1	14
1-level	4	2	1419.8	913.7	506.1	13	3	2	1460.9	959.3	501.6	13
2-level MLD	3	2	1390.5	838.9	551.6	12	3	2	1417.6	866	551.6	13
3-level MLD	3	2	1390.5	838.9	551.6	13	3	2	1312.5	856.4	456.1	14

The table presents the following metrics: the number of vehicles on the SE ($nSEVs$) and FE ($nFEVs$), the total travel time (TT), the travel time on the SE (ST) and FE (FT), and the number of transshipment operations (NT). Tested scenarios are as follows:
1-level: In total, 16 independent destroy operators.
2-level MLD: In total, 4 destroy operators along with removing only 5% neighbor size.
3-level MLD: In total, 16 destroy operators as proposed in this study.

The numeric observations from Table 4.3 indicate that the proposed 3-level MLD within the ALNS framework demonstrates robust performance across both the tightly constrained c201 and the loosely constrained c208 instances. Notably, for c208, the 3-level MLD yields the lowest total travel time among the tested ALNS variants and matches the BK^* for the number of transshipments. This performance contrasts with the 1-level strategy, which, despite employing 16 distinct destroy operators, fails to achieve the best-known fleet size for SEVs, likely due to its less frequent score update mechanism (once per iteration) compared to the 2-level (two updates) and 3-level (three updates) MLD approaches. This suggests that more frequent feedback on operator performance in the 2-level and 3-level strategies potentially facilitates a faster adaptation to more effective destroy operators. Furthermore, the comparison between the 2-level MLD (fixed 5% neighbor size) and the 3-level MLD (multiple neighbor sizes: 5%, 10%, 25%, 35%) suggests that increasing the neighbor size options can improve the total travel time, indicating the benefit of a multi-scale approach to solution perturbation. The comparison highlights the potential advantages of the proposed hierarchical structure in effectively exploring the solution space and achieving competitive results.

4.5.3 Experiments on Amsterdam case study

To evaluate the applicability of the synchronized two-echelon routing problems and proposed ITS for real-life problems, we conduct numerical experiments for optimizing service network design problems (SNDP) on a large-scale case study. It involves the daily scheduling of over 1000 operations across two echelons.

Data and case description

This chapter tests various IWLT systems for supplying hotels, restaurants, and cafés (HoReCa) in Amsterdam. The hospitality sector is essential to the city's tourism- and population-driven economy. Logistics constitutes 14% of all activity within Amsterdam's A10 ring road, with thousands of delivery vehicles operating daily (Gemeente Amsterdam 2024). Integrating waterborne transport into city logistics is promising to improve efficiency, but locating transshipment operations must account for limited space and time.

Table 4.4: Use case problem settings.

System parameters	Estimated (Bijvoet et al. 2024)		
Shift duration	8 hour/day		
Speed of SEV	5 m/s		
Speed of FEV	1.6 m/s		
Service time at customers	1.5 mins		
Transshipment duration	3 mins		
Minimum demand requirement	1 SKU		
Maximum demand requirement	5 SKUs		
Capacity of SEV	5 SKUs		
Capacity of FEV	25 SKUs		
Number of candidate satellites	56		
Number of central depots	1		
Networks on both echelons	Directed		
Daily demand and lower bounds			
dataset	*1*	*2*	*3*
Number of customers to visit	744	689	726
Total load to deliver (SKUs)	1482	1401	1443
Minimum number of transshipments (in load)	297	281	289
Minimum number of FEVs (in load)	60	57	58

To understand the benefits of flexibility in IWLT systems, we analyze the costs of storage and synchronization. We test `Asynch` systems with storage, where deliveries occur independently, and `Synch` systems without storage, where deliveries are coordinated to arrive simultaneously. This analysis allows us to evaluate cost savings, particularly in transportation, relative to investments in resources such as storage infrastructure or synchronized delivery coordination. However, service network design needs to be decided to understand the impacts of the number of satellites and their locations on the overall system performance. To optimize satellite locations for a given number of satellites, we use the classical p-median algorithm (Elloumi 2010), minimizing average customer-satellite distance and ensuring efficient coverage. Satellite scenarios range from 10 to 50 in increments of 10.

Table 4.4 summarizes 3 data sets used in this chapter for Amsterdam case study designed by Bijvoet et al. (2024) for HoReCa distribution system. The solution time is limited to $10h$ for each system and scenario, and mostly, the algorithm terminates before reaching the final iteration in ITS for the case study without time windows for the customers.

Storage and synchronization cost

City logistics aims to reduce the burden on road transportation and minimize freight logistics' contribution to urban congestion. From a waterborne transport service design perspective, this section evaluates the cost-effectiveness of opting for synchronized delivery coordination over dedicating limited urban space to storage. To achieve this, first, the problems are optimized for `Asynch` systems. Due to the storage investments, the number of satellites available to use is limited to 10. Then, we optimize `Synch` systems for the optimal SE schedules of `Asynch` solutions.

Essentially, we are asking, "What if we maintain the same delivery schedules on SE but utilize two different service types on FE?" While these two solutions do not differ in SE logistics costs, this approach allows us to compare FE costs, isolating the expenses associated with storage and synchronization for the same transshipment operations at the assigned satellite locations.

Table 4.5: Synchronization cost analysis.

	`Asynch`			`Synch`		
dataset	*1*	*2*	*3*	*1*	*2*	*3*
Required FEVs	61	58	60	64	60	62
Vehicle kms of FEVs	608	569	602	646	600	666
Total vehicle kms	1050	963	1029	1088	994	1093
Change in fleet size				3	2	2
Change in vehicle kms				38 (6%)	31(5%)	64(11%)

Table 4.5 summarizes the numerical experiments for different service types. For `Asynch` systems, the lower bound on the required number of FEVs is achieved. Imposing spatio-temporal synchronization in the `Synch` system constrains the problem, resulting in an increased number of FEVs used and vehicle kilometers (kms) traveled on waterways. Introducing 2 to 3 FEV trips from the central depot eliminates the daily need for storage, as these vessels act as secure storage while navigating or waiting for synchronization. Thus, LSPs on FE might consider evaluating the cost of operating these additional FEVs daily instead of dedicating storage spaces.

This section compares both systems under identical conditions, with the same satellites assigned with the same transshipment tasks. Serving the same demand results in different vehicle and storage resource investments. However, for a fair comparison, service network design can be further optimized for `Synch` systems to use more satellites as on-demand transshipment locations, rather than limiting the network as in traditional systems for storage investments.

Service network design and synchronization cost

This section analyzes the cost of the `Synch` system under different satellite scenarios to determine if savings in road transportation costs compensate for the increased investment in waterborne fleet acquisition and operation. Our two-echelon framework presents different underlying problems than those found in traditional SNDP literature. Typical SNDP studies involve simpler routing problems that lead to linearized

Table 4.6: Satellite network design and system overall cost analysis.

		Set 1					Set 2					Set 3				
Scenarios	Available satellites	10	20	30	40	50	10	20	30	40	50	10	20	30	40	50
Fleet usage	Required trips	350	359	347	348	349	333	334	337	338	341	343	341	341	339	343
	Required SEVs	8	8	7	7	7	7	7	7	7	7	8	7	7	7	7
	Required FEVs	64	65	65	63	64	60	61	64	60	59	66	64	64	61	63
	Total fleet	72	73	72	70	71	67	68	71	67	66	74	71	71	68	70
Fuel usage	Vehicle kms of FEVs	646	703	675	638	661	604	636	653	611	650	671	660	691	673	676
	Vehicle kms of SEVs	442	386	352	325	321	393	359	329	317	303	424	374	330	327	329
	Total kms	1088	1089	1027	963	982	997	995	982	928	954	1095	1035	1021	1000	1004
	Mode share of streets	41	35	34	34	33	39	36	33	34	32	39	36	32	33	33
	Vehicle kms per customer	1.5	1.5	1.4	1.3	1.3	1.4	1.4	1.4	1.3	1.4	1.5	1.4	1.4	1.4	1.4
Vehicle utilization	Customer per SEV	93	93	106	106	106	98	98	98	98	98	91	104	104	104	104
	Fill rate of SEV(%)	85	83	85	85	85	84	84	83	83	82	84	85	85	85	84
	Fill rate of FEV (%)	93	91	91	94	93	93	92	88	93	95	87	90	90	95	92
Satellite usage	Used satellites	10	19	29	37	44	10	19	29	39	43	10	20	30	38	45
	Min number of transshipments	10	3	1	1	1	4	3	2	1	1	9	1	1	1	1
	Max number of transshipments	45	40	40	39	37	53	41	42	42	41	48	44	45	44	43

relationships as the satellite network expands. We aim to ascertain whether design optimization yields improvements in synchronized coordination in city logistics compared to traditional storage systems.

Average results on the solutions in Table 4.6 show the complexity of the SNDP with respect to the increasing number of the satellites optimized by a clustering algorithm. Various statistics are provided on resource usage in terms of fleet, fuel, and satellite usage, as well as vehicle utilization, to evaluate the consolidation efficiency of FEVs and SEVs.

Increasing the number of satellites favors LSPs on the streets, except demand set 3 with 50 satellites scenario. It provides savings in vehicle kms on the roads, reducing the number of SEVs consequently for sets 1 and 3 having more customers than set 2. While total vehicle kilometers traveled generally decrease with more satellites, the relationship is not strictly linear. The minimum vehicle kms is achieved for scenarios with 40 available satellites. However, the minimum fleet size for set 2 is achieved in the scenario with 50 satellites. This might be due to the complexity of the design problem in terms of the optimality gap of the decomposition framework and computational time needed to achieve the best bounds on SE (Karademir et al. 2025).

Table 4.7: Evaluation of integrating flexibility into city logistics operations via coordination.

	`Asynch`			`Synch`			Comparison of `Synch` against `Asynch` system		
dataset	1	2	3	1	2	3			
Required trips	350	331	342	348	341	339			
Required SEVs	8	7	8	7	7	7	-1	0	-1
Required FEVs	61	58	60	63	59	61	2	1	1
Vehicle kms of FEVs	608	569	602	638	650	673	5%	14%	12%
Vehicle kms of SEVs	442	393	427	325	303	327	-26%	-23%	-23%
Total vehicle kms	1050	963	1029	963	954	1000	-8%	-1%	-3%
Used satellites	10	10	10	37	43	38	27	33	28
Minimum number of transshipments	10	4	11	1	1	1			
Maximum number of transshipments	45	52	49	39	41	44			

Overall, using more satellites produces a slight reduction in total kilometers traveled, increased efficiency in terms of vehicle utilization in load and the number of customers served, a shift towards greater reliance on waterborne transport, and a more even distribution of transshipment workload among satellites. While these operational improvements suggest potential cost savings, a comprehensive cost-effectiveness analysis is necessary. This analysis should account for the expenses associated with acquiring, operating, and maintaining both the expanded fleet and the satellite network in reach. Evaluating these costs in relation to the observed operational benefits will provide a clearer picture of the economic viability of on-demand satellite use within the `Synch` system. This will enable informed decision-making regarding the optimal balance between infrastructure investment and operational efficiency in urban freight logistics.

For comparison with `Asynch` systems, we consider a balanced cost share for `Synch` systems, where the costs of fleets and vehicle kilometers are equal on both echelons. Table 4.7 compares the best-known `Synch` system solutions (with the minimum number of all vehicles) to the `Asynch` system. Using more satellites provides savings in vehicle kilometers on the streets, ranging from 23% to 26%, and fleet reductions of 1 vehicle for demand sets 1 and 3, which have more customers. These savings come at the expense of additional synchronization costs over waterways, resulting in increased vehicle kilometers (ranging from 5% to 14%) and a fleet expansion of at most 2 vehicles. However, using more satellites benefits the overall system by reducing total vehicle kilometers and fleet size. Furthermore, it reduces the maximum number of transshipment operations at the satellites, which reduces the risk of overloaded satellites by balancing workloads more effectively than `Asynch` systems.

4.6 Conclusions

This chapter assessed the role of coordination and storage options within multi-trip two-echelon distribution systems. An Iterated Tabu Search (ITS) metaheuristic, combining ALNS, local search, and tabu search, was developed to address this problem. The proposed ITS demonstrated competitive performance on benchmark instances, achieving a balance between solution quality and computational efficiency.

To assess the practical applicability of the proposed ITS, we conduct numerical experiments on a large-scale case study involving scheduling over 1000 operations in Amsterdam. Initially, the analysis focuses on the cost of synchronization, coordinated IWLT service for the optimal SE schedules of storage systems. It is assumed that the service to be provided does not differ in terms of satellite network and assigned transshipment operations to them. The findings indicate that strategically coordinating 2-3 additional FEV trips can effectively substitute for dedicated storage spaces, achieving the same service levels while using urban spaces only during the transshipment operations in the cities. Furthermore, optimizing the service network design yields significant savings of up to 26% in road transportation vehicle kilometers, ultimately reducing the overall system's costs and negative externalities within the urban environment.

City logistics is a complex multi-player environment where conflicting objectives necessitate stakeholder analysis for global optimality. The limitations of this chapter include the computational complexity of maintaining overall system feasibility and the cost assumptions regarding satellite use. Computational time can be improved by eliminating redundancy when optimizing intermediate solutions, further enhancing system performance. This study neglects satellite usage costs, focusing on minimizing freight costs within cities by promoting a greater modal shift towards waterborne transport.

Future studies should also investigate the impact of satellite locations for `Synch` systems. While this chapter employed the classical p-median method to locate satellites, aiming to reduce distances between customer and satellite assignments, future studies could explore alternative methods such as k-means, which focuses on minimizing distances between customers. Furthermore, the nuisance issues related to the transshipment operations are addressed by penalizing the system for transshipment operations through satellite use cost, c^t. The analysis of satellite usage costs should consider the influence of nearby public places (e.g., hospitals, schools, or parks), population density, and congestion levels. Finally, it is essential to study the implications of synchronized delivery coordination under uncertainty, particularly concerning operational lead times, as such uncertainty can jeopardize the overall system's feasibility and efficiency.

To address **SQ3**, this chapter introduces a novel approach combining approximation algorithms and decomposition modeling to efficiently solve real-life large-scale problems in multimodal city logistics. This hybrid heuristic-MILP method offers enhanced solution speed and accurately represents real-world complexities, allowing for the assessment of system performance under various service design options.

Chapter 5

Reliability of IWLT systems

In this chapter, we address **SQ4** for the reliability issue within the city logistics context, aiming at minimizing lateness as a measure of customer inconvenience, logistics costs for LSPs, and road mode share for reaching greener logistics systems. To tackle the complexity issue for 2E-MVRP-SS, we present a two-stage stochastic optimization with a mixed-integer recourse model and employ logical cuts for the convergence. We test the problem on a small network using scenario-based stochastic optimization to gain insights into IWLT systems under uncertainty. The scenarios represent delay cases in transshipment lead times to quantify the risks associated with the integrated systems with different storage options. The proposed scenario generation approach shows stability over time as the variance of the scenarios within the sample decreases with an increasing number of scenarios. Furthermore, it is shown that even relocating storage units in case of delays cannot match the performance of flexible sailing services in terms of congestion, reliability, and modal shift in cities.

This chapter is organized as follows. Section 5.2 reviews the relevant literature on synchronized two-echelon routing problems and stochastic optimization. Section 5.3 formulates the problem, while Section 5.4 presents a two-stage stochastic optimization with a recourse model. Section 5.5 presents an experimental layout concerning the service network design and sampling approach. Section 5.6 discusses the effects and implications of uncertain transfer times within a two-echelon logistics setting. Finally, Section 5.7 concludes this chapter.

This chapter will be submitted to a journal. [1]

[1] Karademir, C., Zwaginga, J. J., Beirigo B. A., & Atasoy, B., A two-stage stochastic optimization model for synchronized two-echelon routing problems (2025).

5.1 Introduction

Light electric freight vehicles (LEFVs), such as bikes, vans, and drones, offer a sustainable approach to city logistics, mitigating congestion by optimizing the use of the transportation network (Carrese et al. 2021). However, effective LEFV implementation within multimodal logistics systems requires methodologies that synchronize multiple vehicles in terms of time, space, and cargo flow (Crainic 2008). These systems typically involve multi-echelon supply chains with transshipment operations between different transport modes. A key challenge, inadequately addressed in the literature (Sluijk et al. 2023), is the risk of delay propagation through the network, disrupting the synchronized operation of these integrated systems and potentially increasing operational costs.

Operational resilience is crucial in multimodal transportation systems, which are highly susceptible to uncertainties causing delays at satellites where transshipment operations occur between modes. These uncertainties stem from external events like accidents and natural disasters, as well as operational variations such as demand fluctuations and service time variability. Such disturbances often lead to infeasibilities and cascading delays across the network (Drexl 2012). To remain competitive with road transport, multimodal logistics services must incorporate these uncertainties into offline planning, minimizing disruptions and re-planning costs (Delbart et al. 2021).

This chapter addresses these challenges by considering a stochastic two-echelon logistics problem to optimize reverse flows in multimodal city logistics. Reverse logistics encompasses activities such as product returns, recycling, and waste collection, aiming to recapture value and minimize environmental impact (Cruz-Rivera & Ertel 2009). Focusing specifically on flexible Integrated Water- and Land-based Transportation (IWLT) systems, which utilize waterways for efficient and sustainable freight movement, we illustrate a waste collection problem as a potential application area for waterborne transport (Dimitrova 2021, CBCNY 2015, Roboat 2024). Flexibility is defined as the synchronization of vehicles to eliminate the need for storage investments.

This chapter extends the deterministic IWLT system described previously in Karademir et al. (2022b) to incorporate regional uncertainties that affect transshipment lead times at the satellites. These uncertainties, such as congestion or disruptions, can delay the arrival of vessels and LEFVs. To address this, we propose a two-stage stochastic programming model with recourse for the Two-echelon Multi-trip Vehicle Routing Problem with Satellite Synchronization (2E-MVRP-SS). This model minimizes both customer lateness and re-routing costs.

In the first stage, we optimize LEFV schedules, prioritizing the planning of reliable service times for pickups due to the time- or storage capacity-sensitive nature of reverse logistics. The second stage introduces corrective actions, such as re-allocating transshipment operations and re-routing vehicles, to mitigate the impact of delays. This approach allows for flexibility in responding to disruptions while minimizing overall costs.

Within this two-stage stochastic optimization framework, we utilize a Benders' decomposition approach, adapted from Karademir et al. (2025). We introduce simple logical cuts derived from solving simplified but synchronized routing problems to handle the non-convex cost function in the second stage. To handle the uncertainty inherent in transshipment lead times, we use a scenario sampling approach. Instead of considering all possible future outcomes, which is often computationally intractable, we generate a representative set of scenarios where mean delays at the satellites are randomly distributed. This allows us to approximate the uncertain future and develop robust solutions.

This research contributes to the field in the following ways:

- To the best of our knowledge, this is the first study to address the impacts of satellite delays on vehicle synchronization in a two-echelon system with no storage capacity, requiring a high degree of spatiotemporal coordination.

- We introduce a two-stage stochastic programming model with a mixed integer recourse to re-optimize location-routing decisions under uncertainty, minimizing the expected cost of the overall system. Due to the non-convexity of the second stage, combinatorial Benders cuts are employed within an enumeration method.

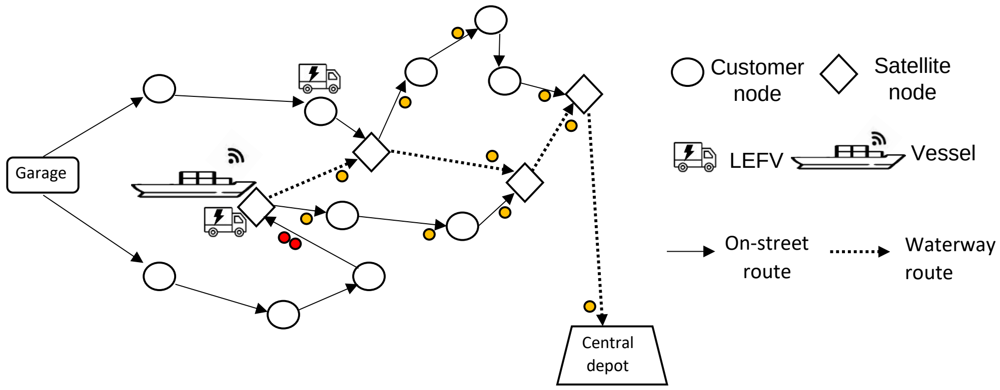


Figure 5.1: Propagation of delay on a two-echelon network, where the red dot represents the delayed arrival of a LEFV to the satellite while orange dots are operations possibly to delay.

- We compare the performance of the proposed flexible transport system, where vessels act as mobile depots, to a stationary system with fixed vessel locations under uncertainty.

The goal of this chapter is to provide a framework to analyze the extent of the complexity of stochastic synchronized two-echelon routing problems under delays at the satellites. The complexity changes concerning service network design (synchronization and storage options for flexible and stationary systems in restoring efficiency), which is further complicated by time windows and multi-trip attributes. They increase the operational cost of the system by amplifying the propagation of delays in transshipment lead times due to interdependent operations of synchronized routing problems. Figure 5.1 illustrates this synchronized two-echelon system's operations and potential delay propagation, shown as the delay scenario in the first transshipment operation of a 10-node problem. The complexity is tackled in two ways: i) two-stage stochastic optimization using an enumeration method for non-convexity issues in recourse actions, and ii) scenario sampling approach using joint distributions to model regional uncertainties for non-convexity issues in the expected costs of the delays. Further research could use the enumeration and pricing framework to develop approximation approaches such as heuristics for routing problems or min cost flow algorithms for location-routing problems to tackle large-scale problems regarding the number of operations or plausible scenarios.

5.2 Related work

Reverse logistics, encompassing the return of materials like components, products, and end-of-life disposals, back up the supply chain, is a significant cost driver for shippers, receivers, and consumers. To improve sustainability and profitability, logistics service providers (LSPs) are refining their reverse logistics systems. For instance, e-commerce applications incorporate backhauling and return services into delivery operations to minimize empty trips. Reliable pickup services are crucial, impacting both last-mile delivery and the efficiency of reverse logistics processes like waste collection, recycling, and e-commerce returns. In these domains, increasing consolidation at pickup locations is key to minimizing trips and maximizing efficiency. However, reliable reverse logistics must also prioritize minimizing lateness at pickup services to reduce consumers' inconveniences or overflows at these sites.

An IWLT is a Two-echelon Vehicle Routing Problem (2E-VRP) that broadly covers such settings where the logistics service is managed by routing and consolidating freight through intermediate satellites (Crainic et al. 2004). Each echelon has its fleet; typically, one has larger vehicles than the other, enabling consolidation between levels. Consolidation takes place at the satellites that connect two echelons to transfer the items to their final destinations. Following the introduction of 2E-VRP by Gonzalez-Feliu

(2008), different variants are proposed to handle more realistic applications including time windows, time-dependent travel times, satellite synchronization, multi-trips, pickups, or deliveries (Cuda et al. 2015).

The complicating characteristic of 2E-VRP is the synchronization between the vehicles on different levels. Most of the studies have focused on the basic variant of 2E-VRP, where synchronization is required only for cargo flow (Sluijk et al. 2023). Successful exact methods are based on branch-and-cut and branch-and-price algorithms, (see, e.g., Jepsen et al. (2013), Santos et al. (2013), Marques et al. (2020), Mhamedi et al. (2021), Baldacci et al. (2013)). For more complex variants with temporal synchronization, time windows, and other constraints, there exist several heuristics such as Large Neighborhood Search (LNS) (Anderluh et al. 2021), Adaptive Large Neighborhood Search (ALNS) (Grangier et al. 2016), Greedy Randomized Adaptive Search Procedure (GRASP) (Anderluh et al. 2017), and memetic algorithms (He & Li 2019). Dellaert et al. (2019) and Dellaert et al. (2021) propose a branch-and-price algorithm for a 2E-VRP with time windows and satellite synchronization. Although a common approach iteratively decomposes echelons and routes, most studies neglect satellite capacity as a limiting factor for cargo throughput. Existing research frequently assumes simultaneous transfer operations, enabling the splitting of transshipment operations across multiple vehicles and echelons. However, these assumptions are often unrealistic, particularly when dealing with multimodal systems where echelons utilize different transportation modes or when satellites possess limited real-time resources. These limitations amplify the risk of delays within the system if ignored.

Stochastic optimization is a mathematical framework for making decisions to find optimal solutions that perform well on average or under certain risk criteria, considering the range of possible future scenarios (Birge & Louveaux 2011). To solve stochastic problems, we need a model, deterministic parameter values, and a description of the stochasticity. Defining the stochasticity, scenario generation means the process of creating a manageable approximation of the often complex and continuous probability distributions of the stochastic parameters. The solutions obtained from the stochastic program should be relatively insensitive to small changes in the scenario tree, defined by its stability for the reliability, quality, and robustness of the solutions. While the models become computationally intractable or expensive with the number of stochastic variables, the stages, and the scenarios, approximation methods are applied to reduce one or two of these aspects, such as bounding approaches (Maggioni & Pflug 2016).

Several studies that deal with VRP have included time delays through a stochastic representation of possible delays. For example, Chang (2005) considers a stochastic recourse program that adds a late delivery penalty in customer pickup scheduling, Zang et al. (2020) uses recourse with stochastic time delays and demand in a petrochemical supply chain, and Boujlil & Elhaq (2020) also look into both stochastic time and demand for freight transport. For 2E-VRPs, however, as mentioned in a recent literature review by Sluijk et al. (2023), cost-efficient recourse is still a challenge that needs more research. Wang et al. (2017) describe a two-stage stochastic program with simple recourse for a two-echelon problem considering deliveries from a depot to a satellite and from a satellite to customers. In this chapter, we aim to add a stochastic representation of delays in transshipment lead times to the second echelon to be able to further research the applicability of the effect of delays within a separate echelon on the other.

Existing studies primarily focus on stochastic demand, assuming either satellite storage or neglecting transshipment lead times in cases without storage. Temporal synchronization relies on heuristic approximations, and the impact of delays remains unaddressed. In reverse logistics, real-time decisions can be adjusted, reallocating unvisited locations to vehicles within feasibility and cost-efficiency constraints. Essentially, any available vehicle can visit any pickup location if capacity allows; a LEFV then picks up the goods and delivers them to any vessel. Conversely, in delivery services, unserved customers are limited to either the vehicles initially carrying their products or available vehicles that can reload those products.

In synchronized two-echelon routing problems, any uncertainty in any operation delays the starting time of the next operation and propagates over the dependent upstream and downstream operations if enough buffer time is not scheduled for the vehicles at the satellites. In a multimodal system, the delays might result from longer service times at the customers, travel times on the streets or over waterways, or handling times during transshipment operations. Unlike single echelon systems, if a delay in a vehicle operation cannot be offset before the upcoming transshipment operation, it also jeopardizes the reliability of the services provided by interacting vehicles (Drexl 2012). To study the impact of the uncertainties for reliable IWLT systems, we extend the MILP formulation of the 2E-MVRP-SS outlined in Chapter 3 by incorporating a stochastic temporal delay variable.

This chapter presents a compact formulation for the two-echelon problem with uncertain transshipment lead times, solved using two-stage stochastic programming with recourse. The first stage determines on-street vehicle schedules, while the second stage relocates scheduled transshipment operations at satellites to respond to delays. If any relocation exists, then the on-street vehicle only has to detour to the newly assigned satellite while the sequence of the operations is fixed. Therefore, the goal of the first stage is to optimize the trip schedules on the vehicles such that they can be relocated efficiently in real-time when the lead times differ from the average transshipment time due to daily uncertainties. We test our approach using different geographical demand distributions representing sectors and different degrees of flexibility for service network design options.

5.3 Problem definition and formulation

Unlike the deterministic formulation of the 2E-MVRP-SS, which assumes constant transshipment times across satellites, this chapter considers stochastic process times. This accounts for the impact of regional factors (e.g., infrastructure, traffic) on satellite processing times, which is crucial for identifying robust schedules for on-street operations and ensuring reliable customer service.

5.3.1 Expected operations' scheduling problem

The first echelon is the street level, where we have K_1 identical LEFVs with a capacity of Q_1 units. These LEFVs start their journey at the garage (g), visit a set of pickup locations (C), and return to the garage without exceeding their capacity at any point. Each pickup point i requires q_i units of goods to be collected within a time window of (a_i,b_i) associated with a service time of τ_i. t_{ij} denote the shortest travel time between points i and j, respectively. LEFVs can unload the goods onto vessels multiple times at a set of transshipment satellites P. Transferring goods requires an expected U_p time unit at satellite p. The second echelon is the water level where K_2 identical vessels with a capacity of Q_2 units start at the central depot (w), visit satellite(s) when LEFVs require transshipment operations, and return to the central depot.

Tactical and operational decisions

The x_{ij} variable determines whether a LEFV serves pickup location j immediately after serving pickup i while v_{ip} decides whether the LEFV visits satellite p immediately after serving location i. If v_{ip} is 1, then there is a transfer task at satellite p with a demand equal to the collected goods on the LEFV. In this way, the model jointly decides the first echelon routes and transfer tasks for the second-level routing problem. The second echelon subproblem (vessel routing) is a basic VRP where a fleet of vessels serves all the transfer tasks required by the first echelon decisions respecting the capacity of the vessels and the maximum time duration, operational times represented by a_w and b_w for the central depot. The vessel routing decisions are taken by y variables. The synchronization is achieved by the earliest service start time for a transfer task at a satellite and delayed arrival time to the next point, according to the service end time of the transfer task plus travel time to the next point. Each transshipment operation should be assigned to a single vessel, prohibiting splitting the operation between multiple vessels. All sets, parameters, and decision variables are presented in Table 5.1.

5.3.2 Stochastic elements

We assume the mean transfer time at satellite p follows a random distribution $\widetilde{U_p}$, where $\widetilde{U_p}$ takes values from a finite set. The model minimizes a cost function that includes:

- **Penalty costs.** A penalty cost c^i_{late} is incurred for each unit of lateness at pickup location i to discourage lateness, whereas to prevent overtime, c^g_{pen} and c^w_{pen} penalize maximum lateness to the garage and central depot, respectively.

Table 5.1: Notation for the stochastic 2E-MVRP-SS model adapted from Karademir et al. (2025).

Sets and Indices	
g, w	garage for LEFVs and central depot for vessels, respectively
C	Customer nodes indexed by i and j
C_s	Customer nodes and the garage g, $C \cup \{g\}$
C_w	Customer nodes and the central depot w, $C \cup \{w\}$
P	Satellites indexed by p
N	All nodes indexed by n, $C \cup \{g\} \cup \{w\} \cup P$
Parameters	
q_i	Demand at node $i \in C$
a_i	Earliest service time of node $i \in N$
b_i	Latest service time of node $i \in N$
τ_i	Service duration of node $i \in C$
t_{ij}	Shortest travel time from node $i \in N$ to $j \in N$
c^s/c^w	Cost of traveling a unit of time on the streets/water
Q_s/Q_w	Capacity of a LEFV/vessel
K_s/K_w	Number of available LEFVs/vessels
β_s/β_w	Fixed cost of a LEFV/vessel
M^s_{ij}	Sufficiently large number for constraint linearization, $M^s_{ij} = b_i + \tau_i + t^{max}_{ip} + U + t^{max}_{pj} - a_j$
M^w_{ij}	Sufficiently large number for constraint linearization, $M^w_{ij} = b_i + \tau_i + t^{max}_{ip} + U + t^{max}_{pr} - (a_j + \tau_j + t^{min}_{jp})$
c^i_{late}	Lateness at node $i \in C_s \cup w$
$\widetilde{U}_p$	Uncertain transshipment lead time at satellite p
Variables	
x_{ij}	(Binary) 1 if node $j \in C_s$ is visited immediately after node $i \in C_s$ by a LEFV, 0 otherwise
m_i	Total load on the LEFV after visiting node $i \in C$, $q_i \leq m_i \leq Q_s$
h_i	Service start time at node $i \in C$ with a LEFV, $\max\{a_g + t_{gi},\ a_i\} \leq h_i \leq \min\{b_g - t_{ig} - s_i - U,\ b_i\}$
ϕ_i	(Binary) 1 if there is a transfer task immediately after node $i \in C$ is served, 0 otherwise
v_{ip}	(Binary) 1 if satellite $p \in P$ is assigned to the transfer task $i \in C$ (if exists), 0 otherwise
$y_{ip,jr}$	(Binary) 1 if the transfer task ip is served by a vessel immediately after the transfer task jr
$y_{w,ip}$	(Binary) 1 if the transfer task ip is served as the first task by a vessel
$y_{ip,w}$	(Binary) 1 if the transfer task ip is served as the last task by a vessel
u_i	Service start time of the transfer task $i \in C$ with a vessel and LEFV
l_i	Total load on the vessel after serving the transfer task $i \in C$
f^s_{ij}	Total travel time for a LEFV from node i to node j if it visits $i, j \in C_s$ consecutively
f^w_{ij}	Total travel time for a vessel from the transfer task $i \in C_w$ to the transfer task $j \in C_w$ if it serves tasks i, j consecutively
pen_i	Lateness at node $i \in C_s \cup w$

- **Logistics costs.** To minimize fleet size and travel distance across both echelons, transshipment delays are incorporated as uncertain parameters, affecting the scheduling of vehicle arrivals and departures, thereby locating and routing decisions. These delays are propagated through pen_i, pen_g, and pen_w variables, representing lateness at customer locations, the garage, and the central depot, respectively.

5.3.3 A novel formulation to stochastic two-echelon routing problem

Therefore, the integrated formulation in Chapter 3 is extended for the stochastic two-echelon routing problem by introducing stochastic parameters, formulated as follows:

$$\min \quad \overbrace{\sum_{i \in C_s \cup w} c^i_{late} pen_i}^{\text{Customer inconveniences: } z^{late}} \tag{5.1}$$

$$+ \overbrace{\sum_{i \in C} \beta_s x_{gi} + \sum_{i,j \in C_s} c^s f^s_{ij}}^{\text{Street Level Cost: } z^s} \tag{5.2}$$

$$+ \overbrace{\sum_{\substack{i \in C \\ p \in S}} \beta_w y_{ip,w} + \sum_{\substack{i,j \in C \\ p,r \in S}} c^w t_{pr} y_{ipjr} + \sum_{\substack{i \in C \\ p \in S}} c^w t_{wp} y_{w,ip} + c^w t_{pw} y_{ip,w}}^{\text{Water Level Cost: } z^w} \tag{5.3}$$

subject to

Street Level Routing Problem

$$\sum_{j \in C_s} x_{ij} = \sum_{j \in C_s} x_{ji} = 1 \qquad \forall i \in C \tag{5.4}$$

$$\sum_{i \in C} x_{gi} = \sum_{i \in C} x_{ig} \leq K_s \tag{5.5}$$

$$\phi_i \geq x_{ig} \qquad \forall i \in C \tag{5.6}$$

$$m_j - m_i \geq q_j - Q_s(1 - x_{ij} + \phi_i) \qquad \forall i, j \in C, i \neq j \tag{5.7}$$

$$h_i + \tau_i + f^s_{ij} + \min_{p \in P}\{\widetilde{U_p}\}\phi_i \leq h_j + M^s_{ij}(1 - x_{ij}) \qquad \forall i \in C, j \in C_s, i \neq j \tag{5.8}$$

$$f^s_{ij} \geq t_{ij} x_{ij} + \min_{p \in P}\{t_{ip} + t_{pj} - t_{ij}\}(x_{ij} + \phi_i - 1) \qquad \forall i, j \in C_s, i \neq j \tag{5.9}$$

$$x_{ij} \in \{0,1\} \qquad \forall i, j \in C_s, i \neq j \tag{5.10}$$

$$\phi_i \in \{0,1\} \qquad \forall i \in C \tag{5.11}$$

Synchronization Problem

$$\sum_{p \in P} v_{ip} = \phi_i \qquad \forall i \in C \tag{5.12}$$

$$u_i \geq h_i + \tau_i + \sum_{p \in P} t_{ip} v_{ip} \qquad \forall i \in C \tag{5.13}$$

$$u_i + \sum_{p \in P} (\widetilde{U_p} + t_{pj}) v_{ip} \leq h_j + M^s_{ij}(1 - x_{ij}) \qquad \forall i \in C, j \in C_s, i \neq j \tag{5.14}$$

$$a_g + \sum_{p \in P} t_{gp} v_{ip} \leq u_i \leq b_g + pen_g - \sum_{p \in P} (\widetilde{U_p} + t_{pd}) v_{ip} \qquad \forall i \in C \tag{5.15}$$

$$f^s_{ij} \geq \sum_{p \in P} (t_{ip} + t_{pj})(x_{ij} + v_{ip} - 1) \qquad \forall i \in C, j \in C_s, i \neq j \tag{5.16}$$

$$v_{ip} \in \{0,1\} \qquad \forall i \in C, p \in P \tag{5.17}$$

$\underline{Water\ \ Level\ \ Routing\ \ Problem}$

$$y_{w,ip} + \sum_{j\in C}\sum_{r\in S} y_{jr,ip} = v_{ip} \qquad i \in C, p \in S \qquad (5.18)$$

$$\sum_{j\in C}\sum_{r\in S} y_{ip,jr} + y_{ip,w} = v_{ip} \qquad i \in C, p \in S \qquad (5.19)$$

$$\sum_{i\in C}\sum_{p\in S} y_{w,ip} = \sum_{i\in C}\sum_{p\in S} y_{ip,w} \leq k_2 \qquad (5.20)$$

$$l_i \geq m_i \qquad i \in C \qquad (5.21)$$

$$l_j - l_i \geq m_j - Q_2(1 - \sum_{p\in S}\sum_{r\in S} y_{ip,jr}) \qquad i,j \in C, i \neq j \qquad (5.22)$$

$$a_w + t_{wp}v_{ip} \leq u_i \qquad i \in C, p \in S \qquad (5.23)$$

$$u_i + \widetilde{U_p} + t_{pr} \leq u_j + M(1 - y_{ip,jr}) \qquad i,j \in C, p,r \in S, i \neq j \qquad (5.24)$$

$$u_i + (\widetilde{U_p} + t_{pw})v_{ip} \leq b_w + pen_w \qquad i \in C, p \in S \qquad (5.25)$$

$$v_{ip},\ y_{w,ip},\ y_{ip,w} \in \{0,1\} \qquad i \in C, p \in S \qquad (5.26)$$

$$y_{ip,jr} \in \{0,1\} \qquad i,j \in C, i \neq j, p,r \in S \qquad (5.27)$$

$$a_i \leq h_i \leq b_i + pen_i \qquad i \in C, \qquad (5.28)$$

$$pen_i \geq 0 \qquad i \in C_s \cup \{w\} \qquad (5.29)$$

where the objective has three main components: the first part is the cost of lateness at the pickup points as well as at the depot and central depot considering operational hours of LEFVs and vessels, respectively; the second part is the cost of street level logistics; and the third part is the cost of water level logistics.

The integrated problem comprises three optimization problems.

- *Street level routing:* This problem formulates the multi-trip VRP for LEFVs. Constraints 5.4 and 5.5 govern vehicle assignment, while constraints 5.6 and 5.7 ensure load synchronization. Temporal synchronization is guaranteed by constraints 5.8 and 5.9.
- *Satellite synchronization:* This problem locates transshipment operations at satellite satellites (constraints 5.13) and schedules vehicle arrivals and departures (constraints 5.13–5.16) to achieve spatiotemporal synchronization.
- *Water level routing:* This problem formulates the VRP for vessels, with constraints 5.18–5.20 governing vehicle assignment. Load synchronization is ensured by constraints 5.21 and 5.22, and temporal synchronization by constraints 5.23–5.25.

Furthermore, the cost of inconvenience is introduced for each customer node by Eq. 5.28 and vehicle in the system through a lateness variable for violating time window ends for the customers and violating the shift end for the latest vehicles by Eq. 5.15 and by Eq. 5.25.

Modeling one-to-one transfers under uncertainty

Due to the unitary transshipment capacity at the satellites, any delay in a transshipment operation also delays consecutive loading/unloading operations. The stochastic transshipment lead times are modified to propagate the delays proportionally if they exist. The temporal distance between two operations assigned to the same satellite is defined as follows:

$$|u_i - u_j| \geq \widetilde{U_p}(v_{ip} + v_{jp} - 1) \qquad i,j \in C, i \neq j, p \in S \qquad (5.30)$$

The time interval between two transshipment operations, denoted as r_{ij}, is used in linearization as follows:

$$r_{ij} \geq \widetilde{U_p}(v_{ip} + v_{jp} - 1) \qquad i,j \in C, i < j, p \in S \qquad (5.31)$$

5.4 A two-stage stochastic programming model with mixed-integer recourse

This section first presents a two-stage formulation of the stochastic two-echelon routing problem. Then, we propose an L-shaped method using combinatorial Benders' cuts for the convergence. The L-shaped method is an iterative approach for solving two-stage stochastic linear programs (Van Slyke & Wets 1969). It begins by decomposing the problem into a master problem, representing the first-stage decisions, and subproblems for each possible scenario in the second stage. The master problem is initially a relaxed version, ignoring second-stage constraints. The algorithm then iterates between solving the master problem to obtain a candidate first-stage solution and solving the subproblems using this candidate. Based on the subproblem solutions, feasibility cuts are generated to ensure the first-stage solution leads to feasible second-stage solutions, and optimality cuts are generated to approximate the expected second-stage cost. These cuts are added to the master problem, refining the solution until convergence is achieved.

The method gets its name from the characteristic "L" shape formed in the constraint matrix of the master problem due to the addition of these cuts. With valid feasibility and optimality cuts, the L-shaped method is guaranteed to find an optimal solution (if it exists) in finitely many steps for solving two-stage stochastic optimization problems with mixed-integer at both stages (Laporte & Louveaux 1993).

5.4.1 Modeling the problem as a two-stage stochastic problem

A 2E-MVRP-SS involves two interconnected VRPs. To address the complexity introduced by stochastic variables, we propose an L-shaped method that employs a decomposition approach. First, the street level problem is solved to find routes for LEFVs such that they visit the closest satellite if it requires a transfer due to capacity limitations. This stage can be classified as a multi-depot, multi-trip VRP with time windows at pickup points (MDMVRPTW). Subsequently, we solve VRP on the waterway network, optimizing vessel routes to perform the required synchronized transfers with LEFVs in a given scenario defining the mean transshipment lead times at the satellites. This constitutes a VRP with time windows (VRPTW) for transfer tasks. Time windows can be considered as dynamic slots that are determined by the execution of other tasks Drexl (2012), respecting the earliest and latest start time of a transshipment operation for the feasibility. At the operational level, to ensure reliable services, operational start times can be re-optimized by relocating the transshipment operations across satellites and re-routing affected vehicles on both echelons to the corresponding satellites.

This section studies a two-stage stochastic programming problem formulated as follows:

$$min_{\substack{x\in X\\ \phi\in\Phi}} f(x,\phi) + \left\{ \mathrm{E}_{\xi}\left[g(\xi,x,\phi)\right]\right\}, \tag{5.32}$$

where $\mathrm{E}_{\xi}\left[g(\xi,x)\right]$ is the second stage optimal decisions made after realizing ξ random variables:

$$\mathrm{E}_{\xi}\left[g(\xi,x,\phi)\right] := min_{\substack{v\in V\\ y\in Y}} g(v,y). \tag{5.33}$$

Variables x and ϕ represent the first-stage decisions to determine the routing of LEFVs and transfer decisions, respectively, outlined in Section 5.3. Variables v and y represent the second-stage decisions regarding satellite assignments to transfer decisions and the routing vessels, respectively. Each possible scenario in a two-echelon setting, $\xi \in \Xi$, represents a joint realization of all satellite transfer times, $\xi = \{\cup\widetilde{U_p}, \forall p \in P\}$. It has an associated probability π_{ξ}. Each scenario can be optimized separately to estimate the expected cost. Therefore, the problem can be formulated as:

$$min_{\substack{x\in X\\ \phi\in\Phi}} f(x,\phi) + \sum_{\xi\in\Xi} \pi_{\xi}\, g(\xi,x) \tag{5.34}$$

Due to the non-convexity, the two-stage stochastic approach employs logical cuts for the certificate of the feasibility and optimality of street level decisions and their expected cost. This cost, determined in the second stage, accounts for water level choices, their associated costs, and penalties for late pickups due to uncertain transfer times, ξ.

5.4.2 Stage 1: master problem

The aim is to find a solution to MDMVRPTW such that complete schedules for LEFVs, including the order of customer services (x) and transfer tasks in between them (ϕ), are determined. The master problem is relaxed in terms of additional travel time for LEFVs to visit satellites and water level logistical costs. It assumes that if there is any transfer assignment after a pickup node, the LEFVs must travel at least to the closest satellite, enabling the earliest possible time to arrive at the next node. The formulation of the master problem is provided as the street level routing problem in Section 5.3.

5.4.3 Stage 2: subproblem

Given the routes for the LEFVs and transshipment decisions, the resulting problem is to find the best solution to the overall problem. At this stage, the model takes routing (x) and transfer decisions (ϕ) as inputs and solves the overall model for 2E-MVRP-SS. It decides the satellite assignments for the transfer tasks, which are chosen as the closest satellite as an approximate solution in the master problem. The subproblem at any iteration is way smaller than the whole network since the transfer tasks and routing of the street level are decided. The subproblems are formulated using a 4-index formulation to improve early pruning of the solutions based on the bounds obtained from relaxations of the subproblems. Therefore, the synchronization and water level routing problem, provided in Section 5.3, constitute the subproblem for a given feasible solution under a given scenario.

Remark 5.1 Note that both the first and second stages include mixed-integer decisions. □

5.4.4 Outline of the two-stage stochastic programming algorithm

The proposed decomposition modeling approach ensures a complete recourse matrix. In other words, for each feasible solution to the master problem, a feasible solution exists for the subproblem, considering that the limit on the number of vessels is ignored. The worst-case scenario is that each pickup point is assigned to a separate LEFV, and a vessel is assigned to each transfer required by a LEFV. If the master problem is feasible, the subproblem as well as the integrated problem is feasible.

Adding the logical cut (Equation 5.35) to the master problem removes a unique solution from the feasible space. The optimality cut (Equation 5.36) incorporates the subproblem's cost into the current solution's objective. This enumeration method checks every feasible solution in the master problem until no feasible or promising solutions remain. These combinatorial Benders cuts, while each removing a single feasible solution combination, simplify the problem within the branch-and-bound tree. They are proven to converge in a finite number of steps (Rahmaniani et al. 2017).

The subproblem, a mixed-integer program (MIP) addressing satellite assignments and vessel routing, presents computational challenges within the two-stage stochastic model. Solving N MIPs for each scenario to calculate expected costs increases solution time. To improve efficiency, the proposed method first solves a relaxed subproblem model for each scenario, calculating the best lower bound. If this lower bound is better than the current stochastic solution to 2E-MVRP-SS, exact subproblem solutions are computed. Otherwise, solving the expensive subproblems is avoided. Following Laporte & Louveaux (1993), the Branch & Bound tree of the master problem is re-initialized whenever the best-known solution improves. Algorithm 5.1 outlines the steps of the proposed two-stage stochastic program.

Algorithm 5.1 Two-stage stochastic programming algorithm for the 2E-MVRP-SS.

1: Get a different feasible solution to the master problem $\{\overline{x,\phi}\}$.
2: For each scenario, solve the relaxed subproblem given $\{\overline{x,\phi}\}$. Calculate a lower bound on the expected cost of the solution. Note that the expected cost is calculated by Eq.5.34.
3: If the lower bound is worse than the incumbent solution, set the solution as infeasible. Go to step 6. Else, continue 4.
4: For each scenario, solve the subproblem optimally given $\{\overline{x,\phi}\}$, calculate the expected cost. If the cost is worse than the incumbent solution, set the solution as infeasible. Otherwise, set it as feasible and improving.
5: If the solution is feasible with solution value $z(\overline{x,\phi})$, then:

   i. Update the upper bound.

   ii. Terminate the Branch & Bound process of the master problem.

   iii. Add the following constraint as an optimality cut:

$$z(\overline{x,\phi})[\sum_{y_j \notin \{\overline{x,\phi}\}} y_j + \sum_{y_j \in \{\overline{x,\phi}\}} (1-y_j)] + z >= z(\overline{x,\phi}) \tag{5.35}$$

6: If infeasible, then add the following lazy constraint as a feasibility cut:

$$\sum_{y_j \notin \{\overline{x,\phi}\}} y_j + \sum_{y_j \in \{\overline{x,\phi}\}} (1-y_j) >= 1 \tag{5.36}$$

7: If not optimal and the time limit is not achieved, go to step 1.
8: **return** *the best-known stochastic solution to 2E-MVRP-SS.*

5.5 Experimental layout

Table 5.2 summarizes the experimental settings regarding (1) **Scenario** (Section 5.5.1), detailing delay and scenario parameters; (2) **Service** (Section 5.5.2), describing the service configuration; (3) **Instances** (Section 5.5.3), specifying the test instances and their spatial configurations; and (4) **Benchmark** (Section 5.5.4), explaining the system designs and delay models used.

The models are implemented in Python language using a computer with 16 CPUs on Intel(R) Xeon(R) Gold 5218 with 2.30 GHz clock speed. They are solved by a commercial solver, Gurobi 9.12. The computation time limit is set to ten minutes for every instance.

5.5.1 Scenario generation and sampling

Transshipment lead times are modeled with regional uncertainties, where each satellite has a distinct delay distribution. Any observed delay at a satellite applies to all transfers assigned to it that day. We assume that delays in transfer times at satellites (ξ_p) follow a normal distribution with a mean of 0 and a standard deviation of σ.

$$U_p \sim \overline{U} + \xi_p$$

$$\xi_p \sim N(0,\sigma)$$

$$min_{p\in P}\widetilde{U_p} = \overline{U}$$

Each scenario set, Ξ, has a no-delay scenario, indicated as scenario “0”, ξ^0. To sample ξ_p and create N discrete scenarios, the following discretization is used:

$$\pi_p^0 = Pr\{\xi_p^0 \leq 0\}, \qquad \xi_p^0 = 0, \qquad p \in P \tag{5.37}$$

$$\pi_p^n = Pr\left\{\frac{3\sigma n}{N-1} \geq \xi_p^n \geq \frac{3\sigma(n-1)}{N-1}\right\}, \qquad \xi_p^n = \frac{3\sigma n}{N-1}, \qquad p \in P, n \in \{1,2,\ldots,N-1\} \tag{5.38}$$

Eq. (5.38) enables us to divide the random interval of positive delays within 3σ into $N-1$ discrete intervals with a probability determined by related distribution such that randomly distributed delay falls into the corresponding interval. For each scenario and each satellite, a random number from a given distribution is generated. This number is then compared against the discretized probability distribution according to the π_p^n values to determine the random delay variable ξ_p^n for that satellite. Scenario probabilities are calculated by multiplying the probabilities of the corresponding delay intervals, $\pi_{\xi^n} = \prod_{p \in P} \pi_p^n$. Then, they are normalized across all scenarios to 1. Equations 5.37 and 5.38 enable the creation of N discrete scenarios for a given theoretical and empirical distribution of transfer delays. The scenario with zero transfer delay at each satellite is equivalent to deterministic 2E-MVRP-SS.

To model normal distributions, we assume $3\sigma = \overline{U}$ for each satellite, implying no delay exceeds the expected transshipment lead time. Delay probabilities are then determined using the corresponding normal distribution. Any scenario with a probability below 0.0001 or that duplicates an existing scenario is discarded and replaced with a newly generated one. Less likely scenarios are removed to maintain the assumption of mean transfer duration $\overline{U}$ and normality of residuals. The proposed generation method can create worst-case scenarios by removing duplicates and randomly assigning delays between 0 and 3σ, thus incorporating joint distributions and their impact.

5.5.2 Recourse action settings

The model operates in two stages. First, it determines LEFV routes and associated transfers. Second, it minimizes the expected cost of lateness by optimally planning satellite assignments and vessel routes without altering LEFV schedules for customer service in response to observed transfer delays. This decomposition allows for rescheduling vessels and satellite assignments to mitigate overall lateness. To quantify lateness at each pickup point, we introduce the variable pen_i, defined by delay propagation inequalities 5.15, 5.25, and 5.28. This variable is minimized in the objective function with a penalty parameter c_{pen}^i, which varies based on the tightness of the time window at each pickup point as follows:

$$c_{pen}^i = J * \frac{(b_0 - a_0)}{(b_i - a_i)} \qquad i \in C, \tag{5.39}$$

Where $b_0 - a_0$ represents the operational horizon for LEFVs, and the ratio indicates the tightness of the time window at pickup point i. Nodes with tighter time windows are prioritized due to customer convenience, as customers generally pay more for tighter time windows. The J parameter allows adjusting the importance of a unit of lateness, regardless of time window selections. For the vehicles in the system, we only penalize the maximum lateness among all LEFVs and vessels with c_{pen}^g and c_{pen}^w parameters, respectively.

5.5.3 Instance configuration

We use modified Solomon's VRPTW instances Solomon (1987) as proposed in Chapter 1 for geographical configuration, where we choose satellites outside of the city. Let $x_{\min}$, $x_{\max}$, $y_{\min}$, and $y_{\max}$ be the minimum and maximum values of the coordinates of the nodes to collect. Four satellites are located at ($x_{\min}$,$y_{\min}$), ($x_{\min}$,$y_{\max}$), ($x_{\max}$,$y_{\min}$), and ($x_{\max}$,$y_{\max}$). The earliest and latest operational times of the satellites and the central depot are equal to the depot's, as given in the instances.

To better observe multiple trips and transfer tasks, the capacity of LEFVs is set to 50 units in 2E-Stationary and 2E-Flexible systems. The capacity of the barges and vessels is set to 250 units. The fixed cost of the LEFVs (β_s) is set to 1000, the travel cost on the streets is equal to 1, while the fixed cost for

Table 5.2: Experimental Settings

Parameter	**Value**
Scenario	
Delay distribution (ξ_p)	$\mathcal{N}(0,\sigma)$
Discretization range	$[0,3\sigma]$
Scenario count (N)	Variable
Service	
Capacity of LEFVs	50 units
Capacity of barges and vessels	250 units
Fixed cost of LEFVs (β_s)	1000
Fixed cost of vessels (β_w)	100
Travel cost (street, c^s)	1
Travel cost (water, c^w)	0.1
Lateness factor (J)	2
Penalty for depot lateness (pen_g)	100
Penalty for central depot lateness (pen_w)	100
Expected transshipment lead time ($\overline{U}$)	150 time units
Standart deviation for delay distribution(σ)	$\overline{U}/3$
Instances	
Computation time limit	10 minutes
Number of satellites	4
Number of pickup locations	10
Distribution types of pickup locations	Clustered (C) Random (R) Randomly Clustered (RC)
Benchmark	
System network design	2E-Flexible (LEFV-vessel synchronization at satellites) 2E-Stationary (Fixed vessels at satellites)
Delay model	NS (Deterministic, no-delay) TS (Two-stage, stochastic)

the vessels (β_w) is 100, and the travel cost is 0.1 of the travel times. The main motivation is to reduce the heavy movements and congestion on the streets. Lastly, U is assumed to be 150-time units, more than twice the service time at pickup locations, lateness factor, J, is set to 2, and penalty of violating shift for LEFVs and vessels, pen_g and pen_w, are set to 100. To test the effect of different uncertainty levels, we use the first ten nodes of Solomon *class-2* instances with wide time windows and long scheduling horizons, reflecting the structure of neighborhood collection hours. The big number used for vehicle shift durations is set to twice the latest time defined for the depot in these instances to bound the problem. We test the proposed stochastic algorithm on small instances with 10 pickup points and 4 satellites, all solved to optimality.

5.5.4 System network design

The proposed IWLT system—referred to as 2E-Flexible—is a two-echelon VRP with flexible vessels where LEFVs and vessels operate in synchronization. We benchmark this system with a two-echelon VRP with LEFVs and stationary barges system—referred to as 2E-Stationary— where barges are transported from and to the depot.

We evaluate each system under two optimization models: NS, corresponding to deterministic modeling without delays, and TS, the two-stage stochastic optimization over scenarios. The modeling approaches are summarized in Table 5.3.

Table 5.3: Bounding approaches

Method	Uncertainty set[1]	Penalty	Corrective actions
No-delay optimization (NS)	ξ^0	No[2]	Not applicable
Deterministic optimization	Ξ^N	Yes	Yes[3]
Stochastic optimization (TS)	Ξ^N	Yes	Yes

ξ^0 indicates a single scenario with zero delays at the satellites, while Ξ^N has N scenarios, including zero delays at the satellites.
1: Penalties are introduced only if delays exist.
2: $pen_i = 0, \forall i \in C$
3: First-stage decisions are fixed at no-delay optimal schedules.

5.6 Results

This section analyzes the quality of scenario generation, the importance of stochastic information, and the implications of transfer delays on a synchronized IWLT network. The objective is hierarchical, prioritizing street logistics operations to reduce congestion and infrastructure damage, followed by minimizing water-based logistics costs. In the proposed recourse model, corrective action costs are defined as incurring a penalty for every unit of time window violation at the pickup locations and maximum shift violations of the vehicles on both echelons. These penalties, prioritized over reducing street travel costs, are influenced by time window choices. Consequently, costs may increase sharply in rare scenarios to maintain service quality.

5.6.1 Parameter tuning for the scenario generation

Accurately modeling random variables is crucial in two-stage stochastic programming. We assume independent, normally distributed delays in transshipment times at each satellite, discretized into scenarios. The scenario generation scheme and the number of scenarios significantly influence the expected cost of a synchronized system with time windows, as this cost is sensitive to the modeled delays. Based on the geographical distribution of the pickup locations, cases are divided into three categories: C type for clustered locations, R type for random locations, and RC type for randomly clustered locations. To analyze the impact of discretization, we select three instances for each demand distribution type with the tightest time windows, where delays can cause substantial lateness penalties. To analyze the effect of delays on different networks, the delay scenarios are the same for the same number of scenarios and different instances. Figure 5.2 shows how the expected cost deviates from the no-delay case (only 1 scenario with zero delays at the satellites) across various instances. This also provides a lower bound on the cost, considering any additional scenario would introduce at least one satellite realizing longer transshipment lead times.

Average cost deviations are 2% for C201, 9% for RC201, and 17% for R201. Node closeness is defined by both spatial and temporal proximity, considering time windows. Increased randomness in the demand network leads to greater cost deviations. This is due to the longer travel distances between distant nodes and reduced buffer times (e.g., waiting times at satellites), which increases the likelihood of delays

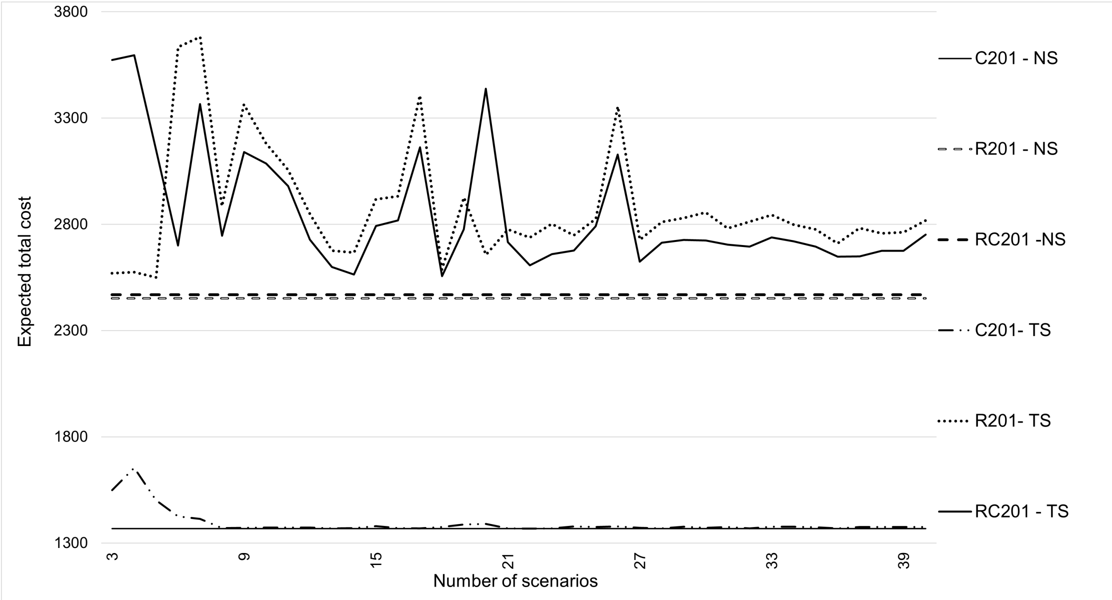


Figure 5.2: The effect of the number of scenarios on the total expected cost

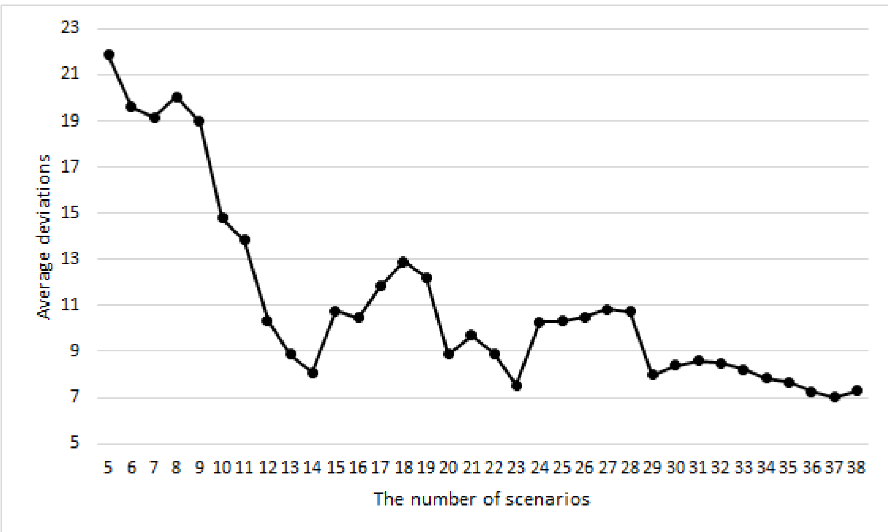


Figure 5.3: The average deviations of 5 consecutive scenarios in total cost concerning the cost of no delay scenario

and lateness penalties. The jumps in the case of a larger number of scenarios are due to the random generation of unique scenarios where there can exist different samples of larger delays for most of the satellites.

Delays at the satellites significantly influence the problem, as a single delay can easily propagate on both networks. This interdependency, coupled with the random sampling of scenarios, may increase the expected cost and hinder convergence, even with a larger number of scenarios. Consequently, selecting the optimal number of scenarios for further computations is not straightforward. Figure 5.3 shows the average deviations of five consecutive numbers of scenarios from the no-delay scenario. The deviations stabilize around 30 scenarios.

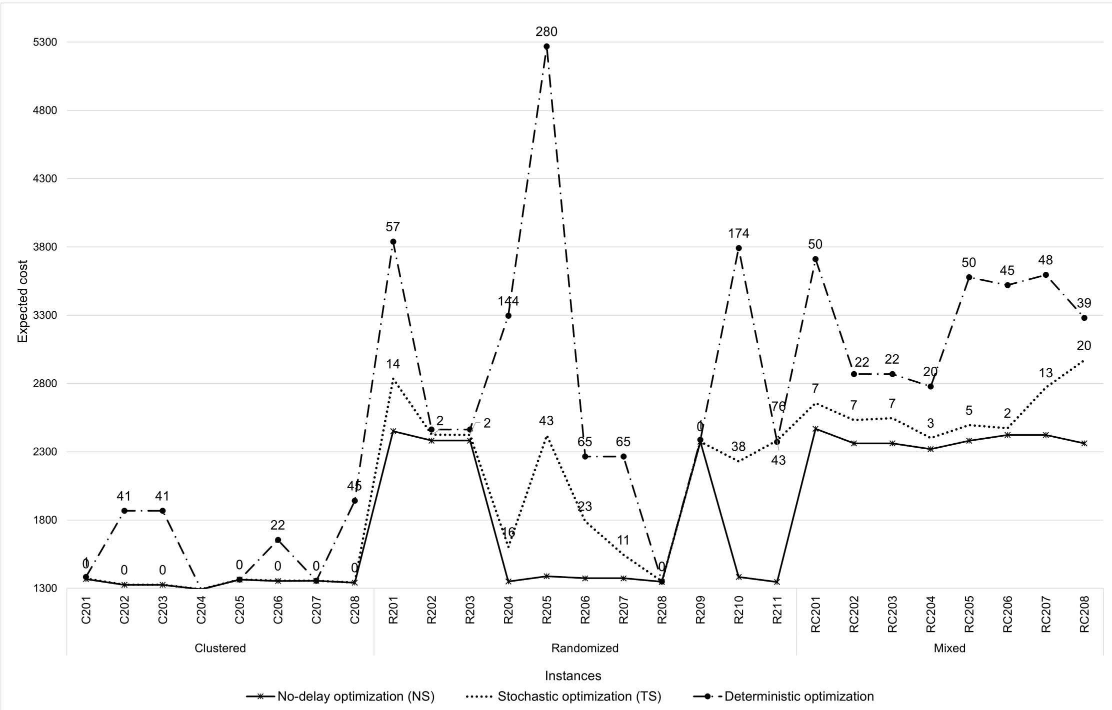


Figure 5.4: Comparison of expected costs of deterministic solutions under no delay scenario, deterministic solutions, and two-stage solutions under delay scenarios considering 30 scenarios on different instances

5.6.2 Solution quality

Figure 5.4 compares the solutions obtained with no delay scenario to those with uncertain information. No delay scenario represents the lower bound on the cost, and it is the minimum cost solution with no penalty. The no-delay scenario provides a valuable benchmark but is often unrealistic in practice. The expected costs of these solutions under delay scenarios provide the upper bounds for stochastic optimization. Therefore, the total expected costs of the deterministic optimization assume that LSPs schedule the first stage decisions considering no delay scenario and apply the recourse actions if any delay occurs. With this strategy, the expected costs deviate within 19% for type C, 37% for type RC, and 79% for type R.

The goal of stochastic optimization is to improve upon deterministic solutions and achieve better solutions capable of mitigating delays in the system. As seen in Figure 5.4, for type C demand networks, the integrated system maintains efficiency and feasibility with minimal cost increase (near 0% on average) due to the high degree of node closeness. For randomized networks (type R), the expected cost can increase by up to 43%, particularly for instances with tighter time windows and higher lateness penalties, such as R201 and R205. Type RC networks present a more complex scenario due to potential trade-offs in demand consolidation at LEFVs. While consolidation can reduce transfers, it may increase street level travel costs, as seen in instance RC208, where wider time windows allow consolidation at the expense of increased travel costs. On average, the total expected cost of two-stage solutions compared to the cost of no-delay solutions is within 0% for type C, 8% for type RC, and 17% for type R. Compared to the deterministic approach, it reduces costs by 37% across all instances. Compared to the deterministic strategy, the stochastic optimization strategy achieves the most savings in randomized networks, incorporating the uncertainty to locate delay-sensitive pickup locations better at the expense of more travel.

Table 5.4: Performance evaluation of flexible (2E-Flexible) and stationary (2E-Stationary) systems under two models: no-delay deterministic (NS) and two-stage stochastic (TS). Results represent average performance across instances for three customer location distributions from Solomon (1987): 8 instances for Clustered (C), 11 instances Random (R), and 8 instances for Randomly Clustered (RC).

Customer Distribution	**System**	**Model**	**#Street Mov.**[1]	**Lateness**[2]	**Street Share (%)**[3]
Clustered (C)	2E-Stationary	NS	269	0	69
		TS	270	0	68
	2E-Flexible	NS	220	0	52
		TS	220	0	52
Random (R)	2E-Stationary	NS	330	0	68
		TS	339	13	65
	2E-Flexible	NS	264	0	53
		TS	278	1	56
Randomly Clustered (RC)	2E-Stationary	NS	274	0	72
		TS	382	26	75
	2E-Flexible	NS	238	0	63
		TS	270	9	58

1: #Street Movements: Total travel time on the streets.
2: Lateness: Total lateness at customer locations (in time units).
3: Street Share (%): Percentage of street travel in total transportation.

5.6.3 Influence of system network design

This section uses the same uncertainty and satellite sets to explore the potential of flexibility in mitigating transshipment delays while minimizing disruptions to promised street-level service schedules. Table 5.4 summarizes the average performance indicators of Figure 5.5 for comparing the two different IWLT systems: 2E-Flexible and 2E-Stationary. *#Street mov.* summarizes average travel times of LEFVs on the streets, *Lateness* is the average lateness at the demand nodes, and *Street share (%)* is the share of street travel times in the total travel times considering both LEFVs and vessels/barges.

The proposed flexible system (2E-Flexible) mitigates the risk of increased street travel costs more effectively than the stationary barge system. This is evident in the smaller deviations from *NS* to *TS* in the *Street mov.* column for all network types under uncertainty. Furthermore, 2E-Flexible reduces expected lateness at nodes, demonstrating its flexibility in reorganizing water logistics with synchronized sailing vessels when delays occur. Finally, compared to the 2E-Stationary system with increased street movements, 2E-Flexible achieves a more balanced modal share between street and waterway transport.

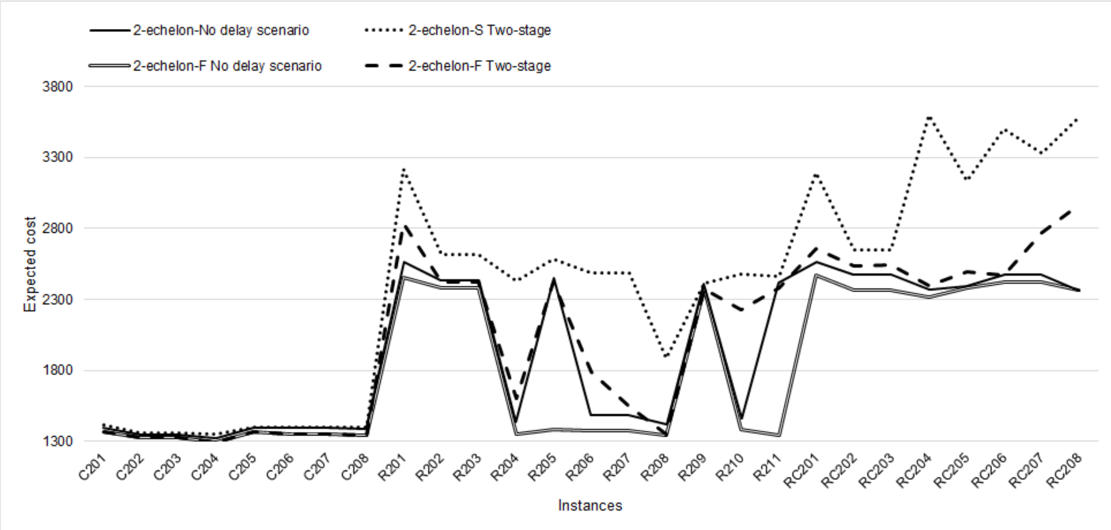


Figure 5.5: Synchronized vessel system (2E-Flexible) and stationary barges system (2E-Stationary) considering no delay case and uncertain case

5.7 Conclusions

In this chapter, we consider an Integrated Water- and Land-based Transportation (IWLT) that aims to remove heavy trucks from the streets to reduce the damage to the infrastructure as well as the congestion. We provide a new formulation for the stochastic 2E-MVRP-SS considering unitary transfers and uncertain transshipment lead times at the satellites. To test the systems' performance under heterogeneous satellites where the mean time to handle a transshipment operation differs, we propose a two-stage stochastic programming with a mixed-integer recourse model. The decisions are categorized as the first stage decisions for scheduling the street vehicles, while in the second stage, the transshipment operations are assigned to the satellites, and vessels and LEFVs are routed to execute these operations considering the lead times and expected scenarios. The goal is to find the most robust schedules for on-street routes that can be re-optimized to respond to delays at satellites at manageable scales while reducing delays at pickup locations to improve the reliability of the services. This is particularly important in reverse logistics where timely service significantly affects the inventory costs at the pickup locations, e.g., waste collection, inventory return management, and mixed operations with pickups in e-commerce.

The results on small-sized test instances considering delays at the satellites show that two-stage stochastic modeling reduces the cost of lateness and keeps the total expected cost within 0% for C type, 8% for RC type, and 17% for R type on average. The flexible system achieves less travel time on the roads. Moreover, it has greater flexibility in recovering the system's efficiency and feasibility by re-organizing water logistics with synchronized sailing vessels in case of delays. Besides the reduced risk of lateness at demand nodes for a reliable integrated system, it also leads to fairer mode shares between roads and inland waterways.

In this chapter, we address **SQ4** by presenting a framework for uncertainty modeling and proposing a recourse model to mitigate reliability issues in two-echelon synchronized routing problems. Initial gains observed in small instances suggest potential improvements for larger-scale applications, with the accuracy of cost approximations potentially enhanced through various sampling techniques. Consequently, the proposed approach, potentially supported by heuristics for faster cost function approximation, can offer valuable insights into the system's performance for large-scale instances. Furthermore, the framework allows for modeling and jointly analyzing various delay sources to enhance the reliability of an IWLT system.

Chapter 6

Conclusions and Future Research

This thesis investigates multimodal transportation systems from an Operations Research (OR) perspective with real-life applications. The aim is to improve city logistics operations by achieving economies of scale and enhanced service reliability. Towards this aim, land-based and water-based transport solutions are considered hand in hand in an integrated framework. Focusing on two primary service system designs—stationary and flexible Integrated Water- and Land-based Transportation (IWLT)—we analyze the benefits and complexities associated with managing synchronization with and without storage options, respectively. To facilitate a systematic evaluation and benchmarking, a generic optimization model is developed for the location, allocation, and routing of vehicles for the service system of interest both in single and two-echelon settings. This model enables users to compare flexible IWLT systems against traditional distribution systems, considering both single-echelon configurations and those utilizing satellite storage locations. Furthermore, this thesis proposes optimization methods designed to enhance the cost-efficiency and reliability of IWLT systems, promoting equitable outcomes for all stakeholders involved in city logistics. The scalability is tackled by the developed algorithms for different applications to address issues in complicated operations' scheduling problems and complex optimization problems associated with them.

This chapter concludes the thesis. Section 6.1 addresses the research questions outlined in Chapter 1. Finally, Section 6.2 explores potential future research directions and acknowledges the limitations of this study.

6.1 Conclusions

This thesis aims to answer the main research question:

RQ: *How can synchronized two-echelon systems leverage new vehicle technologies as well as cities' infrastructure to balance the goals of various stakeholders within the context of IWLT for city logistics?*

In Chapter 1, we defined four research sub-questions, which were subsequently addressed through Chapters 2 – 5. In this section, we first discuss the findings of these questions. Then, we present how the main research question is answered across chapters from the perspectives of various stakeholders in city logistics.

SQ1. How to model IWLT systems to account for systematic resource changes and flexibility of various service network designs?

The literature on synchronized two-echelon routing problems, driven by the motivations and challenges in city logistics, is continually expanding (Sluijk et al. 2023). While the goal is to optimize these systems under realistic capacity constraints at satellite locations, the desired degree of synchronization directly influences the complexity of the problems. However, the literature on multimodal transportation systems lacks a generic model that incorporates strategic, tactical, and operational decisions for evaluating potential logistics solutions.

In Chapter 2, we address this gap by introducing a compact system-wide model that jointly optimizes location, allocation, and routing decisions in IWLT systems. We also identify traditional management approaches for assessments used in Chapters 3, 4, and 5. Using an illustrative example of a small waste collection network, we demonstrate that the proposed flexible IWLT system reduces idle times in road transportation by sharing customer service and middle-mile transport between vessels and LEFVs. This integration yields significant savings in total travel distances and average weighted loads on city streets compared to trucking systems, thus reducing infrastructure and LEFVs maintenance costs. However, operational complexity arises from the multi-trip aspect of LEFVs and the need to design service network capacity to accommodate these trips at satellite locations. Attaining feasibility for those systems is particularly challenging as interacting vehicles share resources in both space and time for transshipment operations.

SQ2. How to design and solve IWLT systems to evaluate their efficiency against alternative systems in practical scenarios?

Traditional distribution systems, like those using solely trucks or LEFVs for single-echelon distribution, or those dedicating storage at transshipment locations for two-echelon distribution, simplify decision-making and operational management. Flexible IWLT systems with multi-trip and no storage options may improve city logistics compared to other approaches. Evaluation of no storage systems is needed to address the issues in limited urban space before shaping cities for future greener transportation. However, such features have been demonstrated to increase problem complexity significantly and, therefore, computational difficulty to achieve feasibility (Marques et al. 2022).

In Chapter 3, we address this complexity issue by enhancing the MILP model proposed in Chapter 2. This enhanced model significantly reduces the number of binary decisions using a two-index formulation. It is designed as modular optimization problems for the routing of vehicles on both echelons and synchronization problems at satellites with spatio-temporal capacity limits. Furthermore, we develop an LBBD approach that first ensures feasible schedules for on-street vehicles (if they exist) while maintaining cost-efficiency in water logistics operations supplying those vehicles. The LBBD method is proven to be more robust than the improved joint formulation in terms of time and solution quality. It provides feasible solutions to improve upon within metaheuristic approaches. This decomposition framework solves both integrated systems and road transportation alternatives within a defined service network and allows us to analyze trade-offs between using transshipment locations with and without storage capacity. Therefore, the location problem for designing IWLT systems, particularly for real-sized problems, requires further investigation to assess the practicality of reduced complexity in operations management in synchronized two-echelon routing problems. This is crucial to evaluate the costs for various stakeholders within city logistics besides the profits of LSPs.

SQ3. How to scale up the solution methods for assessment of IWLT systems considering real-life problems?

Designing a synchronized multimodal transportation system implies that we need to deal with the computational complexity of two-echelon location routing problems for real-sized applications. The feasibility of the tactical decisions for optimizing fleets at both echelons for a given service network design constitutes a two-echelon routing problem to schedule the transshipment operations in the system using the shared resources at the satellites. Existing approximation algorithms typically employ greedy heuristics for local optimization and metaheuristics for global optimization, iterating between the two echelons. However, these methods have limitations. They often fail to adequately address the impact of transshipment lead times, an assumption that significantly affects the feasibility and cost-efficiency of systems and reduces real-world applicability. This causes delays in flexible systems and inventory management issues in storage systems.

In Chapter 4, we address this gap by developing a multi-purpose metaheuristic that incorporates various design choices. This includes the number of satellites, their locations, their capacities regarding the storage option, and the fleet sizing of both echelons to serve the customers. The proposed method is shown to be competitive against the state of the art method in terms of solution quality and time for solving those systems. Next, we provide several design scenarios on a case study consisting of scheduling more than 1000 logistics operations in the city of Amsterdam. It is shown that the capacity planning decision at the satellites impacts the feasibility of the system and the minimal fleet requirements on both echelons. The storage systems reduce the costs in favor of waterborne transport. However, inventory management problems become expensive due to the imbalances in satellites' workloads. Additionally, dedicated storage is cost-efficient only for a smaller subset of the available satellites. It highlights the impact of the strategic decisions on the overall system cost efficiency when the demand varies daily. Conversely, flexible systems relying on synchronizing vehicles reduce the costs in favor of road transport. However, the number of satellites used as on-demand transshipment points increases with savings in the logistics cost of the on-street transport. In order to balance the workloads for IWLT systems with or without storage and provide equity in locating transshipment operations within city borders, we analyze various methodologies for locating the satellites using their distances to the customers.

SQ4. How to model the uncertainty associated with the flexibility of IWLT systems?

City logistics involves a complex interplay between multiple LSPs, whose operations are susceptible to uncertainties like fluctuating travel times and are highly interdependent. These uncertain lead times can stem from congestion, infrastructure failures, or weather conditions. Despite growing research on urban multimodal logistics, re-optimization mechanisms for cost minimization under uncertainty in two-echelon synchronized systems with no operational storage have not been addressed adequately.

In Chapter 5, we address this gap in stochastic two-echelon routing problems by introducing a novel approach to model and optimize IWLT systems. First, we provide a new formulation for the stochastic 2E-MVRP-SS, considering limited space use at the satellites by interacting vehicles. Then, a two-stage stochastic programming with a recourse model is developed to solve the problem using discretized scenarios for uncertainty representation. This model employs logical cuts to effectively manage the complexity of operational decisions. This two-stage decision-making process prioritizes customer service reliability in the first stage and then focuses on optimizing costs for LSPs in the second stage after realizing the delays to minimize the lateness at the customer locations. The proposed approximation method minimizes the cost of delays and maintains the total expected cost within reasonable bounds for different problem types arising in different sectors. Results on small-sized networks demonstrate the flexible IWLT system's ability in re-organizing water logistics to recover from delays, ensuring system efficiency and feasibility. Furthermore, they highlight the potential of an IWLT system to reduce the burden on road transportation.

6.1.1 Managerial insights

We provide the research findings for the stakeholders of city logistics, focusing on managerial insights.

Service users

In a logistics service, the ultimate goal is to meet the demand of the service users. IWLT offers a promising alternative to traditional road-based transport, potentially providing faster, more reliable services and lower costs. This is particularly relevant in congested urban areas where the delays impact the current service quality and regulations are taking place for reducing the street movements. Furthermore, the environmental benefits of reduced emissions align with the growing awareness and demand for sustainable solutions.

LSPs

IWLT presents an opportunity to optimize operations, reduce global costs, and gain a competitive edge under city access regulations. By integrating waterways into their logistics networks, LSPs can enhance efficiency, attract environmentally conscious customers, and drive innovation through the adoption of advanced vehicle technologies and optimization techniques.

Governing entities

IWLT supports sustainable urban development by reducing traffic congestion, emissions, and noise pollution. This is in line with the vision of various government bodies for improving the livability of the cities. Investing in and regulating IWLT infrastructure is essential for its successful integration into the urban landscape. Policymakers need to facilitate coordination among stakeholders to ensure the equitable distribution of benefits and efficient and reliable operation of the system for LSPs to stay in the competition under the regulations.

The society (city)

By promoting a cleaner and more livable environment, IWLT contributes to a higher quality of life in cities, especially vital in densely populated urban areas facing significant health risks from air and noise pollution. Moreover, the efficient urban logistics enabled by IWLT can stimulate economic growth and generate employment opportunities, particularly in the crucial areas of transshipment operations and the daily deployment of LEFVs. Ensuring that all residents and businesses can benefit equitably requires inclusive capacity planning, meaning that the diverse needs of the city's communities and enterprises must be considered when designing and implementing IWLT infrastructure and services.

6.2 Future research directions

In this section, based on the findings and limitations of this thesis, we provide several potential research areas.

- **The impact of waiting times on both echelons:** This thesis did not fully explore the impact of waiting times on the overall system performance. Future research could investigate the trade-off between waiting times and system requirements for LSPs as well as space use. This analysis should include considerations of capacity constraints (e.g., space availability) and the associated costs (e.g., use of satellite facilities, waiting costs incurred by LSPs).
- **Heterogeneity in services and resources:** To better reflect real-world scenarios, future work could expand the modular formulations to incorporate mixed service types, diverse vehicle fleets, and varying satellite capabilities. This could include simultaneous pickup and deliveries, direct-to-customer services, a mix of bikes, vans, and manual vehicles, and satellite locations with or without storage.
- **Transport capacity of inland waterways:** To enhance the realism of IWLT models, future research should incorporate capacity constraints by explicitly modeling waterway congestion and its impact on freight logistics. This could be achieved by simulating demand scenarios that differentiate between public and private users of inland waterway transport, and by considering factors such as lock availability, channel dimensions, and vessel queuing.
- **Accounting for uncertainty:** Future studies could relax the assumptions of deterministic demands and time windows to better reflect the unpredictable nature of real-world city logistics. In Chapter 5, we demonstrate how stochastic optimization can mitigate the effects of uncertainties in transshipment lead times. It is essential to investigate various sources of delays, solve larger instances using exact or heuristic methods, and incorporate uncertain service times.
- **Decentralization:** Recognizing that real-world city logistics involve multiple stakeholders with diverse and often conflicting objectives, future research could develop a decentralized system. This system would model the complex interactions between shippers, carriers, and customers, allowing

for a more realistic evaluation of IWLT systems by considering the trade-offs inherent in decentralized decision-making. To capture the dynamic and nuanced nature of city logistics environments more accurately, future research could utilize agent-based simulation where localized optimization models could improve the systems' response time and efficiency (Sun et al. 2016). This approach allows for the modeling of individual agents (e.g., vehicles, customers) and their interactions, providing a more granular and realistic representation of the system's behavior compared to traditional centralized approaches.

- **Quantum computing:** Given the computational complexity of synchronized two-echelon routing problems, particularly as problem sizes increase, exploring quantum computing frameworks presents an interesting avenue. Quantum computing has the potential to revolutionize how we solve such complex problems, potentially leading to more efficient and effective solutions for large-scale integer optimization. The weak duality in the Lagrangian decomposition method in Chapter 3 could be incorporated within a quantum model to improve the convergence of the problems (Gabbassov et al. 2023).

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Glossary

List of abbreviations

The following abbreviations are used in this thesis:

AV	Autonomous vehicles
BD	Benders Decomposition
EV	Electric vehicles
FE	First Echelon
FEV	First Echelon Vehicle
SE	Second Echelon
SEV	Second Echelon Vehicle
ALNS	Adaptive Large Neighborhood Search
GRASP	Greedy Randomized Adaptive Search Procedure
IWLT	Integrated Water- and Land-based Transportation
LEFVs	Light Electric Freight Vehicles
LSPs	Logistics Service Providers
MILP	Mixed Integer Linear Programming
MIP	Mixed Integer Problem
LBBD	Logic-based Benders' Decomposition
VRP	Vehicle Routing Problem
VRPTW	VRP with Time Windows
MVRP	Multi-trip VRP
e-MVRP	Electric Multi-trip Vehicle Routing Problem
MDMVRPTW	Multi-depot, multi-trip VRP with time windows
Asynch	Asynchronous
Synch	Synchronized
2E-VRP	Two-echelon VRP
2E-LRP	Two-echelon Location Routing Problem
2E-MVRP-SS	Two-echelon Multi-trip VRP with Satellite Synchronization

Summary

City logistics faces numerous challenges in meeting growing freight transport demands, which are further complicated by increasing urban populations, traffic congestion, and city access regulations. To contribute to the development of emission-free cities, this thesis investigates Integrated Water- and Land-based Transportation (IWLT) as a potential solution for urban freight distribution. We focus on optimizing two-echelon systems that combine waterborne and road transport to improve multimodal city logistics. This necessitates a comprehensive analysis of trade-offs among logistical costs, infrastructure investments, and diverse stakeholder needs within the city logistics environment.

This thesis aims to develop innovative methodologies for optimizing and assessing these IWLT systems across strategic, tactical, and operational levels. We show how to integrate advancements in vehicle and computing technologies efficiently into service network and solution design to achieve sustainable urban logistics.

Chapter 2 investigates the viability of IWLT as a solution for improving urban freight distribution, addressing the inherent modeling challenges and demonstrating the benefits of integrating new technologies. Through a practical network example using a Mixed Integer Linear Programming (MILP), we show that synchronized IWLT systems have the potential to reduce the burden on road transport by an average of 18% in vehicle kilometers traveled, even when Light Electric Freight Vehicles (LEFVs) are utilized instead of trucks. However, benchmarking against traditional system alternatives highlights the increased complexity associated with synchronizing waterborne and road transport to achieve coordinated cost-efficiency.

Chapter 3 tackles this added complexity to achieve the benefits of synchronized IWLT systems. The degree of synchronization in city logistics varies with system design and storage options. To address methodological complexity regarding systematic changes within the two-echelon settings, we propose an integrated modular MILP model and a logic-based Benders' decomposition model using the Lagrangian bounding method. We show how the decomposition method outperforms the integrated method in terms of solution quality and time, achieving 22% and 26% reductions in vehicle kilometers traveled for road and waterborne transport, respectively. Service network design results show a strong link between on-street logistics costs and satellite accessibility (number and proximity to demand nodes). Furthermore, the proposed modular formulation accommodates various system variants using both exact and approximate optimization.

Chapter 4 assesses the storage and synchronization options costs for waterborne transport by evaluating infrastructural investments using a configurable metaheuristic. A case study for Amsterdam, consisting of scheduling more than 1000 operations, shows that instead of dedicating storage space to total demand, investing in additional coordinated 2-3 vessel trips achieves the same service level. Furthermore, service network design optimization results in significant savings of up to 26% in vehicle kilometers traveled on road transportation, ultimately reducing the overall system's costs and externalities to the urban environment. Approximate algorithms, particularly within a decomposition framework, reduce complexity and enable the efficient handling of large-scale problems.

To assess the risks associated with synchronized multimodal systems, Chapter 5 tackles modeling uncertainty in two-echelon systems without storage options and discusses the reliability of flexible IWLT systems. We propose a two-stage stochastic optimization model with mixed-integer recourse that effectively mitigates these risks. Compared to storage systems, flexible IWLT systems offer significant

advantages: they reduce customer inconvenience by more than half and decrease road transport costs by efficiently reorganizing water logistics with synchronized sailing vessels in case of delays.

This thesis aims to develop and evaluate optimization approaches for improving the efficiency and sustainability of urban freight transport. It presents exact and approximate methods for optimizing multimodal city logistics within a two-echelon modeling framework. We demonstrate the potential of advanced integration and coordination to enhance the cost-efficiency, resilience, and sustainability of multimodal urban freight transportation.

The developed solution methodologies enable us to tackle large-scale problem instances. The quality of the solutions and the computational efficiency can further be studied. Based on the insights in this thesis, the potential improvements can be achieved through tailored operators within approximate algorithms to solve different case studies, and through approximations of the underlying routing problems within exact algorithms to enhance convergence for a broader range of challenging problems in the literature. The stochasticity we tackled entails transhipments, yet there are various other uncertainties in the system considering the network and demand. Further re-optimization mechanisms can be explored to ensure reliable systems in relation to these uncertainties within synchronized two-echelon distribution systems.

In terms of the case study, we investigated LEFVs as the street-level vehicles. However, city centers typically show heterogeneity in characteristics and a combination of multiple modes, such as cargo bikes, roll containers, and even drones, can be considered depending on the application area. Future research into two-echelon systems with a combination of modes available in each echelon is interesting and practically relevant.

Future research could also explore on-demand transport systems where the demand appears dynamically in the system to reflect recent developments. Specifically, time and space-sliced demand networks can be further explored to further optimize resource utilization (e.g., vehicles, urban space, and labor).

Samenvatting

De stadslogistiek staat voor talloze uitdagingen om te voldoen aan de groeiende vraag naar goederenvervoer, welke worden versterkt door de toenemende stedelijke bevolking, verkeerscongestie en toegangsregulatie voor steden. Om bij te dragen aan de ontwikkeling van emissievrije steden, onderzoekt dit proefschrift integraal water- en landtransport (IWLT) als een potentiële oplossing voor stedelijke goederendistributie. We richten ons op het optimaliseren van twee-echelonsystemen waarin water- en wegtransport gecombineerd worden om multimodale stadslogistiek te verbeteren. Dit vereist een uitgebreide analyse van de afwegingen tussen de logistieke kosten, investeringen in infrastructuur, en uiteenlopende behoeften van belanghebbenden binnen de stadslogistieke omgeving.

Dit proefschrift beoogt innovatieve methodologieën te ontwikkelen voor het optimaliseren en beoordelen van deze IWLT-systemen op strategisch, tactisch, en operationeel niveau. We laten zien hoe vooruitgang in voertuig- en computertechnologieën efficiënt kan worden geïntegreerd in servicenetwerk- en oplossingsontwerp om duurzame stadslogistiek te bereiken.

Hoofdstuk 2 onderzoekt de levensvatbaarheid van IWLT als oplossing voor het verbeteren van de stedelijke goederendistributie, waarbij de inherente modelleringsuitdagingen worden aangepakt en de voordelen van de integratie van nieuwe technologieën worden aangetoond. Aan de hand van een praktisch netwerkvoorbeeld laten we zien dat met behulp van een gemengd-geheeltallige lineaire programmering (MILP) gesynchroniseerde IWLT-systemen het potentieel hebben om de belasting van het wegtransport met gemiddeld 18% in voertuigkilometers (km) te verminderen, zelfs wanneer lichte elektrische vrachtvoertuigen (LEFVs) worden gebruikt in plaats van vrachtwagens. Benchmarking met traditionele systeemalternatieven benadrukt echter de toegenomen complexiteit die gepaard gaat met het synchroniseren van water- en wegtransport om kostenefficiënte coördinatie te bereiken.

Hoofdstuk 3 pakt deze extra complexiteit aan om de voordelen van gesynchroniseerde IWLT-systemen te realiseren. De mate van synchronisatie in stadslogistiek varieert met systeemontwerp en opslagopties. Om de methodologische complexiteit met betrekking tot systematische veranderingen binnen de twee-echelon-instellingen aan te pakken, stellen we een geïntegreerd modulair MILP-model en een op logica gebaseerd Benders' decompositiemodel voor met behulp van de Lagrangiaanse begrenzingsmethode. We laten zien hoe de decompositiemethode de geïntegreerde methode overtreft in termen van oplossingskwaliteit en tijd, met respectievelijk 22% en 26% reductie in voertuigkilometers voor weg- en watertransport. De resultaten van het ontwerp van het servicenetwerk laten een sterke link zien tussen de kosten van logistiek op straat en de toegankelijkheid van satellieten (het aantal en de nabijheid van vraagknooppunten). Bovendien biedt de voorgestelde modulaire formulering plaats aan verschillende systeemvarianten met behulp van zowel exacte als benaderende optimalisatie.

Hoofdstuk 4 beoordeelt de kosten van opslag- en synchronisatieopties voor watertransport door investeringen in infrastructuur te evalueren met behulp van een configureerbare metaheuristiek. Een casestudy voor Amsterdam, bestaande uit het plannen van meer dan 1000 operaties, laat zien dat in plaats van opslagruimte te reserveren voor de totale vraag, investeren in 2-3 extra gecoördineerde scheepsreizen hetzelfde serviceniveau bereikt. Bovendien resulteert het optimaliseren van het ontwerp van het servicenetwerk in een aanzienlijke besparingen tot 26% in voertuigkilometers op wegtransport, wat uiteindelijk de totale systeemkosten en externaliteiten voor de stedelijke omgeving vermindert. Benaderende algoritmen, met name binnen een decompositieraamwerk, verminderen de complexiteit en maken een efficiënte afhandeling van grootschalige problemen mogelijk.

Om de risico's te beoordelen die verbonden zijn aan gesynchroniseerde multimodale systemen, behandelt hoofdstuk 5 het modelleren van onzekerheid in twee-echelonsystemen zonder opslagopties en bespreekt het de betrouwbaarheid van flexibele IWLT-systemen. We stellen een tweetraps stochastisch optimalisatiemodel voor met gemengd-geheeltallige correctieve acties welke deze risico's effectief beperkt. In vergelijking met opslagsystemen bieden flexibele IWLT-systemen aanzienlijke voordelen: ze verminderen het ongemak voor klanten met meer dan de helft en verlagen de kosten van wegtransport door de waterlogistiek efficiënt te reorganiseren met gesynchroniseerde zeilschepen in geval van vertragingen.

Dit proefschrift beoogt optimalisatiebenaderingen te ontwikkelen en te evalueren ter verbetering van de efficiëntie en duurzaamheid van stedelijk goederenvervoer. Het presenteert exacte en benaderende methoden voor het optimaliseren van multimodale stadslogistiek binnen een twee-echelon modelleringskader. We demonstreren het potentieel van geavanceerde integratie en coördinatie om de kostenefficiëntie, veerkracht, en duurzaamheid van multimodaal stedelijk goederenvervoer te verbeteren.

De ontwikkelde oplossingsmethoden stellen ons in staat om grootschalige problemen aan te pakken. De kwaliteit van de oplossingen en de computationele efficiëntie kunnen verder worden bestudeerd. Op basis van de inzichten in dit proefschrift kunnen de potentiële verbeteringen worden bereikt door middel van op maat gemaakte operatoren binnen benaderende algoritmen om verschillende casusses op te lossen, en door middel van benaderingen van de onderliggende routeringsproblemen binnen exacte algoritmen om de convergentie te verbeteren voor een breder scala aan uitdagende problemen in de literatuur. De stochasticiteit die we hebben aangepakt omvat overslag, maar er zijn verschillende andere onzekerheden in het systeem met betrekking tot het netwerk en de vraag. Verdere heroptimalisatiemechanismen kunnen worden onderzocht om betrouwbare systemen te garanderen met betrekking tot deze onzekerheden binnen gesynchroniseerde twee-echelon distributiesystemen.

Wat de casussen betreft, hebben we LEFVs onderzocht als voertuigen op straatniveau. Stadscentra vertonen echter doorgaans heterogeniteit in kenmerken en een combinatie van meerdere modi, zoals vrachtfietsen, rolcontainers en zelfs drones, kan worden overwogen afhankelijk van het toepassingsgebied. Toekomstig onderzoek naar twee-echelonsystemen met een combinatie van modi die beschikbaar zijn in elke echelon is interessant en praktisch relevant.

Toekomstig onderzoek zou ook op-vraag transportsystemen kunnen onderzoeken waarbij de vraag dynamisch in het systeem verschijnt om recente ontwikkelingen te weerspiegelen. Specifiek kunnen tijd- en ruimtegesneden vraagnetwerken verder worden onderzocht om het gebruik van bronnen (bijv. voertuigen, stedelijke ruimte en arbeid) verder te optimaliseren.

Özet

Senkronize iki aşamalı dağıtım rotalama problemleri

Kentsel lojistik, artan kentsel nüfus, trafik sıkışıklığı ve şehir erişim regülasyonları ile daha da karmaşık hale gelen artan yük taşımacılığı taleplerini karşılamada sayısız zorlukla karşı karşıyadır.

Emisyonsuz şehirlerin gelişimine katkıda bulunmak için bu tez, kentsel yük dağıtımı için potansiyel bir çözüm olarak Entegre Su ve Kara Taşımacılığı'nı (IWLT) incelemektedir. Çok modlu şehir lojistiğini iyileştirmek için su ve kara taşımacılığını birleştiren iki aşamalı sistemleri optimize etmeye odaklanıyoruz. Bu, şehir lojistiği ortamındaki taşıma maliyetlerı, altyapı yatırımları ve farklı paydaş ihtiyaçları arasında kapsamlı bir denge analizi yapılmasını gerektirir.

Bu tez, bu IWLT sistemlerini stratejik, taktik ve operasyonel düzeylerde optimize etmek ve değerlendirmek için yenilikçi metodolojiler geliştirmeyi amaçlamaktadır. Sürdürülebilir kentsel lojistiğe ulaşmak için araç ve bilgi işlem teknolojilerindeki gelişmelerin hizmet ağlarına ve çözüm tasarımına nasıl verimli bir şekilde entegre edileceğini gösteriyoruz.

Bölüm 2, kentsel yük dağıtımını iyileştirmek için bir çözüm olarak IWLT'nin uygulanabilirliğini araştırmakta, sistemsel modelleme zorluklarını ele almakta ve yeni teknolojileri entegre etmenin faydalarını göstermektedir. Karışık Tamsayılı Doğrusal Programlama (MILP) kullanarak pratik bir hizmet ağ örneği aracılığıyla, senkronize IWLT sistemlerinin, kamyonlar yerine Hafif Elektrikli Yük Taşıtları (LEFV'ler) kullanılsa bile, araç kilometrelerinde yol taşımacılığı üzerindeki yükü ortalama %18 oranında azaltma potansiyeline sahip olduğunu gösteriyoruz. Bununla birlikte, geleneksel sistem alternatiflerine kıyasla yapılan analiz, koordinasyonla maliyet verimliliği elde etmek için su ve kara taşımacılığı-nın senkronizasyonu ile ilgili artan karmaşıklığı vurgulamaktadır.

Bölüm 3, senkronize IWLT sistemlerinin faydalarını elde etmek için bu ek karmaşıklığı ele almaktadır. Şehir lojistiğinde senkronizasyon derecesi, sistem tasarımına ve depolama seçeneklerine göre değişir. İki aşamalı ortamlardaki sistematik değişikliklerle ilgili metodolojik karmaşıklığı ele almak için, entegre bir modüler MILP modeli ve Lagrange sınırlama yöntemini kullanan mantığa dayalı bir Benders ayrıştırma modeli öneriyoruz. Ayrıştırma yönteminin, çözüm kalitesi ve zamanı açısından entegre yöntemi nasıl geride bıraktığını, sırasıyla karayolu ve su taşımacılığı için araç km'lerinde %22 ve %26'lık azalmalar elde ettiğini gösteriyoruz. Hizmet ağı tasarımı sonuçları, sokak içi lojistik maliyetleri ile transfer merkezlerinin erişilebilirliği (sayı ve talebe yakınlığı) arasında güçlü bir bağlantı olduğunu göstermektedir. Ayrıca, önerilen modüler formülasyon, hem kesin hem de yaklaşık optimizasyon kullanarak çeşitli sistem varyantlarını modelleyebilir.

Bölüm 4, konfigüre edibilen bir metasezgisel metot kullanarak altyapı yatırımlarını değerlendirerek su taşımacılığı için depolama ve senkronizasyon seçeneklerinin maliyetlerini değer-lendirmektedir. 1000'den fazla operasyonun planlanmasından oluşan Amsterdam'daki bir vaka çalışması, toplam talebe depolama alanları ayırmak yerine, koordineli bir şekilde 2-3 ek gemi seferine yatırım yapmanın aynı hizmet seviyesini sağladığını göstermektedir. Ayrıca, hizmet ağı tasarımının optimize edilmesi, karayolu taşımacılığında araç km'lerinde %26'ya varan önemli tasarruflar sağlayarak nihayetinde sistemin genel maliyetlerini ve kentsel çevre üzerindeki negatif etkilerini azaltmaktadır. Yaklaşık algoritmalar, özellikle bir ayrıştırma çerçevesi içinde, karmaşıklığı azaltır ve büyük ölçekli problemlerin verimli bir şekilde ele alınmasını sağlar.

Senkronize çok modlu sistemlerle ilişkili riskleri değerlendirmek için Bölüm 5, depolama seçeneği

olmayan iki aşamalı sistemlerde modelleme belirsizliğini ele almakta ve esnek IWLT sistemlerinin güvenilirliğini tartışmaktadır. Bu riskleri etkili bir şekilde azaltan, karışık tamsayılı düzeltme aksiyonları ile iki aşamalı stokastik bir optimizasyon modeli öneriyoruz. Depolama sistemlerine kıyasla esnek IWLT sistemleri önemli avantajlar sunmaktadır: müşteri memnuniyetsizliğini yarıdan fazla azaltır ve gecikmeler durumunda su lojistiğini senkronize yelkenli gemilerle verimli bir şekilde yeniden düzenleyerek karayolu taşımacılığı maliyetlerini düşürürler.

Bu tez, kentsel yük taşımacılığının verimliliğini ve sürdürülebilirliğini iyileştirmek için optimizasyon yaklaşımları geliştirmeyi ve değerlendirmeyi amaçlamaktadır. İki aşamalı bir modelleme çerçevesi içinde çok modlu şehir lojistiğini optimize etmek için kesin ve yaklaşık yaklaşımlar sunar. Çok modlu kentsel yük taşımacılığının maliyet verimliliğini, güvenirliliğini ve sürdürülebilirliğini artırmak için gelişmiş entegrasyon ve koordinasyonun potansiyelini gösteriyoruz.

Geliştirilen çözüm metodolojileri, büyük ölçekli problemleri çözmemizi sağlamaktadır. Çözümlerin kalitesi ve hesaplama verimliliği daha fazla incelenebilir. Bu tezdeki içgörülere dayanarak, potansiyel iyileştirmeler, farklı vaka çalışmalarını çözmek için yaklaşık algoritmalar içinde özel operatörler ve literatürdeki daha fazla sayıda zorlu problemlerdeki yakınsamayı iyileştirmek için kesin algoritmalar içindeki temeldeki rotalama problemlerinin yaklaşımları yoluyla elde edilebilir. Ele aldığımız stokastisite, aktarma işlemlerini içerir, ancak hizmet ağı ve talep göz önüne alındığında sistemde çeşitli başka belirsizlikler vardır. Senkronize iki aşamalı dağıtım sistemleri içindeki bu belirsizliklerle ilgili olarak güvenilir sistemler sağlamak için daha fazla yeniden optimizasyon mekanizması araştırılabilir.

Vaka çalışması açısından, sokak seviyesindeki araçlar olarak LEFV'leri inceledik. Bununla birlikte, şehir merkezleri tipik olarak heterojenlik gösterir ve uygulama alanına bağlı olarak kargo bisikletleri, rulo konteynerler ve hatta dronlar gibi birden fazla mod kombinasyonu düşünülebilir. Her aşamada mevcut modların bir kombinasyonuna sahip iki aşamalı sistemlere yönelik gelecekteki araştırmalar ilginç ve pratik olarak ilgilidir.

Gelecekteki araştırmalar ayrıca, son gelişmeleri yansıtmak için talebin sistemde dinamik olarak ortaya çıktığı talebe bağlı taşıma sistemlerini de araştırabilir. Özellikle, kaynak kullanımını (örneğin, araçlar, kentsel alan ve işgücü) daha da optimize etmek için zaman ve uzay dilimlenmiş talep ağları daha fazla araştırılabilir.

About the author

Çiğdem Karademir was born on June 1st, 1992, in Mersin, Türkiye. She obtained her B.Sc. degree in Industrial Engineering from Boğaziçi University in 2017, followed by her M.Sc. degree in the same field from the same institution in 2020, under the supervision of Prof. Ümit Bilge. Throughout her Master's program, she gained experience teaching the fundamentals and applications of operations research and collaborated with industry partners on projects focused on last-mile delivery logistics optimization.

In January 2021, Çiğdem Karademir started pursuing her PhD degree under the supervision of Dr. Bilge Atasoy and Prof. Rudy R. Negenborn at the Department of Maritime and Transport Technology, Delft University of Technology. In her PhD project, she investigated optimization strategies to improve efficiency, resilience, and sustainability of multimodal city logistics. Her research interests include operations research, integer optimization, and their applications in large-scale supply chains.

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1. Karademir, C., Beirigo, B. A., & Atasoy, B. To be submitted. Optimizing city logistics: Decision-making and synchronization in urban space competition.

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Chapter 2: Designing and modelling IWLT systems

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