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Smart Urban Waste Collection Routing under Uncertainty: Mixed Fleets, Shared Demand, and Vehicle Rerouting

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Abstract

Urban waste collection systems must optimize performance under uncertain and variable waste volumes. This thesis presents a hybrid approach combining mathematical optimization and discrete-event simulation to design and evaluate robust fleet strategies. A deterministic MILP identifies the most cost-efficient fleet composition, recommending two multi-compartment vehicles (MCVs) and a rerouted single-compartment vehicle (SCV). However, simulation under increasing uncertainty—modeled via an expanded uniform distribution—reveals that, instead of rerouting an SCV, sending a two-compartment vehicle significantly improved vehicle utilization and reduced excess waste at collection stations. These findings demonstrate that static routing plans degrade under real-world variability, and that true operational efficiency is achieved through dynamic, adaptive routing strategies. By minimizing underutilization and avoiding unnecessary trips, the proposed approach supports more sustainable urban logistics, with potential to reduce emissions and empty vehicle mileage.

Abstrakt

Urbane Abfallsammelsysteme müssen ihre Leistungsfähigkeit unter unsicheren und variablen Abfallmengen optimieren. Diese Arbeit entwickelt einen hybriden Ansatz, der mathematische Optimierung mit einer diskreten Ereignissimulation kombiniert, um robuste Flottenstrategien zu entwerfen und zu bewerten. Ein deterministisches MILP identifiziert die kosteneffizienteste Flottenzusammensetzung und empfiehlt den Einsatz von zwei Mehrkammerfahrzeugen sowie eines umgerouteten Ein-Kammer-Fahrzeugs. Die Simulation unter wachsender Unsicherheit – modelliert über eine erweiterte Gleichverteilung – zeigt jedoch, dass anstelle des Ein-Kammer-Fahrzeugs der Einsatz eines Zwei-Kammer-Fahrzeugs die Fahrzeugauslastung deutlich verbessert und überschüssigen Abfall an Sammelstellen reduziert. Die Ergebnisse verdeutlichen, dass statische Routenpläne unter realer Variabilität an Wirksamkeit verlieren und dass operative Effizienz durch dynamisch-adaptive Routenstrategien erreicht wird. Durch Minimierung von Leerfahrten und Verbesserung der Auslastung unterstützt der entwickelte Ansatz eine nachhaltigere städtische Logistik mit Potenzial zur Emissionsreduktion und Reduzierung von Leerfahrten.

Inhaltsverzeichnis

Chapter 1: Introduction, Motivation and Research Design

Chapter 1 (Introduction, Motivation and Research Design) chapter emphasizes the significance of urban waste management, specifically addressing the waste collection process. Road freight, being the primary mode of transport, significantly contributes to CO_2 emissions in the sector, highlighting the necessity for optimized and efficient waste collection routing. Improving vehicle utilization and reducing unnecessary trips can substantially decrease emissions and operational expenses. The integration of diverse vehicle types, especially multi-compartment vehicles, is examined as a crucial strategy for enhancing efficiency in urban waste collection. Finally, a summary of the solution strategies discussed in the following chapters is presented.

Chapter 2 (Literature Review and Research Gap) analyzes current research in three specific domains: vehicle types, waste management, and solution methodologies. This thesis provides a clear evaluation of the objectives, solution methodologies, and model types from relevant studies, subsequently identifying the research gaps it addresses.

Chapter 3 (Research Objective, Question, Method, and Contribution) outlines the objective function aimed at minimizing overall costs, alongside supplementary objectives that are not explicitly included in the cost function. This chapter outlines the research question, methodology, and primary contributions.

Chapter 4 (Mathematical Model) offers a comprehensive overview of the mathematical framework, encompassing the sets, parameters, and synthetic data involved. Furthermore, it illustrates that the use of a mixed fleet, particularly through the deployment of various vehicle types, leads to superior optimization compared to the reliance on a singular vehicle type.

Chapter 5 (Simulation Model) chapter presents the simulation interface, outlining its components, including blocks and interactive elements. The optimal scenario, characterized as the mixed fleet from the mathematical model, is subsequently executed to manage uncertain demand, with additional improvements to vehicle utilization achieved through rerouting.

1. Introduction, Motivation, and Research Design

1.1 Motivation and Background

Urban environments are responsible for a significant share of global energy consumption and CO_2 emissions, making the management of urban logistics a critical issue in the context of sustainability and climate action (Peria et al., 2024). Among these logistics activities, Solid Waste Collection (SWC) is an essential municipal service that ensures public health and environmental protection. However, effective waste management remains a major challenge for many municipalities, particularly due to increasing urban populations, evolving consumption patterns, and rising costs (Peña et al., 2024).

According to the World Bank, waste management can consume up to 50% of municipal budgets, with the collection phase representing the most expensive part of the waste management process (Peña et al., 2024). The operational demands of SWC are compounded by the diversity of waste types — including industrial, commercial, and residential waste — as well as the need for environmentally and socially acceptable practices.

In response to growing sustainability concerns, municipalities are under pressure to adopt efficient, low-emission, and cost-effective collection strategies. Most currently operate based on fixed routes using diesel-powered garbage trucks, which are often not optimized for real-time conditions (Luo et al., 2024). Moreover, managing routing decisions is complicated by operational constraints such as vehicle capacity, waste type separation, and limited infrastructure (Fischer et al., 2024).

The challenges are particularly acute in smart city contexts, where increasing waste generation intersects with technological limitations and infrastructure bottlenecks (Kona and Subramoniam, 2024). Poor collection coverage, resource inefficiencies, and health risks caused by mismanaged waste highlight the need for innovation in this sector. Smart and adaptable waste collection systems are essential for improving service quality and environmental outcomes.

Beyond waste-specific concerns, transport-related emissions are a significant contributor to environmental degradation. As shown in Figure 1.1, road freight accounts for 72% of total CO_2 emissions among transport modes in Austria (EEA, 2022). Furthermore, vehicle underutilization is a critical issue, with Statistik Austria (2024) reporting that 45% of all truck trips in Austria in 2022 were conducted empty (Figure 1.2). These inefficiencies lead to unnecessary fuel consumption, emissions, and costs — making vehicle utilization a central optimization target.

Considering these challenges, this thesis investigates opportunities to improve urban waste collection by focusing on vehicle utilization, routing efficiency, and mixed fleet strategies, particularly in contexts of demand uncertainty.

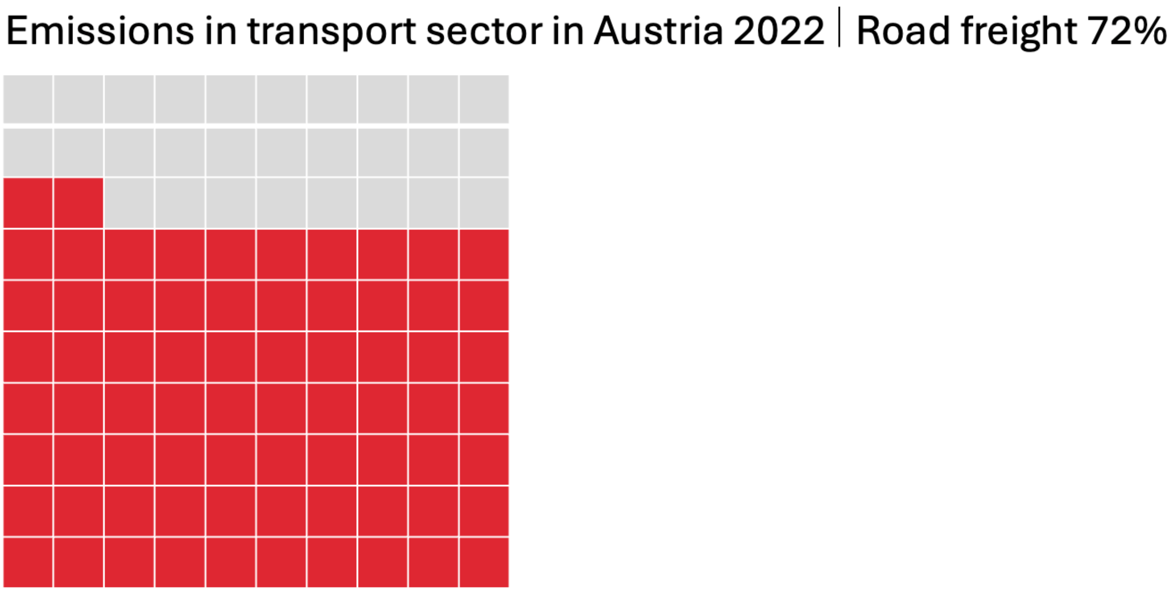


Figure 1.1 Road freight accounts for 72% of transport-related CO_2 emissions in Austria (2022)

This figure uses a 100-block visual representation to show the proportion of CO_2 emissions from road freight. Each red block represents 1%, highlighting that road transport alone is responsible for 72% of total emissions in the transport sector.
(Source: EEA, 2022).

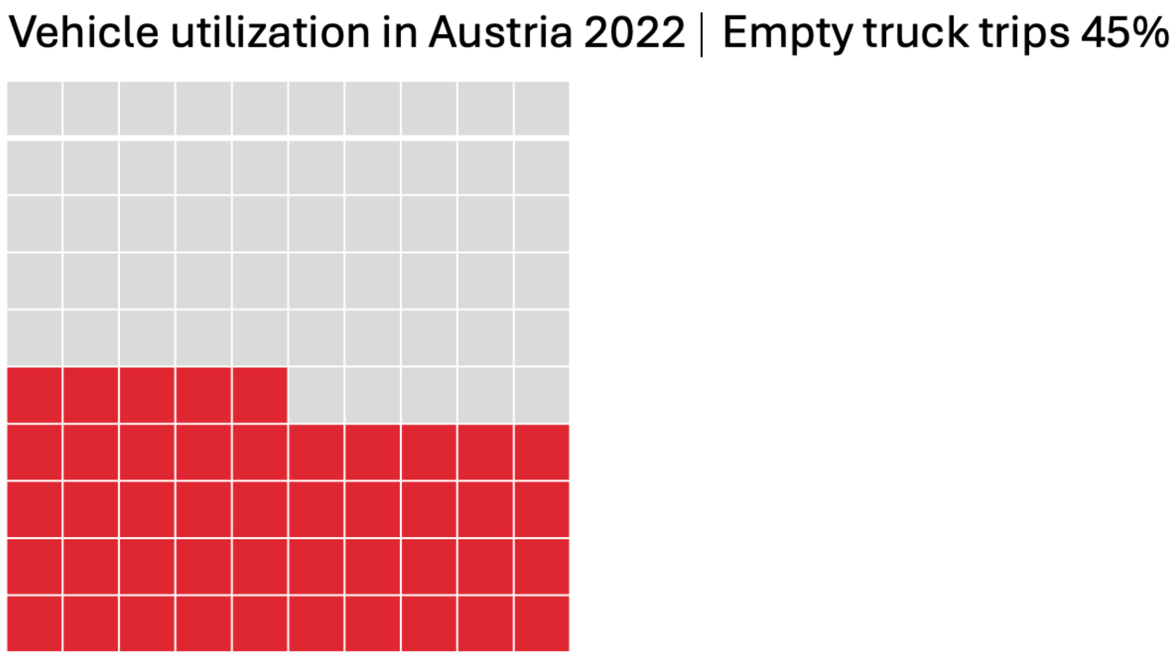


Figure 1.2 Low vehicle utilization in Austria – 45% of truck trips are empty (2022)

According to Statistik Austria, 45% of all truck trips in Austria in 2022 were empty, reflecting substantial inefficiencies in vehicle utilization. These empty trips lead to increased CO_2 emissions and unnecessary operating costs. This thesis addresses this issue by exploring strategies to improve vehicle usage—particularly through optimized routing and compartment-based fleet configurations.
(Source: STATISTIK AUSTRIA, 2024)

1.2 Problem Statement

The core problem addressed in this thesis is the lack of efficient and flexible routing strategies for urban waste collection systems, especially in scenarios involving heterogeneous vehicle fleets and uncertain demand. In most cities, waste is separated into different categories — such as paper, plastic, and glass — and collected by single-compartment vehicles (SCVs) dedicated to each waste type. While this ensures waste segregation, it also increases the number of vehicles required, the number of tours needed, and the total distance traveled, leading to high operational costs and environmental impact.

An illustrative example can be seen in the waste collection practices of cities like Vienna, where dedicated SCVs collect different waste types from multiple stations. Figure 1.3 demonstrates a typical SCV configuration: three vehicles, each assigned to a specific waste type, visit multiple stations to collect their respective material. This results in three separate tours even when a single station contains all three types of waste (Ostermeier et al., 2021).

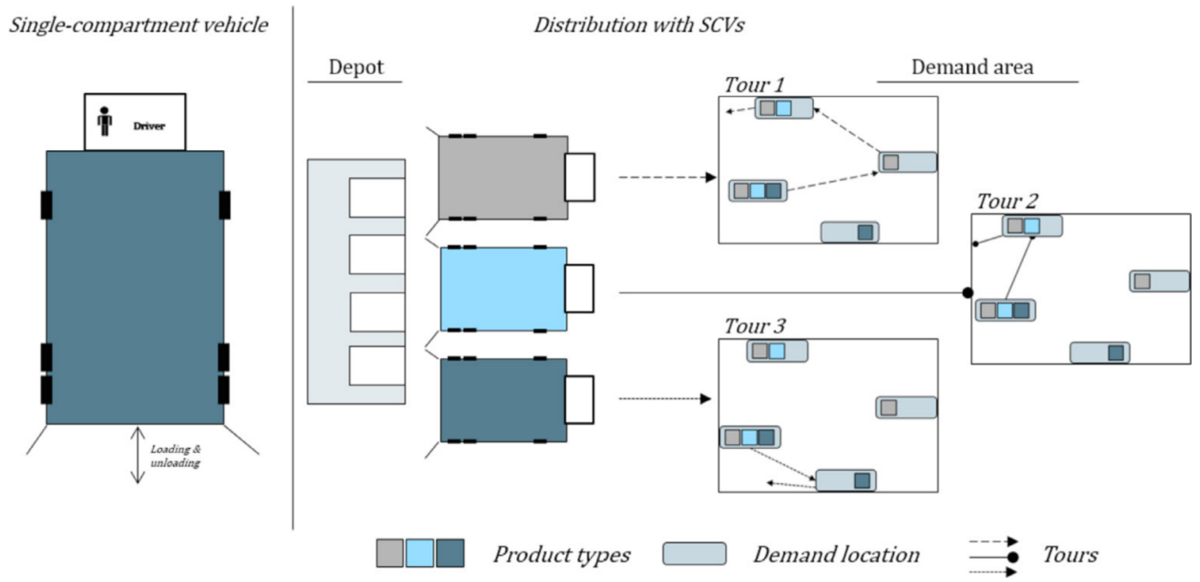


Figure 1.3 single-compartment vehicle routing (adapted from Ostermeier et al., 2021)

This rigid routing system can be improved by employing multi-compartment vehicles (MCVs), which can collect multiple waste types simultaneously. As illustrated in Figure 1.4, one MCV can handle three waste streams in a single tour, reducing the number of vehicles and tours required, and improving both operational and environmental efficiency (Ostermeier et al., 2021).

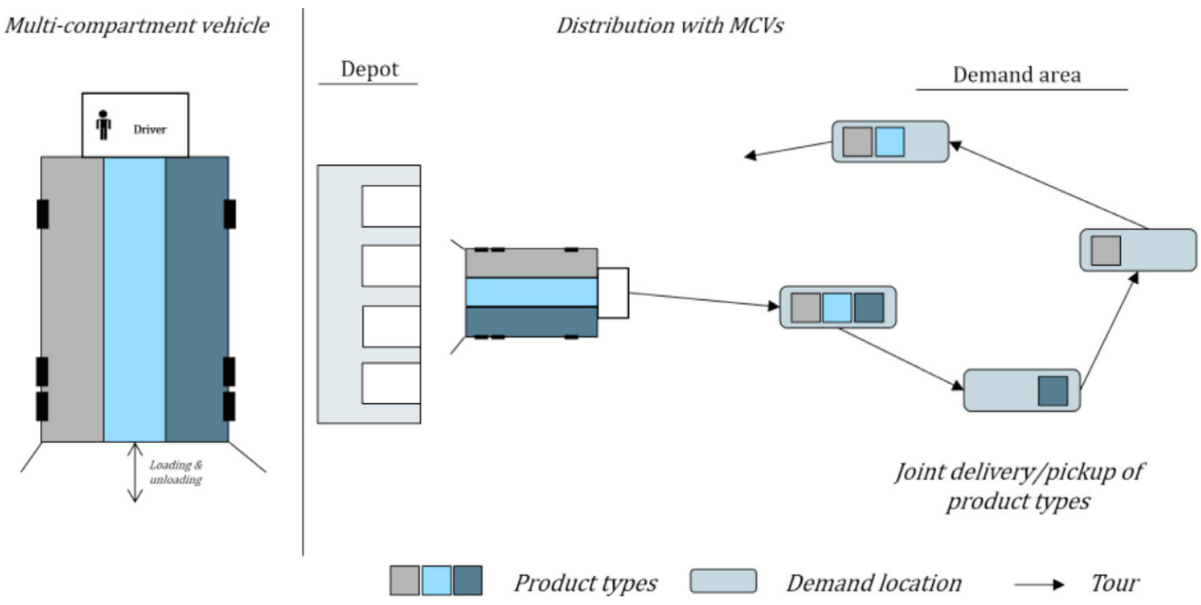


Figure 1.4 multi-compartment vehicle routing (adapted from Ostermeier et al., 2021)

Despite the clear benefits of MCVs, they are not always the most cost-effective option. SCVs may still be advantageous for full truckloads of a single waste type. Therefore, the decision to use SCVs, MCVs, or a mixed fleet depends on demand variability, waste distribution, and routing complexity — factors that are often ignored in existing models.

Moreover, current waste collection systems generally follow static routing plans, assuming fixed demand and ignoring the potential for vehicle rerouting or demand sharing between vehicles. This leads to underutilization and a lack of responsiveness to real-world conditions, particularly in dynamic urban environments.

This thesis aims to address these limitations by exploring routing strategies that incorporate:

- Mixed fleet configurations (SCVs and MCVs),
- Shared demand allocation between vehicles,
- Adaptive rerouting under uncertain waste volumes.

Together, these elements form a complex and practically relevant vehicle routing problem that has received limited attention in current literature and municipal operations.

1.3 Research Design

This section presents the research framework used in this thesis. It outlines the academic and practical motivation for the study, the specific research objectives, the central research question, the methodological approach, and the intended contribution to both theory and practice. An overview of the research process is illustrated in Figure 1.5.

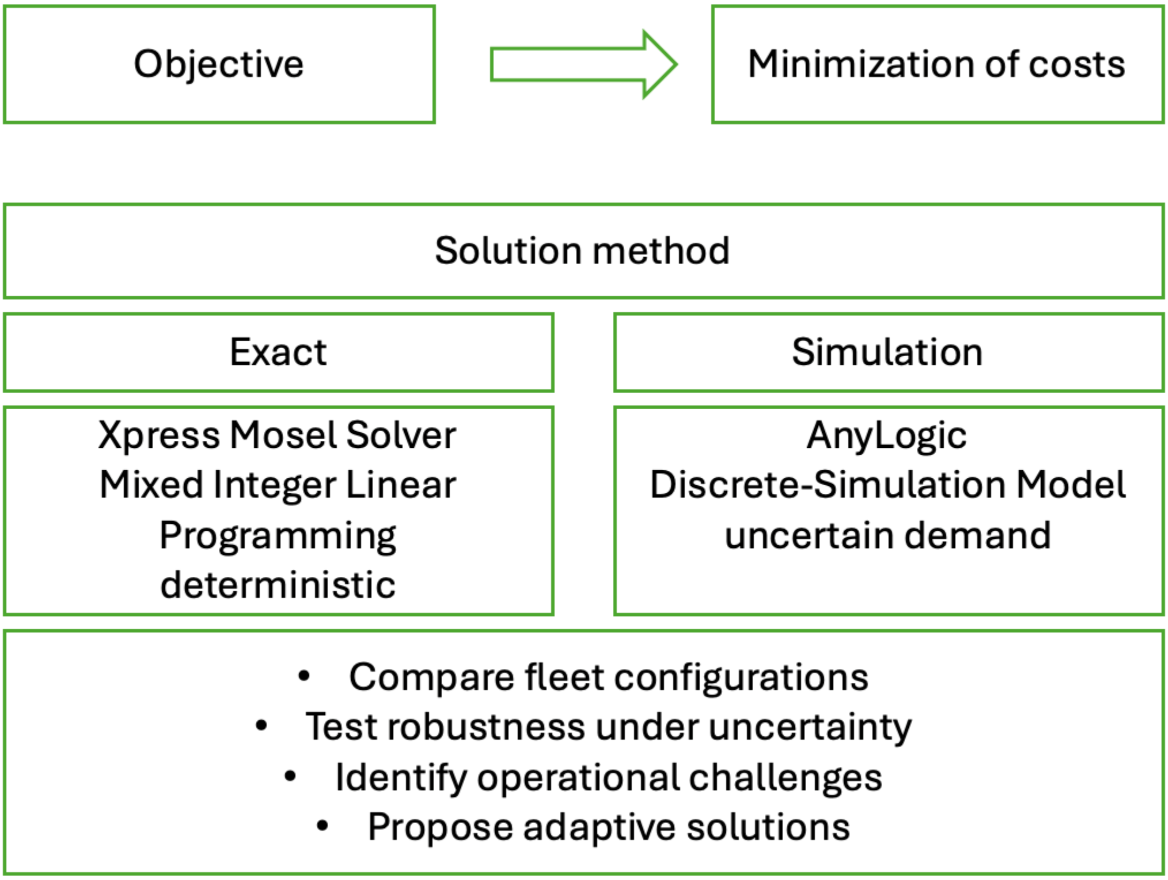


Figure 1.5 Overview of the methodological framework used in this thesis

This figure summarizes the two-phase approach: a deterministic optimization model solved using Mixed Integer Linear Programming (MILP) with Xpress Mosel, and a discrete-event simulation model developed in AnyLogic to test system performance under uncertain waste demand. The methodology supports cost minimization by comparing fleet configurations, testing robustness, identifying operational challenges, and proposing adaptive solutions.

1.3.1 Research Objectives

The primary objective of this thesis is to improve the cost-efficiency and operational robustness of urban waste collection systems through optimized routing strategies. Specifically, the study aims to:

1. Minimize the total cost associated with urban waste collection operations,
2. Improve vehicle utilization by reducing the number of stations visits and overall travel distance,
3. Compare the performance of different vehicle configurations:
   - Single-compartment vehicles (SCVs) only,
   - Multi-compartment vehicles (MCVs) only,

- A mixed fleet of both SCVs and MCVs,

4. Investigate the value of demand sharing between vehicles and dynamic rerouting as strategies for improved flexibility,
5. Evaluate system performance under uncertain waste demand conditions.

1.3.2 Research Question

To guide the analysis, the following central research question is posed:

"How can a mixed fleet of single- and multi-compartment vehicles, combined with inter-vehicle waste sharing and dynamic rerouting, optimize cost efficiency and vehicle utilization in urban waste collection operations?"

This question emerges from gaps identified in the existing literature, where most models either assume homogeneous fleets, ignore vehicle rerouting, or fail to account for demand uncertainty.

1.3.3 Methodological Approach

To address the research question and objectives, a two-stage methodological framework is adopted, integrating both exact mathematical optimization and discrete-event simulation modeling. This hybrid approach enables the development of cost-efficient fleet configurations under idealized assumptions and their evaluation under realistic, uncertain conditions.

Stage 1: Mathematical Optimization (MILP)

The first stage involves developing a MILP model using Xpress Mosel. This model solves the urban waste collection routing problem under deterministic conditions across three fleet configurations: SCV only, MCV only, and a mixed fleet. The objective function minimizes total operational cost, while considering factors such as vehicle capacity utilization, travel distances, and the number of visited waste stations. This structured optimization provides an analytically robust solution framework for identifying the most cost-effective and efficient fleet setup in a static environment.

Stage 2: Simulation Modeling (AnyLogic)

In the second stage, the best-performing fleet configuration from the MILP model is implemented in AnyLogic using a discrete-event simulation model. Here, waste generation at each station is treated as a stochastic variable, changing across simulation runs through random seed variation. The simulation incorporates key dynamic features such as waste sharing, vehicle

rerouting, and the handling of excess waste — all of which are difficult to realistically capture within a mathematical model without making strong simplifications or increasing computational complexity.
Simulation is thus not a duplication of the MILP model, but a necessary extension. It allows the evaluation of system robustness, vehicle utilization, and operational flexibility under uncertain and fluctuating real-world conditions.

Rationale for the Two-Stage Approach

While the MILP delivers an optimal solution under idealized, deterministic assumptions, it inherently models a static system — assuming that all information is known in advance and does not change. However, real-world urban waste collection is dynamic and unpredictable: waste volumes fluctuate, vehicle compartments may become full unexpectedly, and routing conditions can vary in real time. Therefore, the theoretical optimum obtained from the MILP cannot be considered optimal in practice unless it proves adaptable under uncertainty.

The true operational optimum is the solution that can respond effectively to changing conditions in the moment — rerouting vehicles, reallocating capacity, and preventing unnecessary trips. In this context, the MILP solution serves as a strategic starting point, which the simulation model then tests and improves. The simulation reveals whether the optimized plan remains valid under real-world uncertainty and identifies operational enhancements, such as the value of rerouting or the benefit of two-compartment vehicles.

1.3.4 Evaluation Focus and Contribution

The core focus of this study is to evaluate how fleet configuration, demand variability, and routing flexibility interact to impact key operational outcomes. The specific evaluation goals are:

- Compare fleet configurations under different operational settings,
- Test robustness of routing strategies under uncertain demand,
- Identify operational challenges not visible in deterministic models,
- Propose adaptive solutions, such as rerouting and load sharing.

These evaluations generate several key contributions to the field of urban logistics and supply chain modeling:

- The integration of mixed fleet design, demand sharing, and dynamic rerouting into one cohesive optimization-simulation framework,
- A novel combination of exact optimization (MILP) and stochastic simulation, which enhances both solution quality and real-world applicability,
- A practical, adaptable model that supports decision-making for municipalities and logistics providers seeking to improve waste collection efficiency under real-world conditions.

1.4 Chapter Summary

This chapter introduced the motivation, background, and research problem addressed in this thesis, focusing on the inefficiencies and challenges associated with urban waste collection routing. It outlined the limitations of current vehicle routing practices, particularly the underutilization of single-compartment and multi-compartment fleets, the absence of demand sharing, and the lack of rerouting under uncertainty. The research objectives were clearly defined, and a central research question was formulated to guide the investigation. To address this question, a two-stage methodological approach was proposed, combining MILP and discrete-event simulation. The chapter concluded by highlighting the intended contributions of this study, which include a novel integration of fleet heterogeneity, adaptive routing, and stochastic modeling to support more efficient and realistic urban waste management strategies.

Chapter 2: Literature review and research gap

2. Literature review and research gap

Urban waste collection systems are critical to sustainable city operations, yet their planning and optimization face increasing challenges due to rising population densities, waste type segregation, and sustainability mandates. To design efficient, cost-effective, and adaptive systems, both researchers and municipalities rely on routing models, optimization techniques, and increasingly, simulation-based tools.

This chapter reviews the academic literature on waste collection and routing, with a specific focus on three interrelated themes: vehicle types and fleet configurations, waste management and routing strategies, and simulation-based modeling for uncertainty and system validation. Each of these domains contributes to how urban waste systems are modeled and optimized yet, as this review will demonstrate, they often evolve in isolation.

The aim of this chapter is not only to map the state of the art but also to reveal where gaps exist — especially in areas where operational realism and academic modeling diverge. To this end, each section concludes with a summary table comparing recent studies and identifying unresolved challenges. The final sections synthesize these findings into a coherent research gap and position this thesis in response to it.

2.1 Vehicle Types

A growing body of literature addresses the vehicle routing problem (VRP) in municipal waste management, with most studies modeling either single-compartment or multi-compartment vehicles in isolation. Multi-compartment vehicles (MCVs), which can simultaneously collect different waste types, are particularly common in modeling studies due to their perceived efficiency and reduced travel frequency (e.g., Song et al., 2024; Liu et al., 2024). However, these models typically assume homogeneous fleets, overlooking the operational flexibility and cost-efficiency that mixed fleets can offer.

In contrast, single-compartment vehicles (SCVs) dominate real-world fleets, especially in cities that lack the infrastructure to support compartmentalized collection. Several studies adopt SCVs exclusively, optimizing for either operational cost, emissions, or service time (e.g., Liao et al., 2025; Idrissi et al., 2024; Norena-Zapata et al., 2024). These models tend to ignore inter-vehicle collaboration or capacity sharing and rarely consider strategic coordination between vehicles.

Only a few works explicitly model heterogeneous fleets. Ostermeier and Hübner (2018) remains one of the rare contributions that examine a mixed SCV-MCV fleet. Their study incorporates waste sharing across vehicles to improve capacity utilization, although it remains deterministic and does not include rerouting. Hashemi-Amiri et al. (2023) and Ghoreishi et al. (2025) also explore limited mixed fleet scenarios, such as combining high- and low-capacity vehicles or diesel and electric SCVs, but without incorporating compartment logic or collaborative routing.

While these studies technically implement heterogeneity in fleet design, they do so primarily through variations in vehicle size or fuel type, rather than through functional diversity. For instance, Hashemi-Amiri et al. (2023) and Han et al. (2024) distinguish between small and large garbage trucks or vehicles of differing capacity, but all vehicles are single-compartment and collect a single waste type. This means their models do not support differentiated waste collection or compartment-specific optimization — key features in realistic urban waste systems. As such, these forms of "heterogeneous fleets" lack the functional heterogeneity needed for practical multi-waste logistics.

Another key observation is the general absence of dynamic or adaptive routing strategies. Only Mohammadi et al. (2023) integrate a dynamic component through a discrete choice model, and even this is limited to MCVs. Most models rely on fixed routes, static demand, and pre-assigned waste types, which diminishes their applicability in real-world urban environments where demand fluctuates daily.

Moreover, none of the reviewed studies validate their models through simulation or test their robustness under uncertainty. Many methods rely on metaheuristics or MILP formulations, yet they fall short in capturing operational volatility or in evaluating performance under stochastic demand scenarios. Table 2.1 summarizes key characteristics of 20 recent studies, categorized by fleet type, waste-sharing mechanism, rerouting capabilities, and methodological approach.

As the final row in Table 2.1 illustrates, this thesis addresses several of these gaps. It proposes an integrated optimization-simulation framework that models a mixed fleet of SCVs and MCVs, supports inter-vehicle waste sharing, and includes rerouting capabilities under stochastic demand. To the best of the author's knowledge, no existing study combines all of these elements within a unified model — making this contribution both novel and practically relevant.

Table 2.1 Review of Studies Focusing on Vehicle Configurations

Nr	Author	Vehicle Types Considered	Mixed Fleet	Waste Sharing	Vehicle Rerouting	Objective	Method	Research Gap

1	Song et al. (2024)	MCV Only	No	No	No	Minimize total cost	Augmented Lagrangian	No SCV, no waste sharing, no rerouting
2	Liu et al. (2024)	MCV Only	No	No	No	Minimize distribution cost	Hybrid Ant Colony	No SCV, no rerouting, no sharing
3	Sankul et al. (2024)	MCV Only	No	No	No	Minimize transport cost	Adaptive Differential Evolution	No SCV, no rerouting, no sharing
4	Baptista et al. (2024)	MCV Only	No	No	No	Minimize travel distance	Exact (MIP)	No mixed fleet, no sharing
5	Efthymiadis et al. (2023)	MCV Only	No	No	No	Minimize distance and cost	Exact (MILP)	Lacks hybrid fleet, no rerouting
6	Eshtehadi et al. (2020)	MCV Only	No	No	No	Minimize vehicle costs	Adaptive Large Neighborhood Search	No SCV, no rerouting, no sharing
7	Ostermeier and Hübner (2018)	Mixed Fleet	Yes	Yes	No	Minimize logistics costs	Large Neighborhood Search	No uncertain demand, no rerouting
8	Hashemi-Amiri et al. (2023)	Low, High Capacity Vehices(single compartment vehicles)	Yes	No	No	Maximize profit & minimize cost	Multi-objective Metaheuristic	No rerouting, no demand sharing
9	Liao et al. (2025)	Single-Compartment	No	No	No	Minimize cost & emissions	Evolutionary Algorithm	No waste sharing, no heterogeneous vehicles, no rerouting
10	Idrissi et al. (2024)	Single-compartment vehicle	No	No	No	Minimize travel cost	IoT	No waste sharing, no heterogeneous vehicles, no rerouting
11	Ghoreishi et al (2025)	EV & Diesel Fleet(single compartment	Yes	No	No	Minimize cost & emissions	Heuristik, Metaheuristic	No waste sharing, no heterogeneous vehicles, no rerouting
12	Norena-Zapata et al. (2024)	Single Compartment-vehicles	No	No	No	Minimize cost	MILP+VNS	No waste sharing, no heterogeneous vehicles, no rerouting
13	Thakur et al.(2024)	Single Compartment vehicles	No	No	No	Minimize cost	Metaheuristik	No waste sharing, no heterogeneous vehicles, no rerouting
14	Han et al. (2024)	Small and Large Garbage vehicle but single Compartment vehicles	No	No	No	Minimize cost & time	Branch-and-Price	No waste sharing, no heterogeneous vehicles, no rerouting
15	Niu et al (2024)	Single compartment vehicle	No	No	No	Minimize dissatisfaction & emissions	ML+Multi objective Optimization	No waste sharing, no heterogeneous vehicles, no rerouting
16	Liao et al. (2024)	Single compartment vehicle	No	No	No	Minimize emissions	Multi objective optimization algorithm	No waste sharing, no heterogeneous vehicles, no rerouting

17	Henaien et al. (2024)	Single compartment vehicles	No	No	No	Minimize cost & delay	IoT+GIS	No waste sharing, no heterogeneous vehicles, no rerouting
18	Rahmanifar et al. (2023)	Single comparment vehicles	No	No	No	Minimize cost & CO2	Two-echelon IoT + Metaheuristics	No waste sharing, no heterogeneous vehicles, no rerouting
19	Mohammadi et al. (2023)	Multi-compartment vehicles	No	No	No	Minimize cost & emissions	Discrete Choice model for dynamic vehicle routing	No waste sharing, no heterogeneous vehicles, no rerouting
20	Caramia et al. (2023)	Single comparment vehicles	No	No	No	Minimize greenhouse emission	Matheuristics solution method	No waste sharing, no heterogeneous vehicles, no rerouting
21	This Thesis	SCVs + MCVs(3 compartments)	Yes	Yes	Yes	Minimize total cost and improve operational flexibility under uncertainty	MILP+Discrete - Event Simulation	Addresses integration of mixed fleets, inter-vehicle sharing, and dynamic rerouting under uncertain demand

2.2 Waste management

Optimization of waste collection operations has been extensively studied, particularly in the context of routing efficiency, environmental impact, and service-level performance. The majority of recent research adopts single-objective or multi-objective formulations to minimize travel distance, operational cost, energy consumption, or collection delays. Heuristic and metaheuristic techniques such as genetic algorithms, simulated annealing, and clustering-based approaches remain dominant (e.g., Peña et al., 2024; Yu et al., 2023). These methods are often chosen for their computational scalability, especially when handling large problem instances.

A smaller subset of studies applies exact methods, including Mixed-Integer Linear Programming (MILP), often combined with time windows, unloading constraints, or depot location planning (e.g., Luo et al., 2024; Fischer et al., 2024). Others explore machine learning, agent-based modeling, or IoT-driven frameworks to improve route adaptability and smart bin responsiveness (e.g., Kona et al., 2024; Palagan et al., 2025). However, across this diversity of techniques, the actual structure of the waste collection system is often modeled simplistically, with homogeneous fleets and no allowance for waste-type separation or operational collaboration across vehicles.

Despite the increasing focus on sustainability and smart city integration, key operational strategies remain absent across almost all studies. None of the reviewed works incorporate waste sharing between vehicles, and only a few consider dynamic or adaptive rerouting. Even studies that aim to address environmental sustainability or uncertainty — such as Ghosh et al. (2023) or Mohammadi et al. (2023) — typically rely on static assumptions about demand or fleet composition. Similarly, while papers like Prata et al. (2025) and Giasoumi et al. (2025) adopt real-time data mechanisms, their models still exclude fleet-level coordination, demand redistribution, or inter-vehicle collaboration.

Another consistent limitation is the reliance on deterministic or average-case demand modeling. Most reviewed works assume static waste volumes, ignoring the high daily variability seen in real urban environments. Only a handful of models explore two-echelon logistics (e.g., Rahmanifar et al., 2024) or incorporate circular economy elements (Xu et al., 2025), yet these remain constrained by simplistic fleet structures and fixed waste-type allocations.

Table 2.2 summarizes the characteristics of 20 recent studies in the field, highlighting the absence of waste sharing, mixed fleet design, and real-time rerouting. The final row includes this thesis, which addresses these limitations through a novel MILP model coupled with a discrete-event simulation. By supporting dynamic demand, inter-vehicle waste sharing, and differentiated fleet configurations, this work contributes a more operationally realistic and scalable framework for urban waste collection logistics.

Table 2.2 Review of Studies Focusing on Waste Management

Nr	Author	Title / Focus Area	Model Type	Objective	Waste Sharing	Mixed Fleet	Vehicle Rerouting
1	Peña et al. (2024)	Genetic algorithm for waste routing	Heuristic	Minimize travel distance and energy use	No	No	No
2	Yu et al. (2023)	Simulated annealing for multi-depot VRP	Heuristic	Minimize total routing costs	No	No	No
3	Luo et al. (2024)	MILP for multi-day waste collection	MILP	Minimize operational costs	No	No	No
4	Kona et al. (2024)	IoT & deep learning for route optimization	Machine Learning	Minimize delays and energy consumption	No	No	No
5	Ghosh et al. (2023)	Multi-objective WM under uncertainty	Fuzzy Multi-objective	Maximize profit, reduce emissions & workload deviation	No	No	No
6	Mohammadi et al. (2023)	Dynamic routing in WM using discrete choice model	Choice Modeling	Reduce cost and environmental impact	No	No	Yes
7	Fischer et al. (2024)	Capacitated multi-vehicle routing for WM	MILP	Reduce operational cost and fleet size	No	No	No
8	Rahmanifar et al. (2024)	2 Echelon-VRP	Metaheuristic	Minimize wait time and cost	No	No	No
9	Xu et al. (2025)	Cooperative VRP in circular economy	Two Heuristic method + Dynamic programming	Optimize cost and profit sharing	No	No	No

10	Giasoumi et al. (2025)	IoT-based dynamic clustering for WCVRP	Heuristic (2-step clustering + KNN)	Reduce emissions and km traveled	No	No	No
11	Palagan et al. (2025)	Blockchain+FL for smart WM	ML+Blockchain	Dynamic routing and transparency	No	No	No
12	Lakhouit (2025)	AI + IoT for smart urban WM	Conceptual	Optimize collection, sorting, recycling	No	No	No
13	Prata et al. (2025)	Real-time WM with RFID and GIS	Operational Optimization	Improve routing and citizen participation	No	No	No
14	Huang et al. (2024)	Multi-trip VRP with time windows and unloading queue	Exact (Branch Price and Cut)	Minimize travel + unload wait time	No	No	No
15	Hussain et al. (2024)	IoT-based WM using multiagent simulation	Simulation (Agent-based)	Reduce distance, cost, and improve satisfaction	No	No	No
16	Khan et al. (2024)	GIS + linear optimization for WM	Linear programming	Route optimization	No	No	No
17	Ishaque & Florence	Deep learning & routing optimization	Hybrid AI + Metaheuristic	Minimize cost	No	No	No
18	Salawudeen et al. (2024)	CVRP using Discrete Smell Agent Optimization	Metaheuristic	Minimize cost & distance	No	No	No
19	Rekabi et al. (2024)	Bo-objective sustainable VRP with IoT	MILP (Bi-objective)	Reduce CO2+costs, boost jobs	No	No	No
20	Yu et al. (2024)	Multi-depot VRP with time windows and self-delivery	MILP + Simulated Annealing	Minimize cost + compensation	No	No	No
21	This Thesis	SCVs + MCVs(3 compartments)	Yes	Yes	Yes	Minimize total cost and improve operational flexibility under uncertainty	MILP+Discrete-Event Simulation

2.3 Methods and simulation modeling

Simulation has become an essential tool in logistics for evaluating system behavior under uncertainty, testing performance under varying conditions, and validating the outcomes of optimization-based strategies. Despite its widespread use in related logistics domains, simulation remains underutilized in waste collection research. Most reviewed works focus on theoretical optimization models or heuristics, with only limited effort to evaluate their robustness or feasibility in real-world scenarios.

Among those that do apply simulation, most use it for high-level performance assessment or cost analysis rather than for modeling full waste collection systems. For instance, Labib and Watfa (2023) and Sawik et al. (2022) apply discrete-event simulation and multi-method frameworks to analyze delivery systems, but not specifically waste logistics. Similarly, studies such as Helo and Rouzafzoon (2023) use agent-based modeling to explore uncertainty in supply chains, yet they do not simulate vehicle behavior, compartment usage, or operational decision-making in waste contexts.

In waste-related applications, simulation is often disconnected from fleet structure or system design. Several works use simulation to evaluate smart bin data integration or adaptive demand forecasting (e.g., Morais et al., 2024; Salehi-Amiri et al., 2022), but do not account for different vehicle types, waste categories, or sharing behavior between vehicles. Real-time adaptability is also limited. While a few studies simulate stochastic inputs or dynamic routes (e.g., Wang et al., 2025; Shen et al., 2024), these are typically abstracted scenarios and lack integration with decision variables such as routing, capacity, or compartment allocation.

Critically, no reviewed study combines optimization-based fleet assignment with discrete-event simulation in a unified framework that includes heterogeneous vehicles, waste-type constraints, or adaptive routing. This absence of integrated modeling limits the ability to explore robustness, flexibility, and operational feasibility — particularly under the dynamic conditions of real-world urban waste systems.

Table 2.3 provides a comparative summary of 20 simulation-based studies. While many use powerful modeling tools such as agent-based simulation, reinforcement learning, or heuristic-simulation hybrids, none evaluate routing behavior under waste-sharing conditions or fleet heterogeneity. Moreover, none of these studies integrate vehicle compartment structures or reallocation strategies at the vehicle level.

As highlighted in the final row, this thesis directly addresses these limitations. It combines a MILP optimization model with a discrete-event simulation framework to assess routing performance under uncertainty, using a mixed fleet of SCVs and three-compartment MCVs. The model simulates adaptive waste collection, inter-vehicle sharing, and rerouting behavior — all of which are absent in the reviewed simulation studies. This integrative approach allows for both optimization precision and simulation-based realism, offering a scalable and operationally relevant contribution to the field of urban waste logistics.

Tabelle 2.3 Comparative Analysis Based on Solution Methods and Simulation Modeling

Nr	Author	Title	Model Type	Simulation Type	Simulation Use Purpose	Share of Waste	Mixed Fleet	Vehicle Rerouting
1	Sawik et al. (2022)	Simulation-optimization approach for cost-effective last-mile delivery	Simulation-Optimization	Discrete-event	Cost analysis in last-mile delivery	No	No	No

2	Helo & Rouzafzoon (2023)	Managing forest supply chains using agent-based simulation	Simulation	Agent-based	Handling uncertain demand in forest supply chains	No	No	No
3	Labib & Watfa (2023)	Multi-method simulation for food delivery performance	Multi-method simulation	Discrete-event + Agent-based	Evaluate cost and customer satisfaction	No	No	No
4	Fu et al. (2022)	Green vehicle management system simulation	Simulation	Discrete-event	Minimizing operational cost	No	No	No
5	Sun et al. (2021)	Simulation for vaccine distribution logistics	Simulation	Discrete-event	Service level and cost-effectiveness	No	No	No
6	Svitunova (2020)	Railway station simulation for passenger flow	Simulation	Discrete-event	Enhancing passenger experience, adaptable to VRPs	No	No	No
7	Serrano-Hernandez et al. (2021)	Agent-based simulation of supermarket cooperation	Agent-based simulation	Agent-based	Cooperation scenarios in multi-depot logistics	No	No	No
8	Wang et al (2025)	Green vehicle routing under time-dependent dynamics	Two phase heuristic	Event triggered + Discrete	Handle real-time requests & emissions	No	No	No
9	Gholizadeh et al. (2025)	Simulation-optimization for resilient supply chain	Simulation-optimization	Discrete event	Improve flexibility, reduce unmet demand	No	No	No
10	Saavedra Sueldo et al. (2025)	Metaheuristic simulation for material handling	Simulation-Optimization	Discrete-event	Minimize routing time & coordination delay	No	No	No
11	Wang et al. (2024)	VRP under cognitive uncertainty	Uncertainty modeling	Uncertain modeling with case testing	Handle disruption & time window variance	No	No	No
12	Hussain et al. (2025)	Reinforcement Learning for route optimization in Internet of Vehicles	Reinforcement learning + Simulation	NS2 simulation	Improve energy use in vehicle routing	No	No	No
13	Shi et al. 2024	Recyclable express packaging network	Simulation optimization	Agent based	Optimize facility and vehicle routing	No	No	No
14	Shen et al. 2024	Medical waste network under uncertainty	Bi-level optimization	Discrete event + risk based	cost, risk and travel time analysis	No	No	No
15	Morais et al 2024	Smart waste routing via real time bin data	Data driven optimization	Dynamic with real time data	Improve route plans using ML + sensor data	No	No	No
16	Fang et al 2023	Review of artificial intelligence in WM	Review	Literature based	Review AI applications across WM	No	No	No
17	Zhang et al 2022	Genetic optimization of urban waste transport	Optimization		Improve vehicle routing efficiency	No	No	No
18	Erdem (2022)	Heterogeneous electric vehicle routing	MILP + Heuristic	Discrete event	Minimize cost & emissions in real scenario	No	No	No

19	Ijemaru et al. (2022)	Internet of vehicles for waste data collection	Simulation	Swarm based	Energy efficient smart city waste strategy	No	No	No
20	Salehi-Amiri et al. (2022)	Sustainable IoT-based SM system	Stochastic Programming	Dynamic, real time	Optimize fleet use, pollution, route timing	No	No	No
21	This Thesis	SCVs + MCVs (3 compartments)	Yes	Yes	Yes	Minimize total cost and improve operational flexibility under uncertainty	MILP+Discrete -Event Simulation	This Thesis

2.4 Research Gap

Despite growing interest in optimizing urban waste collection systems, significant methodological and practical limitations persist across the literature. Most notably, most models rely on static, deterministic frameworks, such as Mixed Integer Linear Programming (MILP), which assume that all demand and system parameters are known in advance. While MILP models can deliver optimal routing solutions under these assumptions, they cannot capture the real-time variability, operational disruptions, or stochastic excess waste generation that characterize real-world urban logistics. In contrast, waste collection systems must adapt dynamically to uncertainty—making simulation models essential to evaluate true operational performance and real-time adaptability.

Another important gap lies in how vehicle heterogeneity is modeled. Many studies claim to address heterogeneous fleets, but this often refers only to variations in vehicle size, capacity, or energy source (e.g., diesel vs. electric). This thesis adopts a technical definition of heterogeneity, focusing on the number and function of vehicle compartments. This allows for modeling of waste-type-specific constraints and opens the possibility of compartment-level optimization—an operational reality that is absent in the majority of existing models.i

Moreover, although the concept of waste sharing between vehicles may appear simple, it is rarely implemented in published models. Yet it plays a critical role in improving vehicle utilization, reducing CO_2 emissions, and avoiding unnecessary tours. In most prior works, vehicles operate independently and are fully responsible for collecting all waste at a station, even when this leads to underutilization and redundancy.

Perhaps the most crucial limitation is the absence of adaptive behavior in vehicle routing. While many models provide a static routing plan, few—if any—allow for real-time rerouting or reactive decision-making under uncertain conditions. This is particularly problematic for systems facing high variability in waste generation, where rerouting a partially filled vehicle to pick up excess waste could drastically improve efficiency. In this thesis, adaptability is not treated as an afterthought but as a core feature enabled by simulation.

Finally, while simulation is increasingly used in logistics research, most simulation models are disconnected from optimization. They are typically used for performance benchmarking or scenario testing, rather than to evaluate optimized fleet strategies under dynamic, uncertain conditions. This lack of integration means that robust, real-world system performance remains untested in most studies.

This thesis addresses these research gaps by introducing an integrated optimization-simulation framework that combines MILP with discrete-event simulation. The proposed model supports technical heterogeneity in vehicle design (e.g., SCVs and MCVs with three compartments), incorporates waste sharing across vehicles, and simulates adaptive rerouting strategies under stochastic demand. To the best of the author's knowledge, no existing work combines all of these features into a unified, practically grounded approach. This contribution aims to bridge the gap between academic optimization and real-world operational feasibility in municipal waste collection logistics.

2.5 Chapter Summary

Although the three streams of literature reviewed—vehicle types, waste management strategies, and simulation models—focus on different elements of the urban waste collection problem, their limitations are closely related. For example, the assumption of homogeneous fleets in routing models carries over into simulation studies, which also fail to simulate inter-vehicle collaboration or compartment logic. Similarly, while simulation tools are often introduced to handle uncertainty, they rarely test systems that were first optimized using exact models like MILP—leading to a disconnect between theoretical design and operational behavior.

Another critical linkage lies in the absence of functional heterogeneity in vehicles. Even when studies consider different vehicle sizes, they fail to account for real-world complexities such as compartment-based allocation, vehicle assignment to waste types, or re-routing based on real-time waste volumes. As a result, simulation and optimization remain siloed, unable to reflect the dynamic coordination needed in real waste systems. These cross-cutting limitations point to a clear opportunity for an integrated, flexible framework—which this thesis proposes.

This thesis addresses these limitations by introducing an integrated optimization-simulation framework that supports a mixed fleet of SCVs and multi-compartment MCVs, enables waste sharing and assignment logic, and allows for real-time adaptive rerouting under demand uncertainty. By combining an exact MILP formulation with a discrete-event simulation model, this work contributes both methodologically to optimization research and practically to the design of sustainable, data-driven municipal waste systems.

This chapter reviewed over 60 academic studies across three major research areas related to urban waste collection. While many offer valuable contributions in fleet modeling, heuristic optimization, or simulation-based analysis, consistent gaps remain: lack of functional vehicle heterogeneity, absence of waste-sharing mechanisms, static routing assumptions, and little integration between optimization and simulation. These limitations reduce the operational applicability of existing models. The next chapter presents the methodology of this thesis, which was designed to overcome these gaps by combining MILP optimization with real-time simulation under uncertainty.

Chapter 3: Mathematical Model

3. Mathematical Model

3.1 Introduction

The objective of this chapter is to develop and present a mathematical formulation for the urban waste collection problem under investigation. This problem involves optimizing vehicle routing operations to minimize overall costs, reduce the number of visited waste collection stations, and improve vehicle utilization.

To assess the impact of vehicle heterogeneity on routing efficiency, the model evaluates three distinct fleet configurations:

- A fleet composed exclusively of single-compartment vehicles (SCVs),
- A fleet consisting solely of multi-compartment vehicles (MCVs),
- A mixed fleet combining both SCVs and MCVs.

Each configuration is analyzed using an exact optimization approach based on MILP. The goal is to determine which setup delivers the most cost-effective and operationally efficient solution under deterministic demand conditions. The best-performing configuration, based on the objective function and utilization metrics, will later serve as the baseline scenario for simulation under uncertain demand in Chapter 4.

To structure the modeling approach, several assumptions, sets, and parameters are introduced. Artificial data is used for demonstration and testing purposes. The schematic problem representation and parameter values are provided in Figure 3.1 and Tables 3.1 through 3.5, respectively.

3.2 Assumptions

The following assumptions are made to ensure the mathematical model is computationally tractable while reflecting key operational characteristics of urban waste collection:

1. Demand is deterministic: Waste amounts at each collection station are known and fixed.
2. Fleet composition is predefined: The model uses a fixed number of SCVs and MCVs; no new vehicles are introduced.
3. Depot routing: All vehicles begin and end their routes at a single central depot.
4. Fixed vehicle capacities: Each SCV has a total capacity of 120 units; MCVs have three compartments of 40 units each.
5. Defined waste types: The model includes three waste types — paper, plastic, and glass — with paper assumed to have higher generation volume.
6. Collection rules:
   - Waste must be fully collected from each station.
   - Waste may be shared across vehicles.

- SCVs may collect only one waste type.
- MCV compartments are assigned to only one waste type each.

7. Symmetric and constant travel costs: Travel cost between any two stations is fixed at 40 units. Travel from a station to itself is disallowed using a large constant (M).
8. Vehicle visit limit per station: Each vehicle may visit a given waste station at most once per tour. However, different vehicles may visit the same station if required to complete the waste collection.

3.3 Indices and Sets

This section introduces the main sets and indices used to define the mathematical model. These form the basis for the formulation of constraints, the objective function, and decision variables. An overview of the sets and their descriptions is provided in Table 3.1.

Table 3.1 Sets of the mathematical model

Symbol (Used in Formulation)	Index	Range/Elements	Definition
W	i, j	{0,1,2,3,4,5} where 0 = Depot	Set of all waste collection stations including the depot.
V	k	{1,2,3,4,5,6}	Set of all available vehicles for waste collection.
$V_{MCV} \subset V$	$k \in V_{MCV}$	{1,2,3}	Subset of multi-compartment vehicles from the total fleet.
$V_{SCV} \subset V$	$k \in V_{SCV}$	{4,5,6}	Subset of single-compartment vehicles from the total fleet.
P	p	{1,2,3}	Set of all waste types to be collected (e.g., PAPER, PLASTIC, GLASS)
C	m	{1,2,3}	Set of compartments available in multi-compartment vehicles.
D ⊂ W	$i = 0$	0	Starting and ending depot for all vehicles routes.

3.4 Parameters

This section defines the key parameters used in the mathematical model. These represent known input values, including vehicle capacities, fixed and travel costs, and waste quantities.

The key parameters used in the model, including cost matrices, vehicle capacities, and waste amounts, are summarized in Table 3.2. Where applicable, parameter values are based on artificial data provided in subsequent tables.

Table 3.2 Model parameters used in the mathematical formulation

Symbol	Definition
d_{ij}	Let d_{ij} denote the travel cost (in euros, €) from station $i \in W$ to station $j \in W$, where W is the set of all waste collection stations. (Values given in Table 3.3.)
a_{pi}	Let $j \in W$ denote the amount of waste of type $p \in P$ generated at station $i \in W \setminus \{0\}$, measured in kilograms (kg). (Values given in Table 3.4.)
Q_k	Let Q_k denote the maximum carrying capacity (in kilograms, kg) of vehicle $k \in V$. (SCV:120 kg; MCV: 120 kg.)
q_c	Let q_c denote the capacity (in kilograms, kg) of compartment $m \in C$ in a multi-compartment vehicle. (Compartment sizes: {40,40,40} kg.)
f_k	Let f_k denote the fixed operational cost (in euros, €) associated with using vehicle $k \in V$. (SCV: 100€, MCV: 150€.)
M	Let M denote a sufficiently large constant (e.g., 100) used for subtour elimination constraints.

3.5 Artificial Data

To test and evaluate the mathematical model, a small artificial dataset was created. The dataset includes simplified travel costs between stations and predefined waste amounts for each type at each station. The purpose of using artificial data is to ensure that the model structure, constraints, and logic can be tested in a controlled environment before applying more complex or real-world data.

Table 3.3 shows a symmetric distance matrix with a constant travel cost of 40 units between any two distinct locations. Travel from a station to itself is not permitted and is represented by a large constant M.

Table 3.3 Travel cost matrix between stations (in € per trip)

Cost matrix	Depot (0)	Station 1	Station 2	Station 3	Station 4
Depot (0)	M	40	40	40	40
Station 1	40	M	40	40	40
Station 2	40	40	M	40	40
Station 3	40	40	40	M	40
Station 4	40	40	40	40	M

Table 3.4 presents the waste quantities (in kilograms) for each waste type at each collection station. Waste generation is assumed to be higher for paper than for plastic and glass, reflecting typical urban waste composition patterns.

Table 3.4 Waste quantities at each collection station (in kilogramms)

Waste Type	Depot (0)	Station 1	Station 2	Station 3	Station 4
Paper	0	50	30	20	20
Plastic	0	20	20	20	20
Glass	0	20	20	20	20

A schematic overview of the problem setup, including the depot, collection stations, waste types, and fleet composition, is shown in Figure 3.1. This illustration supports the conceptual understanding of the artificial dataset and problem structure used in the mathematical formulation.

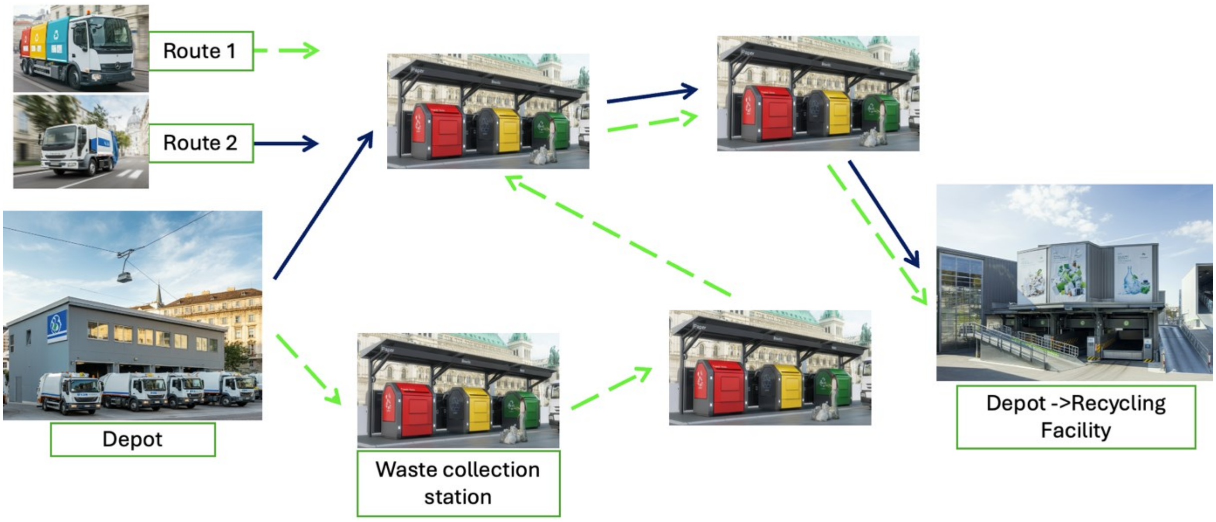


Figure 3.1 Schematic representation of the urban waste collection problem

3.6 Decision Variables

This section defines the decision variables used in the mathematical model. These variables represent routing choices, waste assignments, compartment usage, and vehicle activation status. A summary of the decision variables, including their domains and roles, is provided in Table 3.5.

Table 3.5 Decision variables used in the mathematical model

Variable	Description	Domain
x_{kij}	1 if vehicle $k \in V$ travels from station $i \in W$ to $j \in W$	{0,1}
y_{pkm}	1 if waste type $p \in P$ is assigned to compartment $m \in C$ of vehicle $k \in MCV$	{0,1}

s_{ipk}	Share of waste type $p \in P$ from station $i \in W \setminus \{0\}$ collected by vehicle $k \in V$	[0,1]
u_{ik}	Sequence position of station $i \in W$ in the tour of vehicle $k \in V$	$\mathbb{R}$
z_{pkm}	1 if compartment m $\in C$ of vehicle $k \in MCV$ is used for waste type $p \in P$	{0,1}
v_k	1 if vehicle $k \in V$ is used	{0,1}
c_{pk}	1 if SCV $k \in SCV$ collects waste type $p \in P$	{0,1}

3.7 Mathematical Formulation

This section presents the full mathematical model for the urban waste collection routing problem. The objective is to minimize total operational costs, including routing costs and fixed vehicle usage costs, while ensuring complete waste collection under capacity, routing, and compartment assignment constraints.

3.7.1 Objective Function

The objective function minimizes the total cost of the waste collection operation:

$$\min \left(\sum_{k \in V} \sum_{i \in W} \sum_{j \in W} \mathrm{d_{ij}} * \mathrm{x_{kij}} + \sum_{k \in V_{MCV}} \mathrm{f_k} * v_{\mathrm{k}} + \sum_{k \in V_{SCV}} \mathrm{f_k} * v_{\mathrm{k}} \right) \tag{1}$$

Where:

- d_{ij}: travel cost between stations i and j
- f_k: fixed cost for using vehicle k
- x_{kij}: binary variable indicating if vehicle k travels from i to j
- v_k: binary variable indicating if vehicle k is used

3.7.2 Constraints

Constraint (2) ensures flow conservation at stations, maintaining continuity in the vehicle tours:

$$\sum_{j \in W} x_{kij} = \sum_{j \in W} x_{kji} \;\; \forall k \in V, \forall i \in W \setminus \{0\} \tag{2}$$

Constraint (3) ensures that each vehicle visits each station at most once:

$$\sum_{j \in W} x_{kij} \leq 1 \quad \forall k \in V, \forall i \in W \setminus \{0\} \tag{3}$$

Constraint (4) eliminates subtours using the Miller-Tucker-Zemlin (MTZ) method:

$$u_{ik} + 1 \leq u_{jk} + M * \left(1 - x_{kij}\right) \;\; \forall k \in V, \forall i, j \in W, i \neq j \tag{4}$$

Constraint (5) ensures complete collection of each waste at each station:

$$\sum_{k \in V} s_{ipk} = 1 \quad \forall i \in W \setminus \{0\}, \forall p \in P \tag{5}$$

Constraint (6) links waste collection to routing decisions: collection requires visiting the station:

$$s_{jpk} \leq \sum_{i \in W} x_{kij} \quad \forall j \in W \setminus \{0\}, \forall p \in P, \forall k \in V \tag{6}$$

Constraint (7) ensures that the vehicle capacity is not exceeded:

$$\sum_{i \in W \setminus \{0\}} a_{pi} * s_{ipk} \leq Q_k \quad \forall p \in P, \forall k \in V \tag{7}$$

Constraint (8) ensures that each compartment in MCV is assigned to exactly one waste type:

$$\sum_{p \in P} y_{pkm} = 1 \quad \forall k \in V_{MCV}, \forall m \in C \tag{8}$$

Constraint (9) ensures that collected waste types respect the MCV compartment assignments:

$$\sum_{i \in W \setminus \{0\}} s_{ipk} \leq |W| * \sum_{m \in C} y_{pkm} \quad \forall p \in P, \forall k \in V_{MCV} \tag{9}$$

Constraint (10) restricts SCVs to collect at most one waste type:

$$\sum_{p \in P} \sum_{i \in W \setminus \{0\}} s_{ipk} \leq 1 \quad \forall k \in V_{SCV} \tag{10}$$

Constraint (11) ensures that each SCV is assigned to at most one waste type:

$$\sum_{p \in P} c_{pk} \leq 1 \quad \forall k \in V_{SCV} \tag{11}$$

Constraint (12) links waste collection to SCV assignment: a vehicle collects waste only if assigned to that type:

$$\sum_{i \in W \setminus \{0\}} s_{ipk} \leq c_{pk} \quad \forall p \in P, \forall k \in V_{SCV} \tag{12}$$

3.8 Explanation of Constraints

Constraint (2) ensures that for each vehicle, the number of times it enters a station equals the number of times it leaves that station (except for the depot). It guarantees that all routes are continuous and logically complete.

Constraint (3) prevents any vehicle from visiting the same station more than once. However, a station may still be visited by multiple different vehicles.

Constraint (4) avoid disconnected loops (subtours), this constraint applies the Miller-Tucker-Zemlin (MTZ) method. It maintains a valid sequence of visits for each vehicle by assigning a relative position to each visited station.

Constraint (5) ensures that 100% of the waste for each type at every station is collected — either by one vehicle or shared between multiple vehicles.

Constraint (6) links the collection variable to the routing variable. If a vehicle collects waste from a station, it must also physically visit that station.

Constraint (7) ensures that the total waste assigned to each vehicle (based on the collected share and waste amounts) does not exceed the vehicle's maximum capacity.

Constraint (8) ensures that each compartment of a multi-compartment vehicle is exclusively assigned to one waste type.

Constraint (9) ensures that a vehicle only collects waste of a type if it has a compartment assigned to that type. It prevents a mismatch between collection and configuration.

Constraint (10) restricts single-compartment vehicles to collecting only one type of waste across all stations. This maintains load consistency and reduces operational complexity.

Constraint (11) describes SCV waste type assignment control, limiting each SCV to be assigned to at most one waste type before routing.

Constraint (12) denotes the consistency between collection and assignment for SCVs, ensuring that a vehicle collects waste only if it is assigned to that type.

3.8 Mathematical Model Results

This section presents and analyzes the results of the three vehicle fleet configurations evaluated using the mathematical model:

(1) a fleet consisting exclusively of single-compartment vehicles (SCVs),

(2) a fleet of only multi-compartment vehicles (MCVs), and

(3) a mixed fleet combining both vehicle types.

Each scenario was implemented and solved using the optimization software Xpress Mosel, based on the artificial data introduced earlier. The results are visualized through vehicle routing diagrams and summarized using key performance indicators, including total cost, number of station visits, vehicle utilization, and travel distance. These outcomes provide insights into the operational efficiency and cost-effectiveness of each configuration, forming the basis for selecting the best-performing setup to be further analyzed in the simulation model.

3.8.1 Single-Compartment Vehicle Scenario

In the single-compartment vehicle (SCV) scenario, each waste collection station contains all three types of waste: paper, plastic, and glass. As SCVs can only transport a single type of waste per tour, each vehicle is assigned to a specific waste type and must complete a separate route.

For example, Vehicle 1 is assigned to collect paper waste. It begins at the depot, visits Station 1 (collecting 50 units), then continues to Station 2 (30 units), Station 3 (20 units), and Station 4 (20 units), before returning to the depot — reaching its full capacity of 120 units.
A similar routing strategy is followed by:

- Vehicle 2, which collects plastic waste from all stations (80 units total),
- Vehicle 3, which collects glass waste (80 units total).

Figure 3.2 illustrates the SCV routing plan and collection output, showing the individual vehicle paths, waste type assignments, number of visited stations, and cost distribution.
Performance Summary:

- Total number of station visits: 12 (4 per vehicle × 3 vehicles)
- Total waste collected: 120 (paper), 80 (plastic), 80 (glass)
- Fixed cost: 3 vehicles × 100 = 300
- Travel cost: 3 vehicles × 200 = 600
- Total cost: 900

This configuration demonstrates the limited efficiency of SCVs in multi-waste environments. Despite full vehicle utilization, the need for separate trips per waste type leads to higher travel costs and increased station visits.

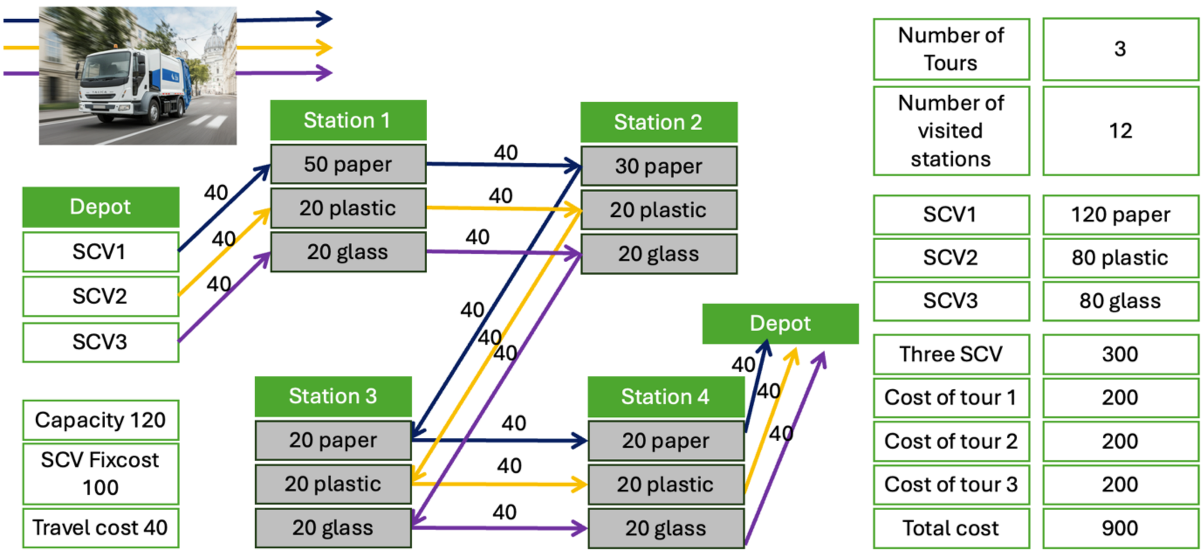


Figure 2.2 Operational Performance of Single-Compartment Vehicle (SCV) Fleet – Routing, Cost, and Utilization

3.8.2 Multi Compartment Vehicle Scenario

In the multi-compartment vehicle (MCV) scenario, each vehicle is equipped with three separate compartments, allowing it to collect paper, plastic, and glass in a single trip. This added flexibility enables the model to consolidate waste collection routes, significantly reducing the total number of station visits compared to the SCV-only scenario.

The vehicle routing strategy unfolds as follows:

- Vehicle 1 begins at the depot and visits Station 2, collecting 30 units of paper, 20 units of plastic, and 20 units of glass. It then proceeds to Station 1 to collect an additional 10 units of paper and 20 units of plastic.
- Vehicle 2 visits Station 3 and collects 20 units of each waste type. It continues to Station 4, where it collects another 20 units of paper, plastic, and glass.
- Vehicle 3 completes the collection by visiting Station 1 again to collect the remaining 40 units of paper and 20 units of glass.

This approach reduces the total number of waste station visits from 12 (in the SCV scenario) to only 5, demonstrating the operational efficiency gained through compartmentalized collection.

Figures 3.3 and 3.4 visualize the vehicle routes and collection breakdown, highlighting how MCVs can consolidate waste types and optimize route efficiency.

Performance Summary:

- Total visited stations: 5
- Fixed cost: 3 vehicles × 150 = 450

- Travel cost: 320
- Total cost: 770

While the total cost is lower than in the SCV-only scenario, this configuration leaves some compartments underutilized. Nevertheless, it offers significant reductions in travel distance and station visits by enabling multi-waste collection per trip.

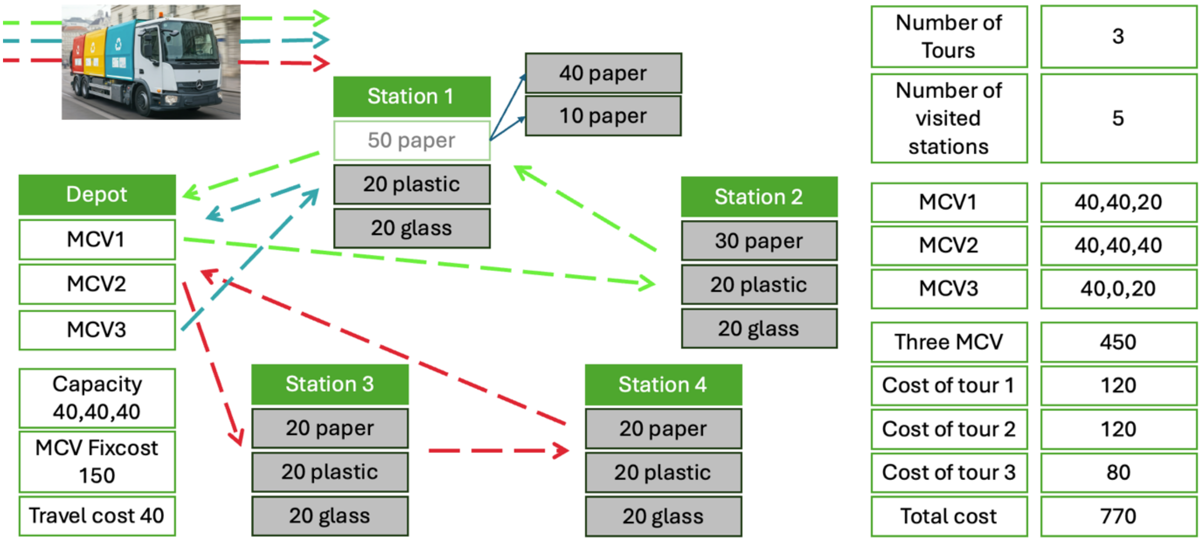


Figure 3.3 Operational Performance of MCV Fleet – Routing and Utilization Summary

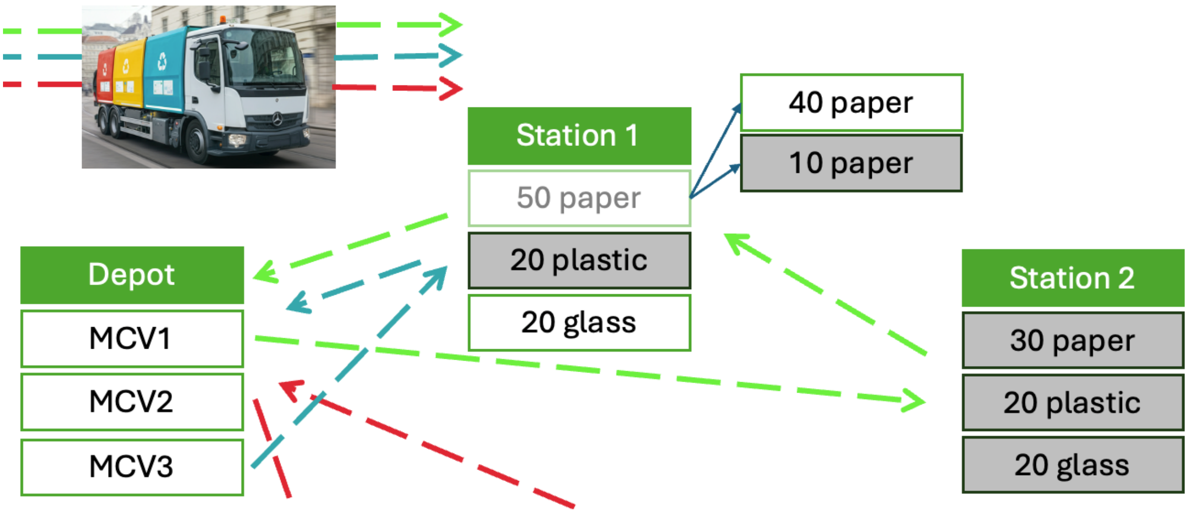


Figure 3.4 Detailed View of Waste Pickup Allocation at Stations 1 and 2 by MCV Fleet

3.8.3 Mixed Fleet Scenario

The mixed fleet scenario combines the strengths of both multi-compartment and single-compartment vehicles, offering a balanced and highly efficient collection strategy. In this configuration, multi-compartment vehicles are prioritized to collect as much waste as possible across multiple types in a single trip, while a single-compartment vehicle is deployed to handle any remaining excess.

The resulting routing strategy is as follows:

- Multi-Compartment Vehicle 1 starts at the depot and visits Station 2, where it collects 30 units of paper, 20 units of plastic, and 20 units of glass. It then proceeds to Station 1, collecting an additional 10 units of paper, 20 units of plastic, and 20 units of glass.
- Multi-Compartment Vehicle 2 is also fully utilized, efficiently collecting waste across multiple stations (full details visualized in Figures 3.5 and 3.6).
- Single-Compartment Vehicle 1 is deployed to collect the remaining 40 units of paper, ensuring full waste removal across all stations.

This hybrid strategy maintains the low number of station visits achieved in the MCV-only scenario, while improving overall vehicle utilization and cost-efficiency.

Figures 3.5 and 3.6 show the optimized routes and vehicle utilization for the mixed fleet, illustrating how each vehicle contributes to minimizing redundancy and maximizing capacity. Performance Summary:

- Total visited stations: 5
- Fixed cost: (2 MCVs × 150) + (1 SCV × 100) = 400
- Travel cost: 320
- Total cost: 720

Compared to both previous scenarios, the mixed fleet achieves the lowest overall cost and the highest compartment utilization, while preserving the reduced number of station visits. Based on these results, the mixed fleet configuration is selected for further testing in the simulation model, where uncertain demand conditions will be introduced.

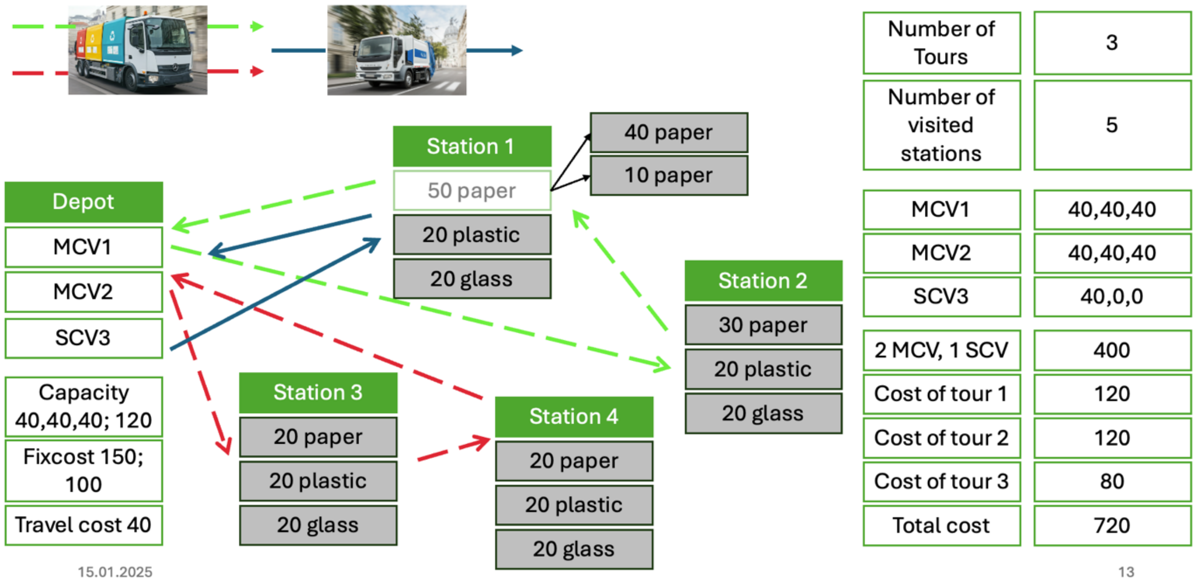


Figure 3.5 Mixed Fleet Operation with Waste Sharing Across MCVs and SCV

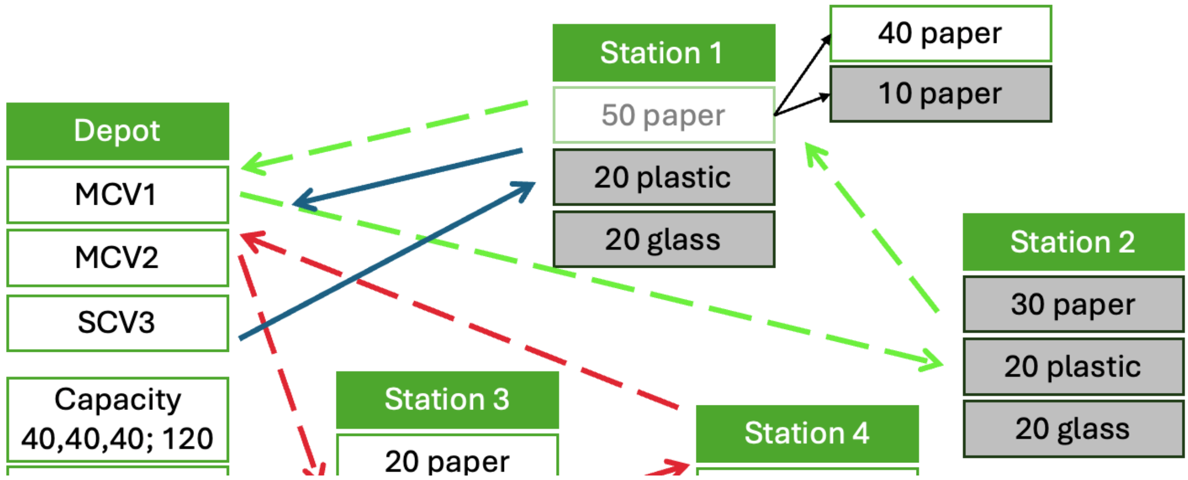


Figure 3.6 Vehicle Routing with Waste Sharing Between MCVs and SCV

3.9 Summary Results

This section summarizes the outcomes of the three fleet configurations—single-compartment vehicles (SCV), multi-compartment vehicles (MCV), and the mixed fleet—based on performance metrics including total cost, number of station visits, travel distance, and vehicle utilization.

Table 3.6 provides a comparative overview of the key results.

Figure 3.7 visually compares travel efficiency and vehicle utilization across scenarios.

Table 3.6 Performance comparison between SCV-only, MCV-only, and mixed fleet configurations in urban waste collection routing.

Metric	SCV Only	MCV Only	Mixed Fleet
Total cost	900	770	720
Fixed cost	300	450	400
Travel cost	600	320	320
Visited Stations	12	5	5
Compartments Fully Utilized	–	1	2
Vehicles Used	3 SCV	3 MCV	2 MCV + 1 SCV

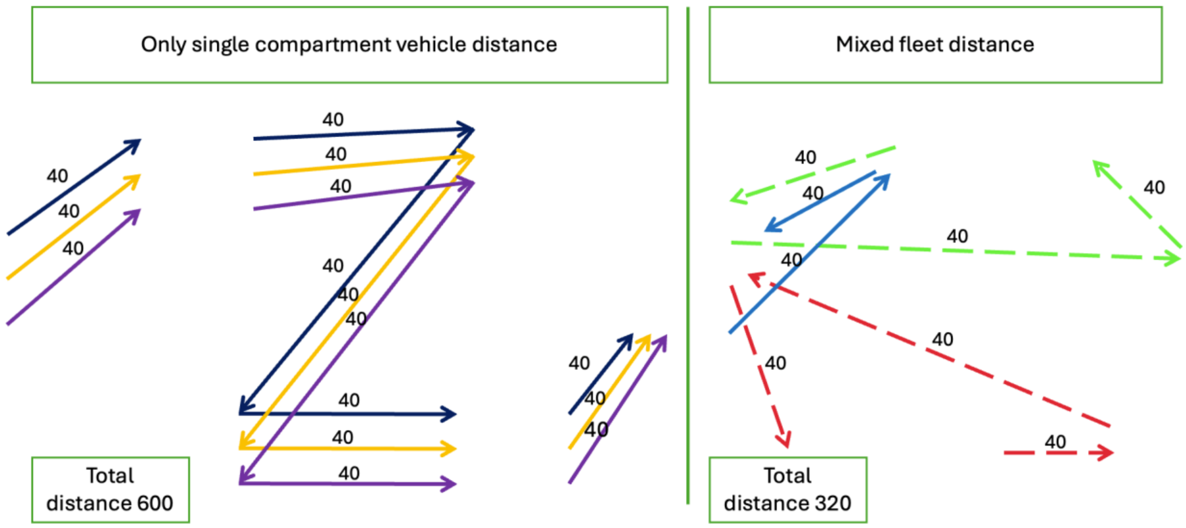


Figure 3.7 Comparison of total travel distance between single-compartment vehicle routing and mixed fleet routing solutions

Key Insights

- Cost Efficiency: The mixed fleet achieved the lowest total cost (720), outperforming both SCV-only (900) and MCV-only (770) scenarios.
- Operational Efficiency: Station visits were reduced by more than 50% compared to SCVs, due to the ability of MCVs to collect multiple waste types in a single trip.
- Vehicle Utilization: The mixed configuration maximized compartment use—two MCVs were fully utilized, while the SCV efficiently handled the overflow.

These findings clearly demonstrate the benefits of using a heterogeneous fleet with shared waste allocation. The mixed fleet scenario combines route consolidation with operational flexibility, making it the most promising configuration.

Accordingly, this fleet structure will be selected as the basis for the simulation model in the next chapter, where uncertain demand conditions will be introduced to test robustness and real-world applicability.

3.10 Chapter Summary

This chapter developed and analyzed a mathematical model for optimizing urban waste collection using three different vehicle fleet configurations: single-compartment vehicles (SCVs), multi-compartment vehicles (MCVs), and a mixed fleet. The model was formulated as a MILP and implemented in Xpress Mosel, based on a controlled artificial dataset. The model considered routing decisions, vehicle capacity constraints, compartment assignments, and waste-sharing strategies.

The results demonstrated that the mixed fleet configuration outperformed both the SCV-only and MCV-only setups. It achieved the lowest total cost, fewest station visits, and highest vehicle utilization, by combining the route flexibility of MCVs with the targeted efficiency of SCVs. A comparative analysis of all scenarios confirmed the value of mixed fleet routing in achieving both economic and operational efficiency.

Given its superior performance under deterministic demand conditions, the mixed fleet configuration is selected as the baseline for the next phase of the thesis. In the following chapter, a simulation model will be introduced to evaluate how this configuration performs under uncertainty, capturing dynamic factors such as fluctuating waste volumes and operational disruptions.

Chapter 4: Simulation Model

4. Simulation Model

This chapter presents the development and implementation of a discrete-event simulation model designed to complement the mathematical optimization results. While the mathematical model provided deterministic fleet configurations under fixed conditions, the simulation introduces stochastic elements to capture the variability inherent in real-world waste collection operations. The simulation environment enables the testing of fleet performance, operational robustness, and responsiveness to uncertain demand scenarios. The chapter details the simulation objectives, model structure, process flow, control mechanisms, scenario analyses, and the identification of operational challenges.

4.1 Simulation Objectives

This chapter presents the development and application of a discrete-event simulation model designed to evaluate the performance of the optimized mixed fleet under conditions of demand uncertainty. The simulation is implemented in AnyLogic and executed across multiple runs using a uniform probability distribution to model variations in daily waste generation.

The primary objective of the simulation is to assess the robustness of the mixed fleet configuration derived from the mathematical model. Key evaluation criteria include operational feasibility, vehicle utilization, cost efficiency, and responsiveness to fluctuating demand. By introducing stochastic elements into the simulation environment, the model enables the identification of inefficiencies and operational challenges that may not surface under deterministic assumptions.

The insights derived from this analysis serve two purposes:

1. To validate the effectiveness of the MILP-derived mixed fleet strategy under real-world variability.
2. To inform the development of adaptive strategies aimed at improving the flexibility and efficiency of the waste collection system.

The subsequent sections present the simulation structure in detail, including its user interface, process flow, logic, run scenarios, and findings.

4.2 Simulation Settings and Assumptions

To ensure a manageable and realistic representation of the urban waste collection system, the simulation model incorporates several configurations, assumptions, and simplifications. These design choices help balance system complexity with computational feasibility and focus the analysis on key operational dynamics.

Waste Generation

- Stochastic Waste Amounts: Waste volumes are generated at the beginning of each simulation run using a uniform probability distribution, reflecting day-to-day variations in urban waste generation.
- Distribution Ranges:
    - Paper: 35 to 45 units
    - Plastic: 25 to 30 units
    - Glass: 25 to 30 units

Paper waste is assumed to be generated in higher quantities based on empirical observations from urban recycling trends and is used as the dominant waste type for routing decisions.

Vehicle Types

- Multi-Compartment Vehicles (MCVs): Represented in the model with red icons, MCVs can simultaneously collect paper, plastic, and glass, using three separate compartments with a capacity of 8 pallets (40 units) each.
- Single-Compartment Vehicles (SCVs): Represented with green icons, SCVs are limited to collecting only one waste type — in this case, paper. Each SCV has a total capacity of 24 pallets (120 units).

Simplified Network Structure

- The simulation model includes three waste collection stations (rather than four, as in the MILP model) to enhance visibility and reduce visual and logical complexity within the AnyLogic environment.

Palletization Strategy

- For ease of tracking and loading, the simulation aggregates every 5 units of waste into one pallet. Thus, a vehicle with 8 pallet capacity per compartment can carry up to 40 units of a given waste type.

Vehicle Capacity and Cost Modeling

- MCV Compartment Capacity: 8 pallets (40 units) per compartment
- SCV Capacity: 24 pallets (120 units total)
- Fixed Costs:
    - MCV: 150 units per deployment
    - SCV: 100 units per deployment

These values are aligned with the parameters used in the mathematical model, allowing for direct comparison of performance across deterministic and stochastic environments.

This configuration ensures that the simulation model accurately reflects real-world operational conditions while remaining computationally efficient and analytically transparent. The next sections present and analyze two specific simulation runs, each illustrating different operational outcomes based on varying input conditions.

4.3 Simulation scenario 1

This section presents the results of the first simulation run, designed to evaluate the performance of the mixed fleet configuration under stochastic demand conditions. The goal is to assess vehicle utilization, route efficiency, and the system's ability to fully collect waste using a combination of multi-compartment and single-compartment vehicles.

Waste Generation

At the start of the simulation, waste volumes were generated randomly for each waste collection station using a uniform distribution:

- Paper: 35–45 units
- Plastic and Glass: 30–35 units

Figure 4.1 shows the resulting waste amounts at each station. For example, Station 1 generated 8 pallets of paper (40 units), 6 pallets of plastic (30 units), and 6 pallets of glass (30 units).

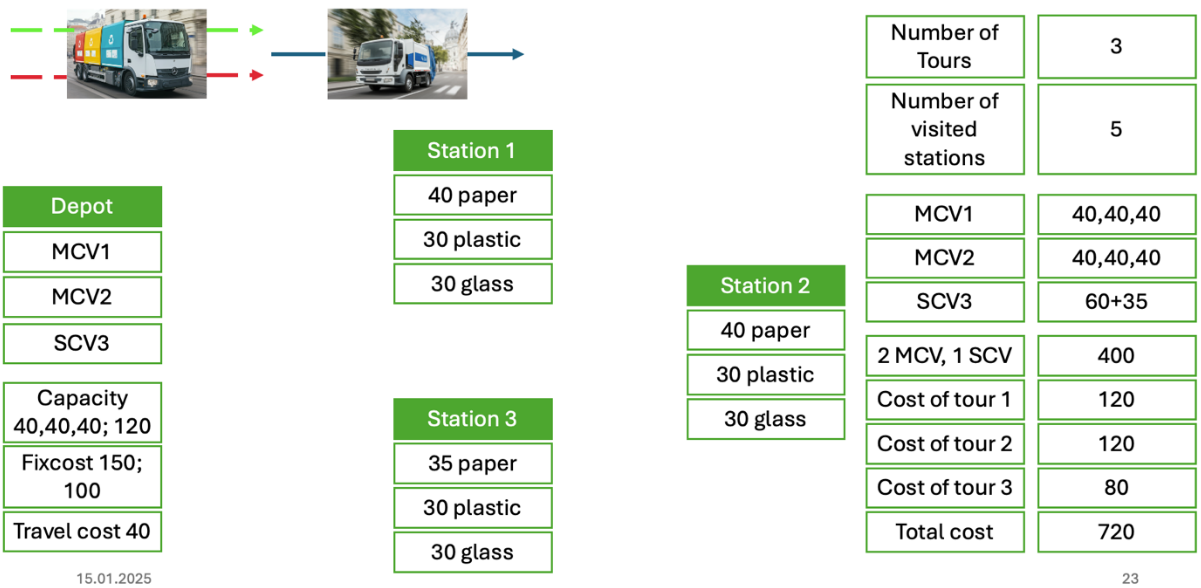


Figure 4.1 generation of waste amount with uniform distribution

Figures 4.2, 4.3 and 4.4 show vehicle deployment and pickup sequences of the vehicles

1. First Multi-Compartment Vehicle (MCV1):
   - Visits Station 1: picks up all available paper, plastic, and glass pallets

- Continues to Station 2: picks up 3 more pallets of plastic and 3 of glass
- Upon reaching full compartment capacity, it returns to the depot.

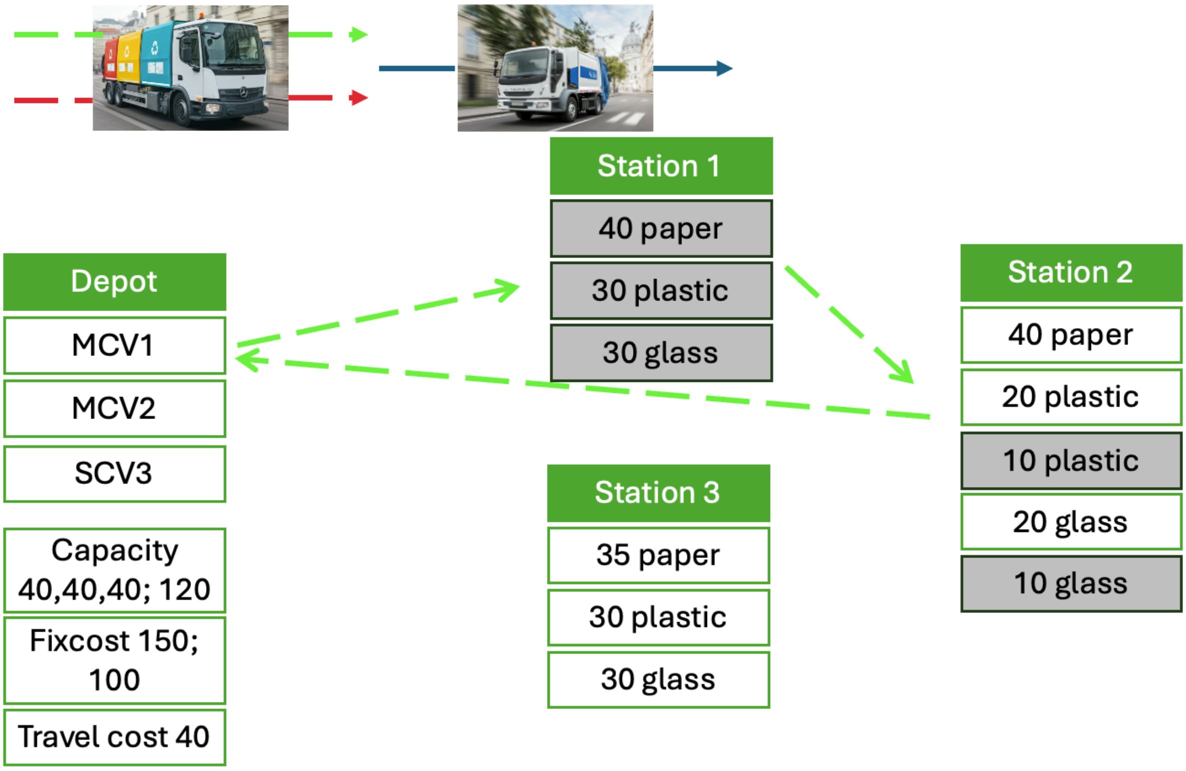


Figure 4.2 waste pick by the first multi-compartment vehicle

2. Second Multi-Compartment Vehicle (MCV2):
   - Visits Station 2: picks up 8 pallets of paper, 2 of plastic, 2 of glass
   - Visits Station 3: collects 3 pallets each of plastic and glass
   - Also returns to depot at full capacity

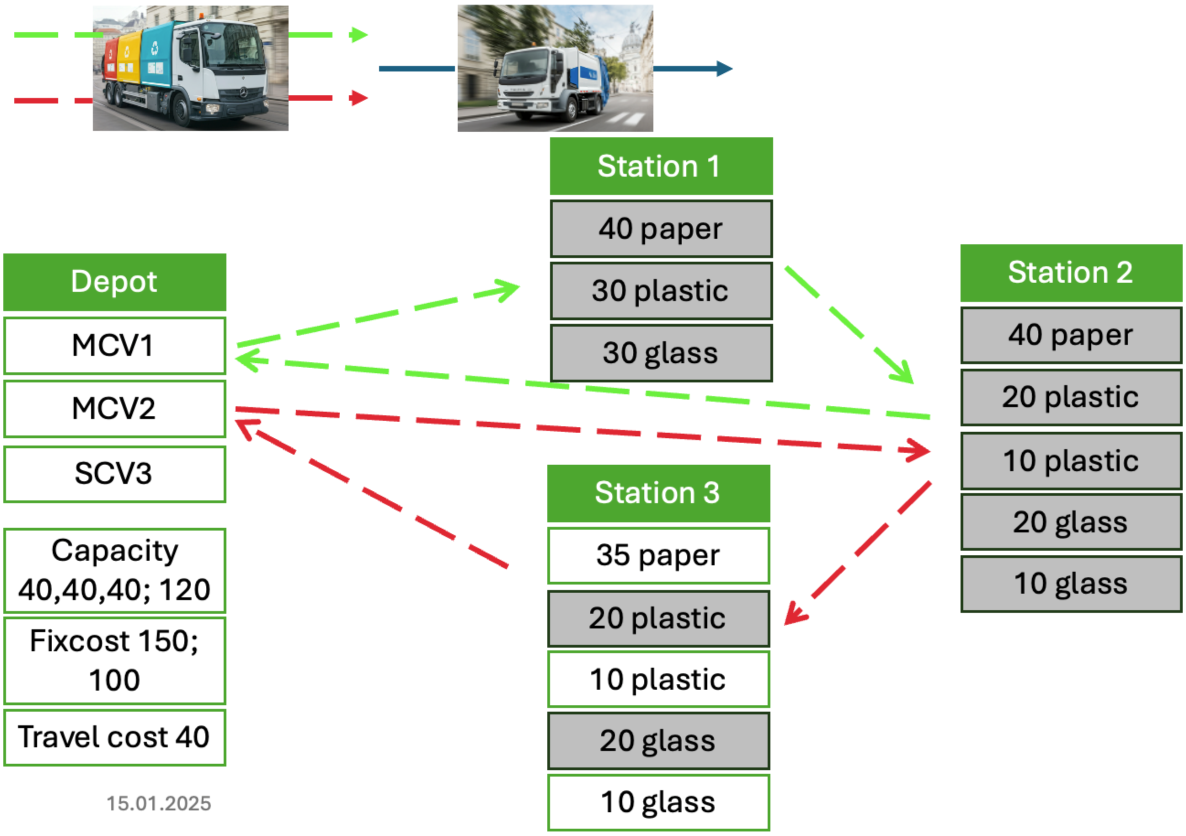


Figure 4.3 waste pick up by the second multi-compartment vehicle

3. Single-Compartment Vehicle (SCV):
   - Dispatched to collect the remaining 7 pallets of paper (35 units) from Station 3
   - Utilizes approximately 29% of its total capacity

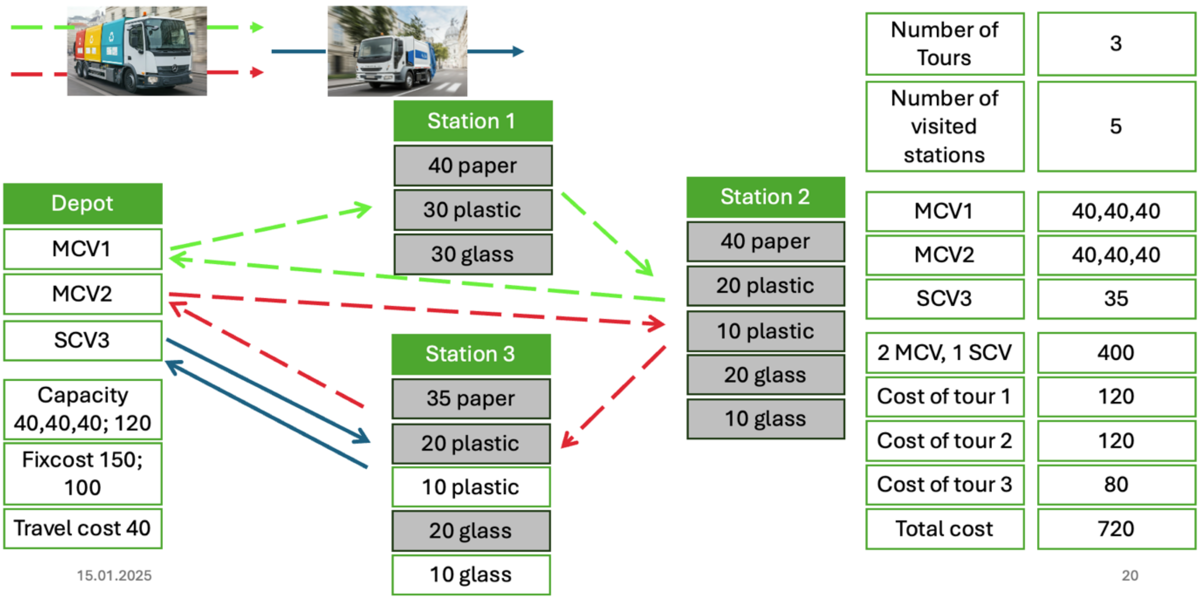


Figure 4.4 waste (paper) pickup by the single-compartment vehicle

Result Summary

- Total system cost: 720 units
    - MCVs: 2 × 150 = 300
    - SCV: 1 × 100 = 100
    - Travel cost: 8 × 40 = 320
- Total visited stations: 5
- MCV compartment utilization: 100%
- SCV utilization: ~29%

4.3.1 Summary of Simulation Scenario 1 Results

The results of the first simulation scenario are summarized in Table 4.1. In this run, two multi-compartment vehicles (MCVs) were fully utilized by collecting waste from multiple stations across all three waste types. However, due to the relatively high volume of paper waste—exceeding the per-compartment limit of 40 units—residual paper remained uncollected after the MCVs reached full capacity.

To ensure complete service, a single-compartment vehicle (SCV) was dispatched to collect the remaining 35 units of paper. While this ensured full waste removal, the SCV operated at only 29% capacity. This underutilization highlights a key limitation: when waste generation is uneven across types, fixed compartment sizes in MCVs can lead to fragmented pickup assignments, requiring additional vehicles for relatively small volumes.

This scenario illustrates a critical operational trade-off: prioritizing route consolidation via MCVs improves overall system efficiency, but without adaptive planning, it can result in inefficient use of secondary vehicles like SCVs. The cost remained moderate (720 units), but vehicle utilization was suboptimal for the SCV.

Table 4.1 Waste Collection Summary – Scenario 1

	Mixed fleet	Waste Station 1	Waste Station 2	Waste Station 3
Multi-Compartment Vehicle 1	24*5=120->100% fully utilized	X	X	
Multi-Compartment Vehicle 2	24*5=120->100% fully utilized		X	X
Single-Compartment Vehicle	7*5=35->29% underutilized			X
Total cost	720			
Number of Tours	3			
Number of visited stations	5			

4.4 Simulation Scenario 2 with rerouting

This scenario uses the same stochastic waste generation values as in Scenario 1. Each station generates a combination of paper, plastic, and glass waste, with paper as the dominant type.

The deployment of the two multi-compartment vehicles (MCVs) follows the exact sequence as described in Simulation Scenario 1. The difference lies in the routing behavior of the single-compartment vehicle (SCV):

- Instead of dispatching a new vehicle from the depot, the single-compartment vehicle (SCV) was rerouted in real-time to Station 3 after the initial deployment of multi-compartment vehicles (MCVs). This approach allowed the SCV to collect the remaining 7 pallets of paper waste. Crucially, rerouting the SCV proved more efficient than sending an additional MCV, which would have been significantly underutilized. This strategy reduced fixed costs and improved vehicle utilization without increasing fleet size.

This flexible reassignment of the SCV improved its utilization rate significantly, from 29% in Scenario 1 to 79% in this run (see Figure 4.5).

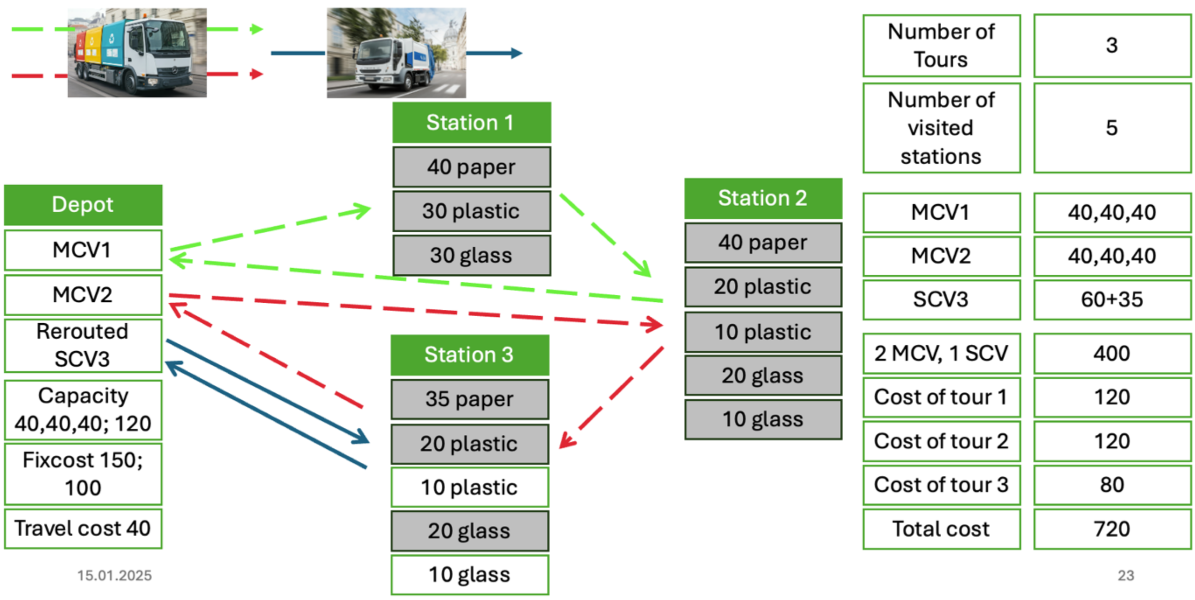


Figure 4.5 waste (paper) pickup by rerouted single-compartment vehicle

4.7.1 Simulation Scenario 2 Results

Table 4.2 summarizes the vehicle utilization for this scenario. Total system cost remains identical to Scenario 1 (720 units) but rerouting increased efficiency in the SCV's deployment.

Scenario 2 builds on the baseline configuration by introducing real-time rerouting of the single-compartment vehicle (SCV). As in Scenario 1, two multi-compartment vehicles (MCVs) are fully utilized across Stations 1 to 3. However, instead of deploying a new SCV from the depot to collect the residual paper waste, the simulation reroutes an already active SCV to Station 3. This rerouting decision led to a significant improvement in SCV utilization, from 29% in Scenario 1 to 79% in Scenario 2. The system was able to respond dynamically to the residual load by leveraging available vehicle capacity more effectively.

This scenario highlights how adaptive vehicle reassignment can substantially increase operational efficiency, even without changing the fleet size or route structure. By allowing in-progress vehicles to be redirected, the system reduces idle capacity and minimizes redundant trips. Rerouting acts as a flexible decision layer that compensates for load imbalances created by compartment constraints and stochastic waste generation.

Table 4.2 Waste collection summary

	Mixed fleet	Waste Station 1	Waste Station 2	Waste Station 3
Multi-Compartment Vehicle 1	40+40+40=120->100% fully utilized	X	X	
Multi-Compartment Vehicle 2	40+40+40=120->100% fully utilized		X	X
Single-Compartment Vehicle	60+35=95->79% efficiently utilized			X
Total cost	720			
Number of Tours	3			
Number of visited stations	5			

4.5 Simulation scenario 3 without waste sharing

Scenario 3 removes the waste sharing capability from the system. Figure 4.6 shows the simulation configuration. In this setup, each multi-compartment vehicle (MCV) is assigned to a single waste collection station and is responsible for collecting all three waste types—paper, plastic, and glass—independently.

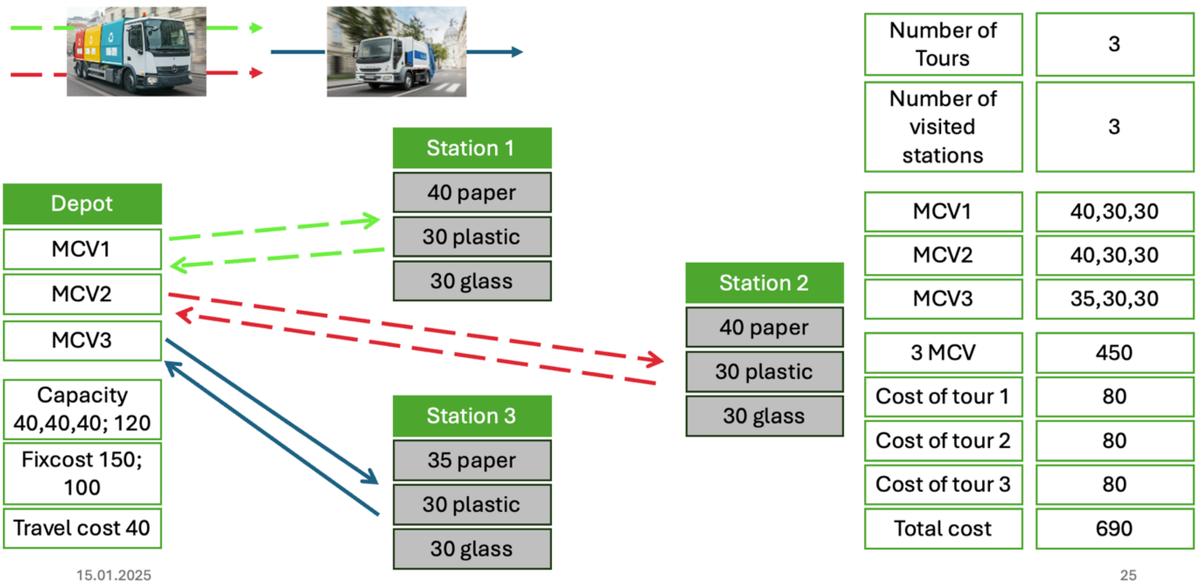


Figure 4.6 shows MCV1, MCV2, MCV3 each completing an isolated collection tour to a single

While this arrangement may appear efficient at first glance—achieving a lower total cost of 690 units—it introduces significant rigidity. Without the ability to coordinate or redistribute load across vehicles, the system becomes inflexible and less capable of adapting to variation in station-level waste generation.

This inefficiency becomes especially evident under high variance conditions. For example, if Waste Station 2 generates only 5 paper, 20 plastic, and 20 glass, the system still dispatches a full MCV to handle this station alone. In a system with waste sharing enabled, the 5 paper and 20 plastics could have been distributed across two MCVs, reducing the number of vehicles used and maximizing fleet utilization. However, in this rigid configuration, an additional MCV must be deployed—even though large amounts of capacity remain unused in the fleet.

Figure 4.7 illustrates this case: MCV2 visits Station 2 and collects only 5 paper, 20 plastic, and 20 glass—resulting in a total load of 45 units. With a maximum capacity of 120 units, the vehicle operates at just 37.5% utilization, representing a clear inefficiency caused by the lack of inter-vehicle coordination.

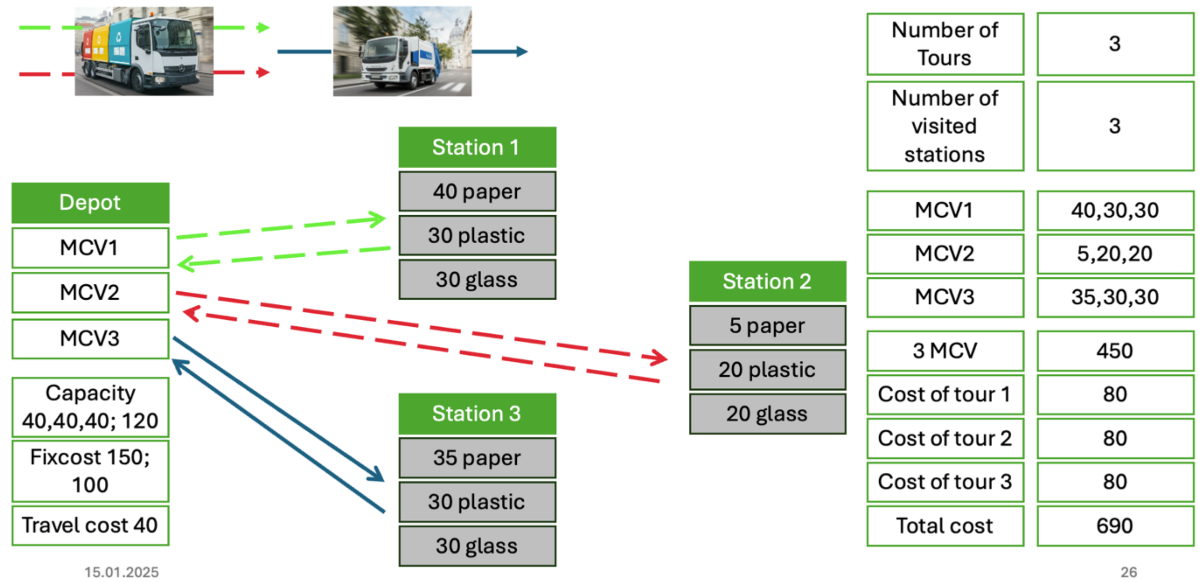


Figure 4.7 shows MCV1, MCV2, MCV3 each completing an isolated collection tour to a single

Table 4.3 summarizes the vehicle utilization in this scenario, including the specific case of underutilization observed at Station 2.

Tabelle 4.3 Waste collection summary

	Mixed fleet	Waste Station 1	Waste Station 2	Waste Station 3
Multi-Compartment Vehicle 1	40+30+30=100->83% utilization	X		
Multi-Compartment Vehicle 2	5+20+20=50->37.5% utilization		X	
Multie-Compartment Vehicle 3	35+30+30=95->79% utilization			X
Total cost	690			
Number of Tours	3			
Number of visited stations	3			

4.6 Simulation results and operational challenges

The simulation results across the three scenarios provide critical insight into the coordination, flexibility, and design of urban waste collection fleets under uncertainty. The interplay between fleet composition, waste sharing, and dynamic rerouting proves essential to achieving high utilization and system efficiency.

Table 4.4 summarizes vehicle utilization across all scenarios. While total system costs are relatively stable, the underlying operational strategies vary substantially. In Scenario 1, the absence of rerouting resulted in a severely underutilized SCV (29%), despite both MCVs being fully utilized. Scenario 2 introduced rerouting of an active SCV, improving SCV utilization to 79% with no increase in total cost. This combination of rerouting and waste sharing allowed the system to dynamically adjust to excess waste while maintaining high efficiency.

In contrast, Scenario 3, which disables waste sharing, enforced a rigid one-vehicle-per-station rule. Although the system completed all collections using only three MCVs, it did so inefficiently. Average MCV utilization dropped to just 66.5%, with one vehicle collecting only 5 paper, 20 plastic, and 20 glass—just 37.5% of its capacity. This example from Waste Station 2 illustrates how the absence of waste sharing can lead to severe underutilization, even when total cost remains low. The system becomes structurally inflexible, unable to reassign or balance loads across the fleet.

Tabelle 4.4 Summary of Vehicle Utilization Across Scenarios

Scenario	Waste Sharing	Rerouting	SVC Utilization	MCV Utilization
Scenario 1 (no rerouting)	Yes	No	29%	100% (2 vehicles)
Scenario 2 (with rerouting)	Yes	Yes	79%	100% (2 vehicles)
Scenario 3 (no waste sharing)	No	Yes	N/A	~66.5% avg (3 vehicles) MCV2: 37.5%

*Note: While rerouting logic was active in Scenario 3, the absence of waste sharing limited its application.

These results clearly show that both waste sharing and rerouting are required to achieve maximum vehicle utilization and operational robustness. Systems that lack sharing mechanisms may appear cost-effective in static conditions but perform poorly under variable demand, leading to underutilization, inefficiency, and structural rigidity.

4.7 Sensitivity Analysis: System robustness under high variance and the Case for Two-Compartment Vehicles

This section evaluates how the proposed fleet performs when the amount of waste at each collection station varies significantly. In real-world operations, waste generation is not constant—it fluctuates due to holidays, missed pickups, or household behavior. To reflect such unpredictability, a stress test was conducted using the same configuration as Scenario 2, but with higher variability in waste amounts.

Five simulation runs were carried out using different random seeds. Waste volumes were drawn from the following expanded uniform ranges:

- Paper: 25–55 pallets
- Plastic: 20–45 pallets
- Glass: 20–45 pallets

Among all stations, Waste Station 3 consistently produced the highest amount of excess waste. As a result, rerouted vehicles were always dispatched to Station 3 in both scenarios.

This analysis compares two configurations:

- Scenario A – Rerouted Single-Compartment Vehicle (SCV):
  The fleet includes two multi-compartment vehicles (MCVs) and a single-compartment vehicle that can collect only paper. The SCV is rerouted only if dispatching another MCV would result in low utilization.
  Assumption: The SCV is already half full when rerouted, meaning it has 12 pallets of free capacity for paper collection.
- Scenario B – Rerouted Two-Compartment Vehicle (2CV):
  The SCV is replaced with a two-compartment vehicle, each compartment capable of holding 12 pallets. It can collect paper plus one other waste type.
  Assumption: Each compartment is already half full (6 pallets), leaving 6 pallets of free capacity per compartment when rerouted.
  In both scenarios, waste sharing is enabled between MCVs. No additional tours are added.

4.7.1 Scenario A - Rerouted SCV

In this setup, the rerouted SCV collects only paper. The following tables show the excess waste before and after rerouting.

Tabelle 4.5 – Excess Waste Before SCV Pickup

Simulation Run	Station 1	Station 2	Station 3

Run 1	1 paper	–	6 paper, 4 plastic, 2 glass
Run 2	2 papers	–	6 papers, 1glass
Run 3	–	–	5 paper, 5 plastic, 1 glass
Run 4	–	–	5 papers, 7 glass
Run 5	–	1 paper	7 paper, 6 plastic, 2 glass

Tabelle 4.6 – Remaining Waste After SCV Pickup

Simulation Run	Station 1	Station 2	Station 3
Run 1	1 paper	–	4 plastics, 2 glass
Run 2	2 papers	–	1glass
Run 3	–	–	5 plastics, 1 glass
Run 4	–	–	7 glasses
Run 5	–	1 paper	6 plastics, 2 glass

Tabelle 4.7 – Vehicle Utilization in Scenario A (SCV)

Run	Picked Up	Already Loaded	Total Load	Utilization
1	6 papers	12 pallets	18 pallets	75%
2	6 papers	12 pallets	18 pallets	75%
3	5 papers	12 pallets	17 pallets	70.83%
4	5 papers	12 pallets	17 pallets	70.83%
5	7 papers	12 pallets	19 pallets	79.17%

- Total cost: 720 units
- Number of tours: 3
- Stations visited: 5

Although the SCV had sufficient remaining capacity (12 pallets), its paper-only limitation left all excess plastic and glass uncollected.

4.7.2 Scenario B – Rerouted Two-Compartment Vehicle (2CV)

In this scenario, the SCV is replaced with a two-compartment vehicle that can collect paper plus one additional waste type. Each compartment has a total capacity of 12 pallets, but is assumed to be 50% full at the time of rerouting, meaning only 6 pallets of free space per compartment.

Tabelle 4.8 – Remaining Waste After 2CV Pickup

Simulation Run	Station 1	Station 2	Station 3
Run 1	1 paper	–	2 glasses
Run 2	2 papers	–	–
Run 3	–	–	1 glass
Run 4	–	–	1 glass
Run 5	–	1 paper	1 paper, 2 glass

Tabelle 4.9 – Vehicle Utilization in Scenario B (2CV)

Run	Picked Up (Paper+Other)	Already Loaded (6 + 6)	Total Load	Utilization
1	6+4	12 pallets	24 pallets	100%
2	6+1	12 pallets	19 pallets	79.17%
3	5+5	12 pallets	22 pallets	91.76%
4	5+6	12 pallets	23 pallets	95.83%
5	6+6	12 pallets	24 pallets	100%

Total cost: 720 units

Number of tours: 3

Stations visited: 5

This sensitivity analysis shows that replacing a single-compartment SCV with a two-compartment vehicle dramatically improves system performance—even when both vehicles are assumed to be half full at the time of rerouting.

The 2CV, with just 6 pallets of available space in each compartment, was still able to collect nearly all excess paper and plastic or glass in each simulation run. Utilization remained consistently high (79.17%–100%), and the amount of uncollected waste dropped sharply compared to the SCV case.

This confirms a key operational insight: vehicle-level flexibility is just as important as routing logic in a waste collection system. By giving one vehicle the ability to carry two types of waste, the system gains efficiency, reduces excess waste, and avoids the need for additional vehicles or tours—even under unpredictable, high-variance conditions.

4.8 Chapter Summary

This chapter introduced a discrete-event simulation model built in AnyLogic to evaluate the operational performance and adaptability of a mixed waste collection fleet under uncertain waste generation. Building on the deterministic results of the mathematical model, the simulation introduced stochastic demand through uniform probability distributions and allowed for dynamic vehicle behavior within a realistic, scenario-based environment.

Three simulation scenarios were explored:

- Scenario 1 showed that, although waste sharing enabled full utilization of the multi-compartment vehicles (MCVs), the single-compartment vehicle (SCV) remained underutilized at just 29% capacity due to its paper-only constraint and the lack of rerouting.
- Scenario 2 introduced rerouting for the SCV, increasing its utilization to 79% without additional costs or tours—demonstrating the benefit of flexible vehicle reassignment.
- Scenario 3 disabled waste sharing, requiring one MCV per station. Although some vehicles operated near full capacity, others were underutilized (as low as 37.5%) due to rigid assignment. This revealed that lack of coordination creates fragility, even when total system cost appears low.

A high-variance sensitivity analysis further evaluated the system under volatile demand. Two configurations were compared: one using a rerouted SCV and another using a rerouted two-compartment vehicle (2CV). Both vehicles were assumed to be half full when rerouted, limiting remaining capacity to 12 pallets (SCV) and 6 pallets per compartment (2CV).

Despite this constraint, the 2CV consistently reduced leftover waste—especially for plastic and glass—and achieved utilization rates above 79% across all runs. In contrast, the SCV was unable to collect non-paper waste, leading to persistent excess volumes at Waste Station 3.

These findings support a practical operational insight for real-world collection systems that must keep waste types separated:

It is most effective to first deploy vehicles with the same number of compartments as the number of separated waste types (e.g., three-compartment vehicles for paper, plastic, and glass). However, due to natural variability in waste generation, one type—such as glass—often appears in much smaller quantities. Once that type is mostly collected, it becomes more efficient to deploy vehicles with one fewer compartment, such as two-compartment vehicles, to focus on the remaining dominant waste types.
This progressive matching strategy ensures that each compartment is used efficiently, while preserving separation requirements and avoiding underutilized large vehicles.

Based on this insight, one targeted design improvement is recommended:

Introduce two-compartment vehicles (2CVs) to efficiently capture remaining excess waste without overcommitting three-compartment capacity.

In the context of this relatively small problem—three waste types and three waste collection stations—the most effective strategy is to first fully utilize the three-compartment vehicles, followed by the use of two-compartment vehicles to collect remaining waste.
However, in larger-scale systems with up to a hundred waste collection stations, this tiered strategy will likely require not only two-compartment vehicles, but also single-compartment vehicles to optimally manage residual waste volumes. The appropriate number and mix of two- and single-compartment vehicles will depend on system-specific factors and should be determined through further simulation-based or analytical research.

Chapter 5: Conclusion

Conclusion

5.1 Introduction

This chapter summarizes the key findings of the study, addresses the research question, discusses the main limitations encountered during the study, and proposes directions for future research. The chapter integrates insights from both the mathematical model and the discrete-event simulation and outlines practical implications for urban waste collection system optimization.

5.2 Answer to the Research Question

The main research question of this thesis was:
"How can a mixed fleet of single-compartment and multi-compartment vehicles improve the efficiency and robustness of urban waste collection operations under demand uncertainty?"

Based on the results obtained through both deterministic modeling and stochastic simulation:

- The mixed fleet approach significantly reduced total operational costs and travel distances compared to using only single-compartment vehicles.
- Multi-compartment vehicles achieved full compartment utilization in various demand scenarios, validating their operational robustness.
- Dynamic rerouting strategies further improved system adaptability, leading to higher vehicle utilization even under fluctuating waste generation.

Thus, the study confirms that the integration of heterogeneous vehicle fleets, waste-sharing, and dynamic routing leads to measurable gains in efficiency, adaptability, and sustainability in urban waste collection systems.

5.3 Summary and Conclusion

This thesis investigated how urban waste collection systems can be optimized through the integration of three critical features: heterogeneous vehicle fleets, waste sharing between vehicles, and dynamic vehicle rerouting. The findings were supported by a two-phase modeling approach that combined a deterministic mathematical model with a stochastic simulation model.

5.3.1 Insights from the Mathematical Model

The mathematical model evaluated three different fleet configurations: only single-compartment vehicles, only multi-compartment vehicles, and a mixed fleet combining both.

The results showed that the mixed fleet—incorporating both SCVs and MCVs—delivered the most cost-efficient and operationally effective outcome. As summarized in Figure 5.1, key improvements included:

- Total cost reduction from 900 to 720
- Reduction in visited waste collection stations from 12 to 5
- Full utilization of both multi-compartment vehicles

These results demonstrated that allowing vehicles to share waste collection responsibilities and combining fleet types significantly improves efficiency.

MILP	Single
Vehicle 1	120
Vehicle 2	80
Vehicle 3	80
Total cost	900
Number of Tour	3
Number of visited stations	12

Heterogenous vehicles

Waste Sharing

MILP	Mixed fleet
MCV 1	120-> fully utilized
MCV 2	120->fully utilized
SCV 3	40
Total cost	720
Number of Tour	3
Number of visited stations	5

Figure 5.1 MILP Comparison – Single vs. Mixed Fleet

5.3.2 Insights from the Simulation Model

To validate the mathematical model under uncertainty, a discrete-event simulation model was developed in AnyLogic. The simulation tested the performance of the optimized mixed fleet under randomly varying waste amounts. As shown in Figure 5.2, multi-compartment vehicles continued to be fully utilized even under stochastic conditions, reinforcing their operational robustness. However, the single-compartment vehicle—used to collect excess waste—was underutilized in the first scenario, revealing an operational challenge related to inflexible vehicle dispatching.

MILP	Mixed fleet
MCV 1	120-> fully utilized
MCV 2	120->fully utilized
SCV 3	40
Total cost	720
Number of Tour	3
Number of visited stations	5

Uncertain Demand

Simulation	Mixed fleet
Multi Compartment Vehicle 1	24*5=120 -> 100% fully utilized
Multi Compartment Vehicle 2	24*5=120 -> 100% fully utilized
Single Compartment Vehicle	7*5=35 -> 29% underutilized
Total cost	600
Number of Tour	3
Number of visited stations	5

Figure 5.2 Transition from Deterministic Optimization to Simulation under Uncertain Demand

In Scenario 2, this challenge was addressed by implementing a rerouting strategy, whereby a nearby, partially filled SCV was redirected to collect the remaining waste. This rerouted SCV was utilized at 87.5% capacity, compared to 29% in Scenario 1, as shown in Figure 5.3.

MILP	Mixed fleet
MCV 1	120-> fully utilized
MCV 2	120->fully utilized
SCV 3	40
Total cost	720
Number of Tour	3
Number of visited stations	5

Uncertain Demand

Rerouting

With waste sharing

Simulation	Mixed fleet
Multi Compartment Vehicle 1	24*5=120 -> 100% fully utilized
Multi Compartment Vehicle 2	24*5=120 -> 100% fully utilized
Rerouted Single Compartment Vehicle	21*5=105 -> 87.5% Efficiently utilized
Total cost	600
Number of Tour	3
Number of visited stations	5

Figure 5.3 Improved SCV Utilization through Rerouting under Uncertain Demand with Waste Sharing

In addition to the base scenarios, a sensitivity analysis was conducted to test the system's performance under high-variance waste generation. Waste volumes were drawn from expanded uniform distributions to simulate real-world fluctuations. The analysis compared a rerouted SCV with a rerouted 2CV, both assumed to be half full when deployed. The results showed that while the SCV was limited to paper collection and left significant excess plastic and glass behind, the 2CV consistently achieved higher utilization and cleared more waste, as shown in

Figure 5.4. This confirmed that two-compartment vehicles offer a robust and efficient solution in scenarios where waste types appear in uneven or unpredictable quantities.

Station 3	Utilization SCV
4 plastic 2 glass	75%
1 glass	75%
5 plastic, 1 glass	70.83%
7 glass	70.83%
6 plastic, 2 glass	79.17%

Two-compartment vehicle

Station 3	Utilization 2CV
2 glass	100%
	79.17%
1 glass	91.76%
1 glass	95.83%
1 paper, 2 glass	100%

Figure 5.4 Enhanced Utilization and Drastically Reduced Excess Waste Using Rerouted Two-Compartment Vehicles at Station 3

This thesis shows that static optimization alone is not sufficient to solve real-world waste collection problems under uncertainty. While the mathematical model identified the most cost-efficient fleet composition — balancing single- and multi-compartment vehicles with inter-vehicle waste sharing — the simulation revealed how these solutions perform under dynamic conditions.

By gradually increasing environmental uncertainty in the simulation (through expansion of the uniform distribution), static plans began to fail. Rerouting single-compartment vehicles led to poor utilization and uncollected waste, while adaptively rerouting two-compartment vehicles significantly improved performance.

This reveals a critical insight: true operational optimality is not static, but dynamic. The most effective solution is the one that adapts to changing real-time conditions — a core requirement for resilient, smart city logistics systems.

Moreover, the simulation demonstrated that the combined use of heterogeneous vehicle types, inter-vehicle waste sharing, and dynamic rerouting enables high vehicle utilization even under extreme uncertainty. The integration of these three features proves that my model can consistently deliver robust, efficient, and near-optimal system performance — even when real-world conditions deviate significantly from static assumptions.

5.3.3 Broader Impact and Practical Relevance

The combined use of heterogeneous vehicles, shared demand allocation, and rerouting strategies not only led to improvements in cost and distance metrics but also resulted in significantly higher vehicle utilization. This has direct implications for real-world logistics and environmental sustainability.

Specifically, this study addresses the issue of inefficient vehicle use in Austria, where 45% of all truck trips are currently empty (as shown in Figure 5.1). By adopting the strategies outlined in this research, the number of empty trips could potentially be reduced to 30%, thereby contributing to:

- Reduced CO_2 emissions from road freight
- Lower operational costs for municipalities and logistics providers
- More resilient and adaptive waste collection systems

In particular, the simulation results showed that two-compartment vehicles can significantly reduce uncollected waste under volatile conditions, where waste types occur in uneven volumes. This supports a tiered vehicle deployment strategy, where fully compartmentalized vehicles are used first, followed by more specialized vehicles (e.g., 2CVs or SCVs) as demand patterns shift. Such a system is not only efficient but also more adaptable to the real-time complexity of urban waste logistics.

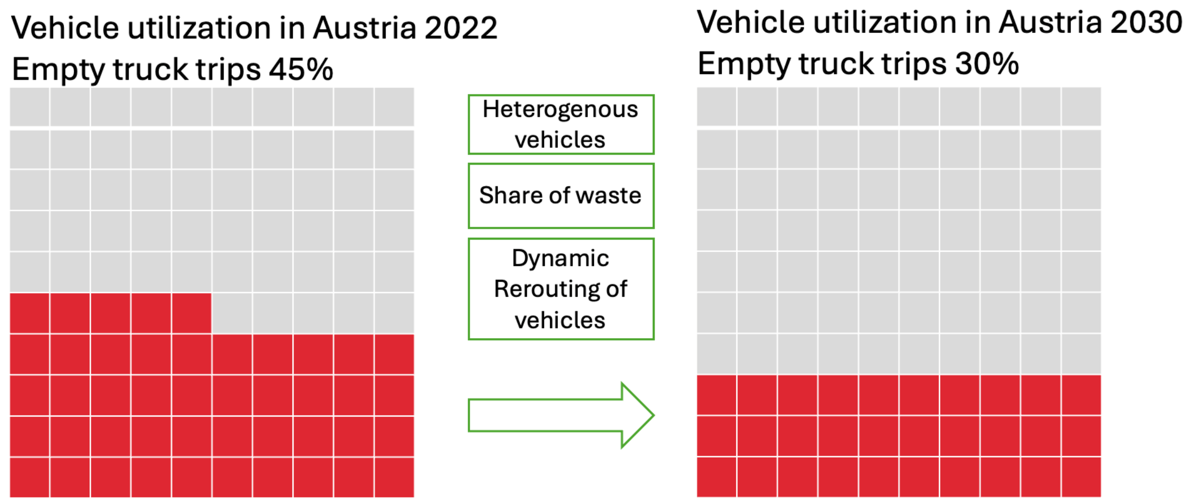


Figure 5.1 Reducing Empty Truck Trips through Mixed Fleets, Waste Sharing, and Rerouting

In summary, this thesis demonstrates that the integration of heterogeneous fleets, waste-sharing mechanisms, and dynamic rerouting into urban waste collection systems leads to measurable gains in cost efficiency, route consolidation, and vehicle utilization. These strategies hold high potential for real-world application, particularly in dense urban areas aiming to reduce environmental impact and improve logistical sustainability.

5.4 Research Limitations

Although this study generated valuable insights, several limitations must be acknowledged:

- Simplified Network Size:

  The simulation model represented only three waste stations to enhance visualization and reduce computational complexity. Real-world urban networks are significantly larger and more complex, involving many nodes, routes, and service zones.
- Deterministic Travel Distances:

  Both the mathematical model and the simulation assumed constant travel distances between stations, without accounting for real-world variability such as traffic congestion, accidents, or dynamic road conditions.
- Fixed Waste Types:

  The study considered only three types of waste: paper, plastic, and glass. In practice, urban waste streams can be more diverse, requiring differentiated collection strategies.
- Stochastic Demand Modeling:

  Waste generation was modeled using a uniform probability distribution. However, actual waste generation likely follows more complex patterns, such as normal, Poisson, or time-dependent distributions.
- Fleet Configuration Assumptions:

  The study focused on single-compartment vehicles (SCVs) and specialized three-compartment multi-compartment vehicles (MCVs). In reality, the majority of urban waste collection fleets operate with single-compartment vehicles, with multi-compartment vehicles being relatively rare and typically custom-designed for specific collection schemes. The exclusion of two-compartment and four-compartment vehicle options limited the exploration of intermediate operational strategies that could offer greater flexibility in managing mixed waste streams.
- Vehicle Reliability and Breakdowns:

  Vehicle breakdowns and maintenance events were not modeled. In real-world operations, mechanical failures can disrupt collection plans and require dynamic reallocation of tasks.
- No Time Windows for Waste Collection:

  The model did not incorporate service time windows, although in practice, waste collection is often subject to time constraints (e.g., early morning pickup hours, restrictions during peak traffic periods).
- No Explicit Environmental Impact Modeling:

Although cost and distance were minimized, no explicit environmental indicators such as CO_2 emissions, fuel consumption, or sustainability scores were included in the model evaluation.

5.5 Future Research

Building on the findings of this thesis, future research can expand the scope and intelligence of urban waste collection systems by integrating emerging technologies and adaptive modeling techniques. A conceptual illustration of such a system is presented in Figure 6.1.

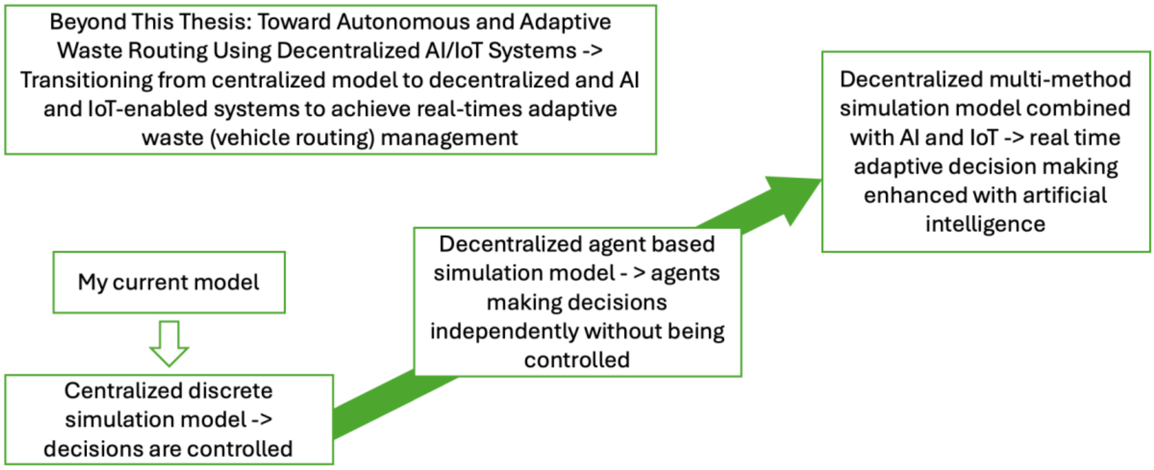


Figure 6.1 Research Roadmap Toward Decentralized and AI-Enabled Waste Collection Systems

This figure presents a forward-looking research trajectory beginning with the current centralized simulation model developed in this thesis. The present model uses a discrete-event simulation approach where vehicle behaviors are centrally controlled.

The next step envisions a decentralized, agent-based simulation environment where vehicles act as autonomous agents capable of making local decisions based on system observations. This lays the foundation for an intelligent, adaptive waste collection system.

The final research stage integrates artificial intelligence (AI) and Internet of Things (IoT) technologies into a decentralized, multi-method simulation framework. Such a system would support real-time, data-driven decision-making across urban waste collection networks, advancing toward autonomous and sustainable operations.

5.5.1 Agent-Based Modeling and Intelligent Behavior

A natural extension of the current discrete-event simulation would be the development of an agent-based simulation model, where vehicles, compartments, and waste stations are treated as autonomous decision-making agents. Unlike fixed-logic models, this approach would allow each entity to optimize its behavior dynamically based on local observations and system-wide objectives.

By incorporating multi-agent reinforcement learning (MARL), vehicles could adjust their routes in real time in response to fluctuating waste levels, traffic, or system constraints—enhancing efficiency, reducing emissions, and minimizing redundant trips.

5.5.2 Integration of IoT and Real-Time Data

Future models could integrate Internet of Things (IoT) technologies and AI-driven optimization to connect the simulation directly with real-time data from smart waste bins and vehicle compartments. Instead of following static, pre-scheduled routes, vehicles would react to live data streams, dynamically re-routing based on:

- Actual waste levels at each station
- Remaining vehicle capacity
- Real-time traffic or weather conditions

Such systems would better reflect the operational conditions faced in smart cities and support adaptive, decentralized control mechanisms.

5.5.3 Customizable Decision-Support Simulation Tool

Another potential direction is the development of a modular, user-configurable simulation environment that serves as a decision-support tool for municipalities, researchers, and logistics firms. This tool could allow users to:

- Adjust fleet composition (MCVs, SCVs, 2-compartment vehicles)
- Define uncertain demand distributions (e.g., normal, uniform, Poisson)
- Modify the number and location of waste stations
- Set routing rules and constraints dynamically

By simulating various what-if scenarios, stakeholders could test system robustness, evaluate investment strategies, and optimize collection policies prior to real-world implementation.

5.5.4 Fleet Design Optimization for Large-Scale Systems

While this thesis focused on a small-scale system with three waste types and a limited number of collection stations, real-world waste logistics systems often include dozens or even hundreds of waste stations and may involve four waste types.

In such cases, the optimal number and mix of fleet vehicles—including single-, two-, three-, and even four-compartment configurations—cannot be assumed a priori. Future research should focus on determining the right number of each vehicle type, based on spatial waste generation patterns, variability, and system constraints.

Importantly, it may not be necessary to deploy all possible vehicle configurations in large numbers. For instance, in a system with four waste types, efficient use of four-compartment vehicles might cover most demand early in the day. As the collection progresses, one or two waste types may become dominant, eliminating the need for continued deployment of three-compartment vehicles—or reducing it to a minimal number.

This suggests the need for a dynamic, data-driven fleet design approach, where the number and type of vehicles are optimized based on how waste compositions evolve over time and space. Simulation-based optimization, heuristic fleet-sizing models, or even real-time decision-support systems could support such scaling efforts in future work.

5.5.5 Outlook for PhD Research

In future academic work—potentially within a PhD project—I plan to further explore the integration of adaptive routing strategies, AI-based learning algorithms, and real-time urban data streams into waste logistics systems. The long-term goal is to design and validate a fully optimized, decentralized waste collection framework that leverages intelligence, sustainability, and operational efficiency for smart cities.

Appendix A: Mathematical Optimization Model (Xpress Mosel)

This appendix presents the complete mathematical model implemented in Xpress Mosel to solve the urban waste collection routing problem using a mixed fleet of single- and multi-compartment vehicles. The model aims to minimize total operational costs while satisfying capacity, waste assignment, and routing constraints.

```
-------------------------------------------------------------------
model WasteCollectionVRP
uses "mmxprs"; ! gain access to the Xpress-Optimizer solver

! === Declarations ===
declarations
   ! Sets
   WASTE_COLLECTION_STATIONS = 0..4
   VEHICLES = 1..10
   MCV_VEHICLES = 1..5
   SCV_VEHICLE = 5..10
   WASTE_TYPES = 1..3
   COMPARTMENTS = 1..3

   ! Decision Variables
   travel: array(VEHICLES, WASTE_COLLECTION_STATIONS,
WASTE_COLLECTION_STATIONS) of mpvar
   assign: array(WASTE_TYPES, VEHICLES, COMPARTMENTS) of mpvar
   share: array(WASTE_COLLECTION_STATIONS, WASTE_TYPES, VEHICLES) of
mpvar
   position: array(WASTE_COLLECTION_STATIONS, VEHICLES) of mpvar
   compartment: array(WASTE_TYPES, VEHICLES, COMPARTMENTS) of mpvar
   vehicle_used: array(VEHICLES) of mpvar
   collected: array(WASTE_TYPES, SCV_VEHICLE) of mpvar


   ! Parameters
   TRAVELCOSTS: array(WASTE_COLLECTION_STATIONS,
WASTE_COLLECTION_STATIONS) of real
```

```
   WASTEAMOUNT: array(WASTE_TYPES, WASTE_COLLECTION_STATIONS) of real
   VEHICLECAPACITY: array(VEHICLES) of real
   COMPARTMENTSIZE: array(COMPARTMENTS) of real
   WASTENAMES: array(WASTE_TYPES) of string

   ! Fixed Parameters
   SCV_CAPACITY = 120
   MCV_CAPACITY = 120
   FIXED_COST_SCV = 100
   FIXED_COST_MCV = 150
end-declarations

M := 100
DEPOT := getfirst(WASTE_COLLECTION_STATIONS)

TRAVELCOSTS:: [ M,  40, 40, 40, 40,
            40, M,  40, 40, 40,
            40, 40, M,  40, 40,
            40, 40, 40, M,  40,
            40, 40, 40, 40, M ]

WASTEAMOUNT::[  0, 50, 30, 20, 20,
            0, 20, 20, 20, 20,
            0, 20, 20, 20, 20 ]

VEHICLECAPACITY::[MCV_CAPACITY, MCV_CAPACITY, MCV_CAPACITY,
SCV_CAPACITY, SCV_CAPACITY, SCV_CAPACITY]
COMPARTMENTSIZE::[40, 40, 40]
WASTENAMES::["PAPER", "PLASTIC", "GLASS"]

! === Constraints ===
! Compartment capacity for MCVs
forall(p in WASTE_TYPES, k in MCV_VEHICLES, m in COMPARTMENTS)
   sum(i in WASTE_COLLECTION_STATIONS - {DEPOT}) WASTEAMOUNT(p, i) *
share(i, p, k) <= COMPARTMENTSIZE(m)

! Flow conservation
```

```
forall(k in VEHICLES, i in WASTE_COLLECTION_STATIONS - {DEPOT})
  sum(j in WASTE_COLLECTION_STATIONS) travel(k, i, j) = sum(j in WASTE_COLLECTION_STATIONS) travel(k, j, i)

! Single visit per station
forall(i in WASTE_COLLECTION_STATIONS - {DEPOT}, k in VEHICLES)
  sum(j in WASTE_COLLECTION_STATIONS) travel(k, i, j) <= 1

! Eliminate subtours
forall(k in VEHICLES, i in WASTE_COLLECTION_STATIONS, j in WASTE_COLLECTION_STATIONS - {DEPOT})
  position(i, k) + 1 <= position(j, k) + getsize(WASTE_COLLECTION_STATIONS) * (1 - travel(k, i, j))

! Demand satisfaction
forall(i in WASTE_COLLECTION_STATIONS - {DEPOT}, p in WASTE_TYPES)
  sum(k in VEHICLES) share(i, p, k) = 1

! Waste share only if vehicle visits station
forall(j in WASTE_COLLECTION_STATIONS - {DEPOT}, k in VEHICLES, p in WASTE_TYPES)
  share(j, p, k) <= sum(i in WASTE_COLLECTION_STATIONS) travel(k, i, j)

! Vehicle capacity constraint
forall(p in WASTE_TYPES, k in VEHICLES)
  sum(i in WASTE_COLLECTION_STATIONS - {DEPOT}) WASTEAMOUNT(p, i) * share(i, p, k) <= VEHICLECAPACITY(k)

! MCV waste-type assignment
forall(k in MCV_VEHICLES, m in COMPARTMENTS)
  sum(p in WASTE_TYPES) assign(p, k, m)  = 1

! Compartment share restriction
forall(p in WASTE_TYPES, k in MCV_VEHICLES)
  sum(i in WASTE_COLLECTION_STATIONS - {DEPOT}) share(i, p, k) <= getsize(WASTE_COLLECTION_STATIONS - {DEPOT}) * sum(m in COMPARTMENTS) assign(p, k, m)
```

```
! SCV waste-type limitation
forall(k in SCV_VEHICLE)
   sum(p in WASTE_TYPES) collected(p, k) <= 1

forall(p in WASTE_TYPES, k in SCV_VEHICLE)
   sum(i in WASTE_COLLECTION_STATIONS - {DEPOT}) share(i, p, k) <= collected(p, k)

! Domain declarations
forall(k in VEHICLES, i in WASTE_COLLECTION_STATIONS, j in
WASTE_COLLECTION_STATIONS)
   travel(k, i, j) is_binary

forall(p in WASTE_TYPES, k in MCV_VEHICLES, m in COMPARTMENTS)
   assign(p, k, m) is_binary

forall(p in WASTE_TYPES, k in MCV_VEHICLES, m in COMPARTMENTS)
   compartment(p, k, m) is_binary

forall(k in VEHICLES)
   vehicle_used(k) is_binary

forall(k in VEHICLES)
   sum(i in WASTE_COLLECTION_STATIONS, j in WASTE_COLLECTION_STATIONS)
travel(k, i, j) <= getsize(WASTE_COLLECTION_STATIONS) * vehicle_used(k)


! === Objective Function ===
Z := sum(k in VEHICLES, i, j in WASTE_COLLECTION_STATIONS) TRAVELCOSTS(i,
j) * travel(k, i, j) +
    sum(k in MCV_VEHICLES) FIXED_COST_MCV * vehicle_used(k) +
    sum(k in SCV_VEHICLE) FIXED_COST_SCV * vehicle_used(k)

minimize(Z)

! === Output Section ===
writeln("Total Travel Cost: ", getobjval)
writeln("Optimal tour: ")
```

```
forall(k in VEHICLES, i in WASTE_COLLECTION_STATIONS, j in WASTE_COLLECTION_STATIONS | getsol(travel(k,i,j)) > 0) do
  if k in MCV_VEHICLES then
    writeln("Travel of MCV: ", k, " from station " + i + " to " + j)
  else
    writeln("Travel of SCV: ", k, " from station " + i + " to " + j)
  end-if
end-do

! Print compartment assignments
forall(k in VEHICLES | sum(i in WASTE_COLLECTION_STATIONS, j in WASTE_COLLECTION_STATIONS) getsol(travel(k, i, j)) > 0) do
  if k in MCV_VEHICLES then
    forall(p in WASTE_TYPES, m in COMPARTMENTS | getsol(assign(p,k,m)) > 0) do
      writeln("Waste type:", WASTENAMES(p), " is assigned: ", getsol(assign(p,k,m)), " to Compartment:", m, " of MCV:", k)
    end-do
  else
    forall(p in WASTE_TYPES | sum(i in WASTE_COLLECTION_STATIONS - {DEPOT}) getsol(share(i,p,k)) > 0) do
      writeln("Waste type:", WASTENAMES(p), " is collected by SCV:", k)
    end-do
  end-if
end-do

! Final checks
forall(k in VEHICLES) do
  collected_weight := sum(i in WASTE_COLLECTION_STATIONS - {DEPOT}, p in WASTE_TYPES) WASTEAMOUNT(p, i) * getsol(share(i, p, k))
  writeln("Vehicle ", k, " collected total weight: ", collected_weight)
  if collected_weight > VEHICLECAPACITY(k) then
    writeln("Warning: Vehicle ", k, " exceeds its capacity!")
  end-if
end-do
```

```
forall(i in WASTE_COLLECTION_STATIONS - {DEPOT}, p in WASTE_TYPES) do
   total_collected := sum(k in VEHICLES) getsol(share(i, p, k))
   if total_collected < 1 then
      writeln("Warning: Not all waste of type ", WASTENAMES(p), " collected at Station ", i)
   end-if
end-do

end-model
```

Appendix B: Simulation Model Logic (AnyLogic)

This appendix contains selected source code and event logic used in the AnyLogic simulation environment for modeling dynamic waste collection. The snippets are grouped by component (buttons, events, logic blocks) and presented with explanatory headers for clarity.

B.1 Event Blocks – Waste Station Monitoring

```
// Waste Station 1
currentPaperCount = waitForTruck.size();
currentPlasticCount = waitForTruck2.size();
currentGlassCount = waitForTruck3.size();

// Waste Station 2
currentPaperCount1 = waitForTruck1.size();
currentPlasticCount1 = waitForTruck4.size();
currentGlassCount1 = waitForTruck5.size();

// Waste Station 3
currentPaperCount2 = waitForTruck6.size();
currentPlasticCount2 = waitForTruck7.size();
currentGlassCount2 = waitForTruck8.size();
```

B.2 Button Logic – Generate Waste

```
// Waste Station 1
int numBoxes = (int) uniform(paperMin, paperMax);
generateBoxes.inject(numBoxes);
int numPlastic = (int) uniform(plasticMin, plasticMax);
generatePlastic.inject(numPlastic);
int numGlass = (int) uniform(glassMin, glassMax);
generateGlass.inject(numGlass);

// Waste Station 2
int numBoxes1 = (int) uniform(paperMin, paperMax);
generateBoxes1.inject(numBoxes1);
int numPlastic1 = (int) uniform(plasticMin, plasticMax);
generatePlastic1.inject(numPlastic1);
int numGlass1 = (int) uniform(glassMin, glassMax);
```

```
generateGlass1.inject(numGlass1);

// Waste Station 3
int numBoxes2 = (int) uniform(paperMin, paperMax);
generateBoxes2.inject(numBoxes2);
int numPlastic2 = (int) uniform(plasticMin, plasticMax);
generatePlastic2.inject(numPlastic2);
int numGlass2 = (int) uniform(glassMin, glassMax);
generateGlass2.inject(numGlass2);
```

B.3 Button Logic – Inject Multi-Compartment Vehicle (MCV)

```
truckMultiCompartment.inject(1);
```

B.4 Button Logic – Update Picked-Up Waste

```
Compartment1 = Math.max(0, Compartment1 - pickedUpPaper);
Compartment2 = Math.max(0, Compartment2 - pickedUpPlastic);
Compartment3 = Math.max(0, Compartment3 - pickedUpGlass);
if (whichVehicle == 1){
   collectedWeight += (pickedUpPaper + pickedUpPlastic + pickedUpGlass);
} else if (whichVehicle == 2){
   collectedWeight2 += (pickedUpPaper + pickedUpPlastic + pickedUpGlass);
}
```

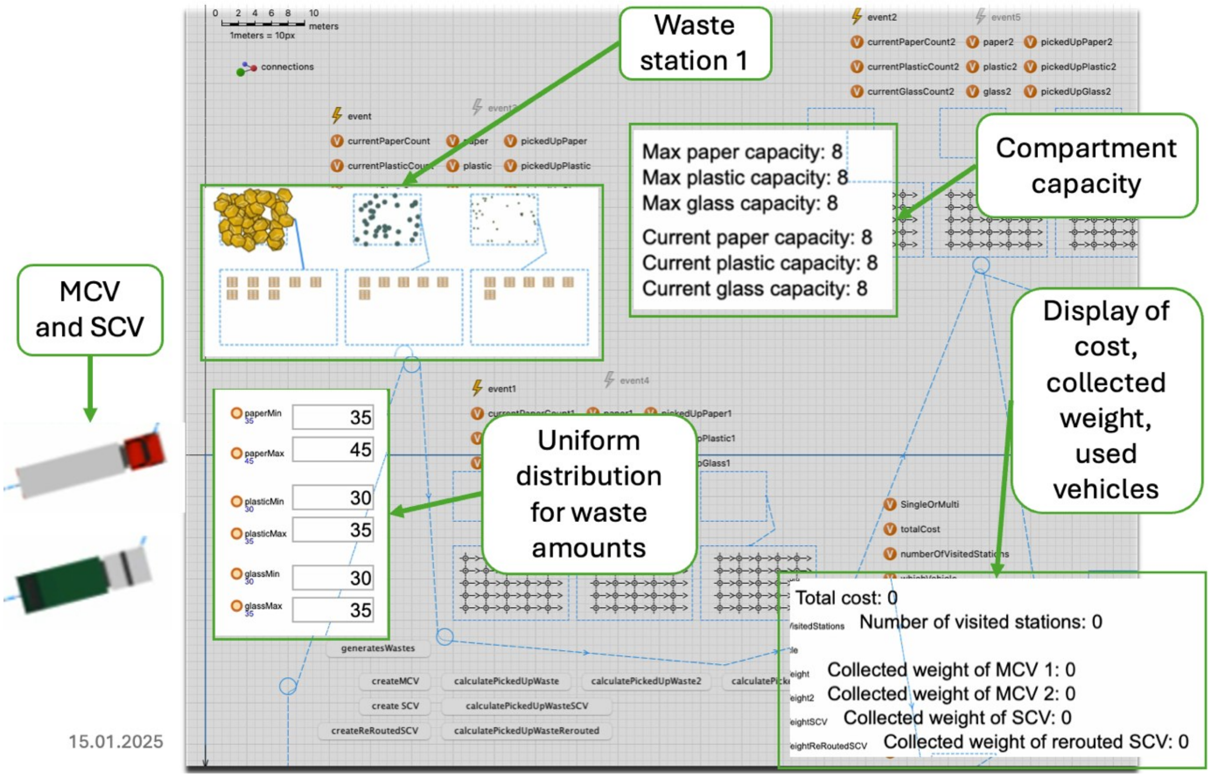
B.5 Logic Block – Output Selection Rule

```
(SingleOrMulti == "Multi" &&
 currentPaperCount > 0 && currentPlasticCount > 0 && currentGlassCount > 0 &&
 Compartment1 > maxCompartment1Capacity * 0.05 &&
 Compartment2 > maxCompartment2Capacity * 0.05 &&
 Compartment3 > maxCompartment3Capacity * 0.05)
||
(SingleOrMulti == "Single" && currentPaperCount > 0)
```

B.6 Logic Block – Pickup Quantity Determination

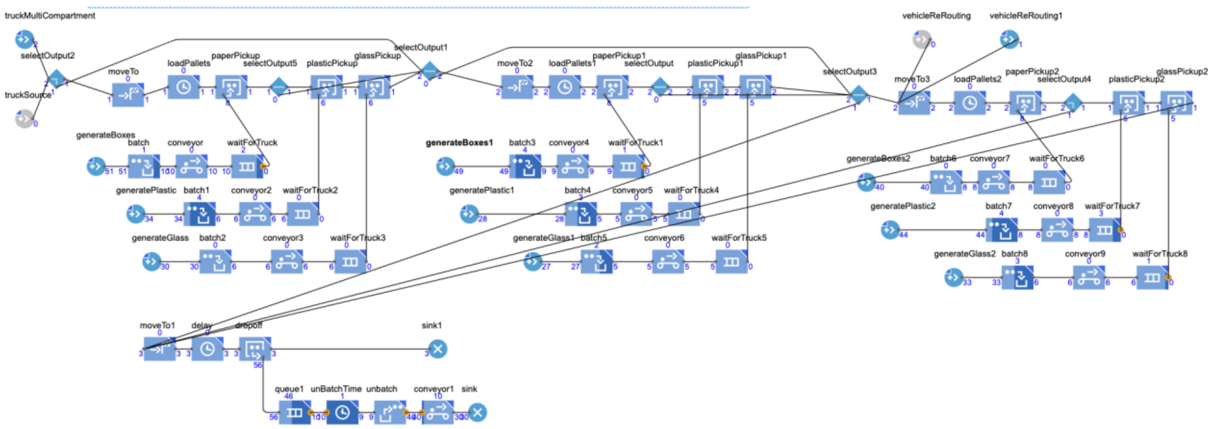
```
Math.min(Compartment1, currentPaperCount);
pickedUpPaper = Math.min(Compartment1, currentPaperCount);
```

B.7 – Simulation Interface Overview



B.8 – Logic Block Structure for Waste Pickup

Figure B.8a – Full Simulation Logic Overview



Note: Due to scale, Figure B.8a may be difficult to read. Figures B.8b–B.8e provide close-up views of each component for clarity.

Figure B.8b – Source Blocks and Waste Collection Station 1 Logic

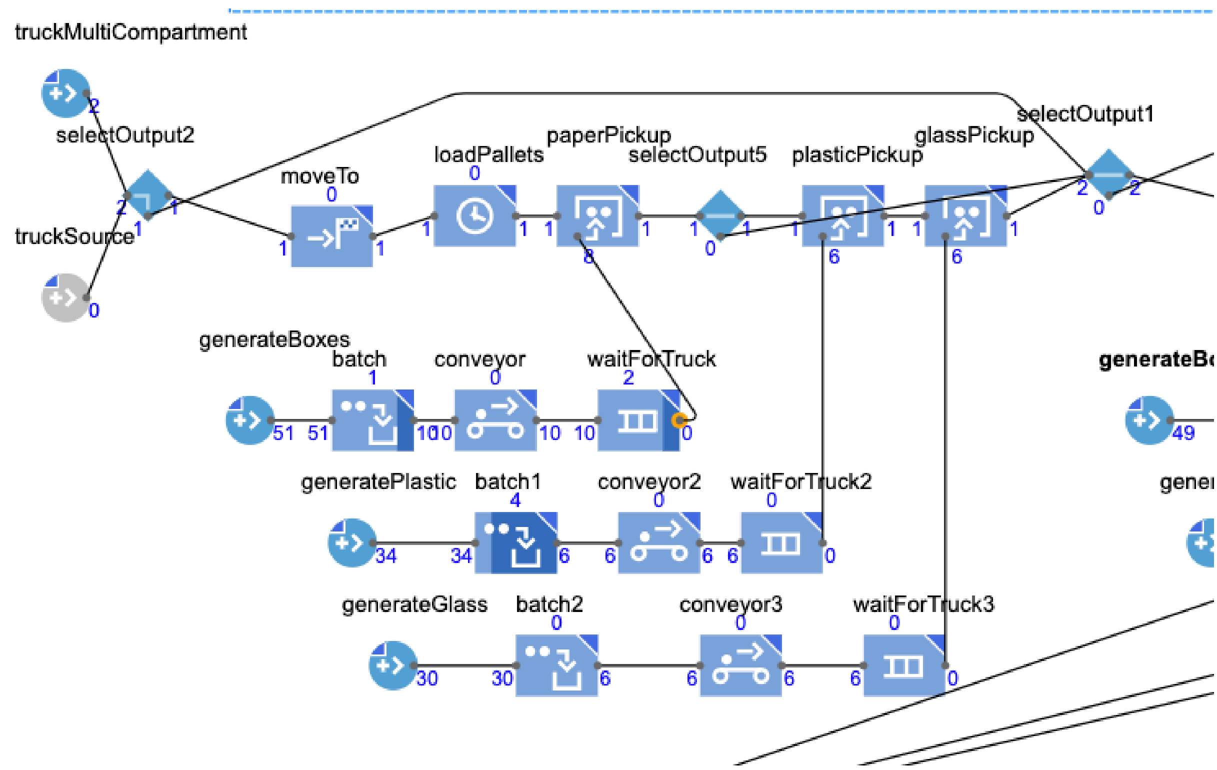


Figure B.8c – Waste Collection Station 2 Logic

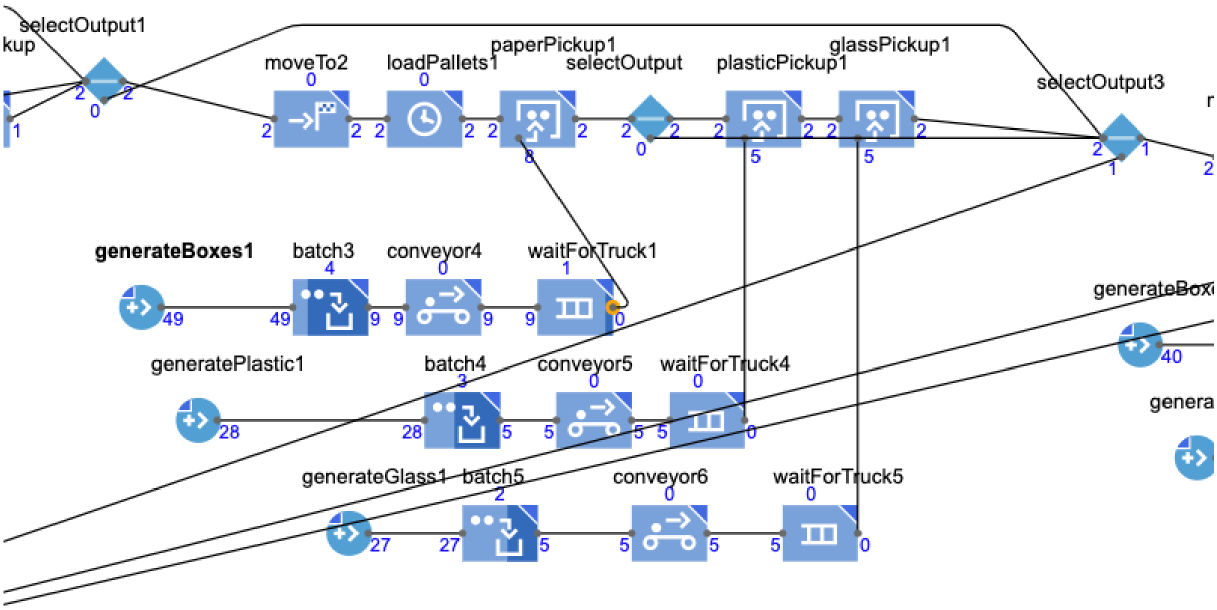


Figure B.8d – Waste Collection Station 3 Logic

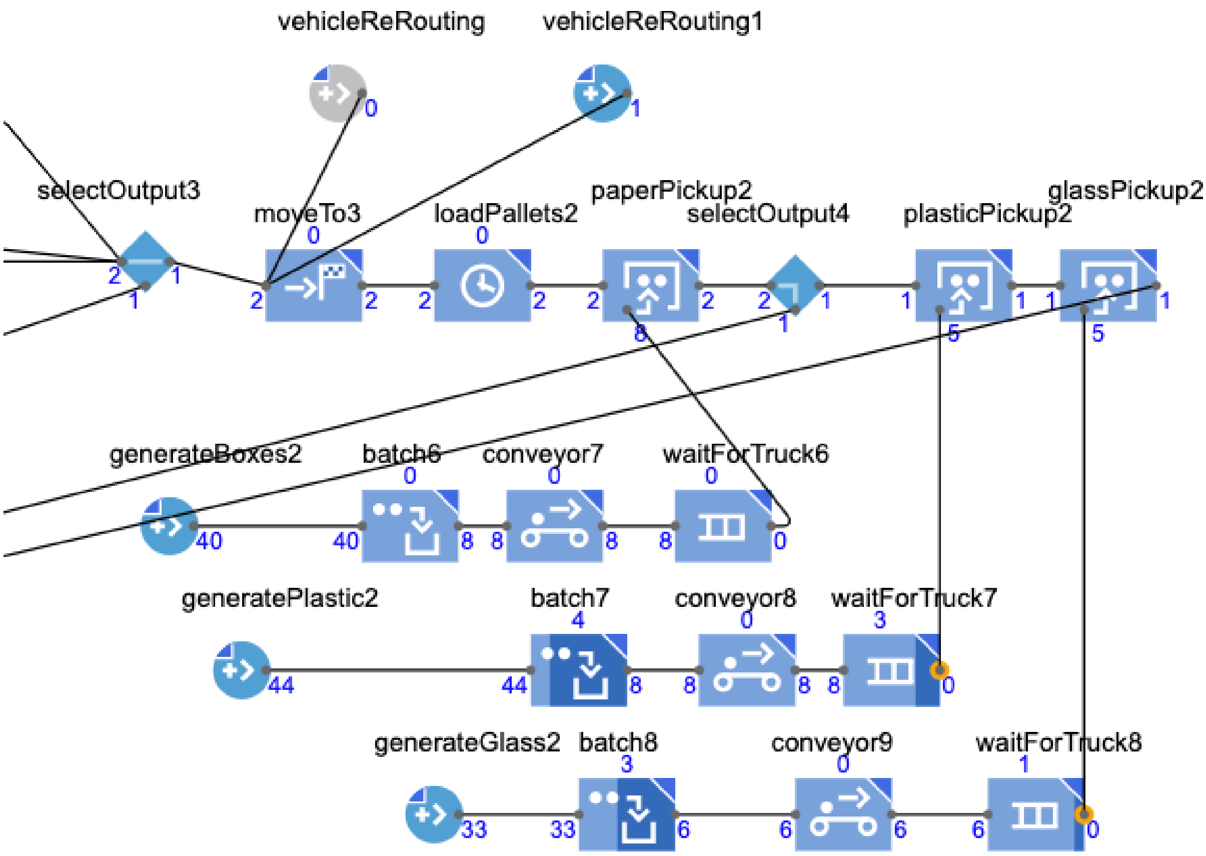
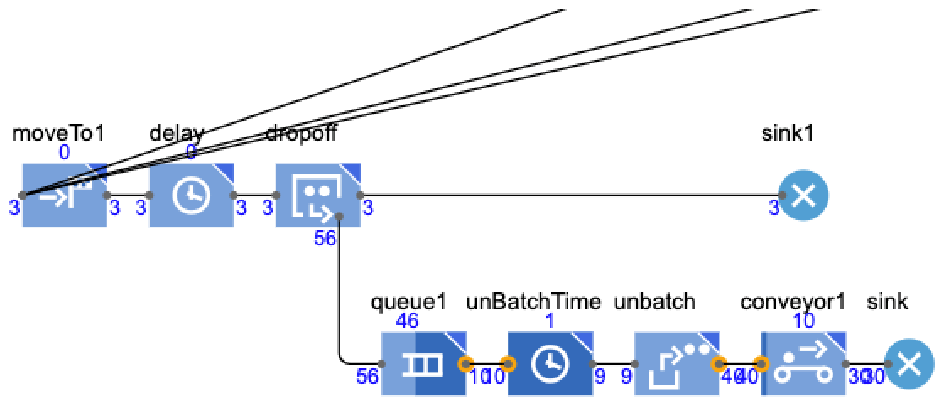


Figure B.8e – Unbatching and Final Disposal Logic (Sink)



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