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Sustainable Solutions for Freight Transport Optimization

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Abstract

In the face of a growing global climate crisis, the transportation sector has come under intense scrutiny for its substantial contribution to environmental degradation. As one of the leading sources of pollution, the freight transport industry is at a critical juncture where the need for sustainable practices has never been more urgent. While multimodal transport systems—combining road, rail, maritime, and air—offer significant benefits in terms of flexibility and efficiency, they also present formidable challenges, particularly regarding emissions and environmental impact. This thesis delves into the concept of green logistics as a transformative approach to optimizing multimodal freight transport, with the dual aim of enhancing operational efficiency and significantly reducing ecological footprints. To tackle these pressing issues, the research introduces a scalable and modular platform designed to address complex logistics challenges through an integrated framework. The platform incorporates a Mixed-Integer Linear Programming (MILP) model specifically designed to integrate multiple transportation modes while optimizing route selection under time and cost constraints. It emphasizes the selection of the shortest, most sustainable routes, reducing the used vehicles and lowering emissions, thereby fostering more sustainable urban and intermodal logistics networks. The platform’s modular design enables adaptability across various logistics contexts, accommodating diverse operational requirements and decision-making scenarios. The second module of the platform addresses the multifacility location-routing problem in urban logistics. This component focuses on balancing the placement of pickup-delivery stations and home delivery services, optimizing their use to minimize total costs and pollutant emissions. By incorporating dynamic customer behaviors—such as their willingness to walk to pickup points—and adjusting for variations in station activation costs, this module delivers tailored solutions for urban freight operations. The combination of these two modules underscores the platform’s ability to scale seamlessly between long-haul multimodal logistics and localized urban delivery challenges. Extensive and realistic test, based on data from the Italian multimodal transport network and case studies in urban logistics in Genoa, confirm the platform’s effectiveness. Results demonstrate significant reductions in carbon dioxide emissions, fuel consumption, and operational costs, while also enhancing the utilization of transport capacity and minimizing resource waste. Moreover, the findings highlight how incentivizing collaborative logistics practices can further enhance system efficiency and environmental sustainability. This study not only enhances the theoretical understanding of multimodal transport optimization but also provides a practical, scalable, and modular solution to real-world logistics challenges. By integrating advanced methodologies and innovative approaches, it lays a robust foundation for developing more sustainable, efficient, and resilient logistics networks for the future.

Keywords: Multimodal Logistic Networks, Environmental Sustainability, Logistics Management, Freight transport, Shortest Paths, Mixed-Integer Linear Programming

Abstract

Di fronte a una crisi climatica globale sempre più pressante, il settore dei trasporti è sotto una crescente attenzione per il suo significativo contributo al degrado ambientale. Essendo una delle principali fonti di inquinamento, il trasporto merci si trova in un momento critico in cui l'adozione di pratiche sostenibili è più urgente che mai. Sebbene i sistemi di trasporto multimodale—che combinano strada, ferrovia, trasporto marittimo e aereo—offrano importanti vantaggi in termini di flessibilità ed efficienza, essi presentano anche sfide considerevoli, soprattutto per quanto riguarda le emissioni e l'impatto ambientale. Questa tesi esplora il concetto di logistica sostenibile come approccio trasformativo per ottimizzare il trasporto multimodale di merci, con il duplice obiettivo di migliorare l'efficienza operativa e ridurre significativamente l'impronta ecologica. Per affrontare queste problematiche, la ricerca propone una piattaforma scalabile e modulare progettata per risolvere le complesse sfide logistiche attraverso un framework integrato. La piattaforma integra un modello di Programmazione Lineare Intera Mista (MILP) appositamente concepito per combinare diversi modi di trasporto e ottimizzare la scelta dei percorsi nel rispetto di vincoli di tempo e costo. Il modello pone particolare enfasi sulla selezione dei percorsi più brevi e sostenibili, riducendo il numero di veicoli utilizzati e le emissioni, favorendo così reti logistiche urbane e intermodali più sostenibili. Grazie al suo design modulare, la piattaforma si adatta a diversi contesti logistici, soddisfacendo esigenze operative e decisioni strategiche variegate. Il secondo modulo della piattaforma affronta il problema di localizzazione e instradamento multifunzionale nella logistica urbana. Questo modulo si concentra sull'equilibrio tra l'attivazione delle stazioni di ritiro-consegna e i servizi di consegna a domicilio, ottimizzandone l'uso per minimizzare i costi complessivi e le emissioni inquinanti. Considerando comportamenti dinamici dei clienti, come la disponibilità a percorrere una determinata distanza per raggiungere i punti di ritiro, e variando i costi di attivazione delle stazioni, questo modulo offre soluzioni personalizzate per le operazioni di distribuzione urbana. La combinazione dei due moduli dimostra la capacità della piattaforma di scalare senza soluzione di continuità tra la logistica multimodale a lungo raggio e le sfide delle consegne urbane localizzate. Test estensivi e realistici, basati su dati della rete di trasporto multimodale italiana e su studi di caso relativi alla logistica urbana nella città di Genova, confermano l'efficacia della piattaforma. I risultati evidenziano riduzioni significative nelle emissioni di anidride carbonica, nel consumo di carburante e nei costi operativi, migliorando al contempo l'utilizzo delle capacità di trasporto e riducendo lo spreco di risorse. Inoltre, i risultati sottolineano come l'incentivazione di pratiche di logistica collaborativa possa migliorare ulteriormente l'efficienza del sistema e la sostenibilità ambientale. Questa tesi non solo approfondisce la comprensione teorica dell'ottimizzazione del trasporto multimodale, ma offre anche una soluzione pratica, scalabile e modulare per le sfide logistiche del mondo reale. Integrando metodologie avanzate e approcci innovativi, pone solide basi per lo sviluppo di reti logistiche più sostenibili, efficienti e resilienti nel futuro.

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Acronyms

AI Artificial Intelligence

API Application Programming Interface

FSTSP Flying Sidekick Traveling Salesman Problem

GHG Global Greenhouse Gas

GUI Graphical User Interface

HTTP Hypertext Transfer Protocol

IoT Internet of Things

IPCC Intergovernmental Panel on Climate Change

JSON JavaScript Object Notation

JVM Java Virtual Machine

MILP Mixed Integer Linear Programming

MINLP Mixed-Integer Non-Linear Programming Solvers

ML Machine Learning

NLP Non-Linear Programming

PDSTSP Parallel Drone Scheduling Traveling Salesman Problem

QCP Quadratic Constrained Programming

QP Quadratic Programming

SDG Sustainable Development Goals

SQL Structured Query Language

TSP Travelling Salesman Problem

UAVs Unmanned Aerial Vehicles

VRP Vehicle Routing Problem

XML eXtensible Markup Language

Chapter 1

General Introduction

1.1 Motivation and Background

Logistics processes inherently involve numerous resources and activities that directly influence the sustainability outcomes of an organization. Among these, transportation stands out as the logistics function with the most substantial impact on sustainability efforts [2]. The transportation sector, while critical to economic growth, remains one of the most significant contributors to both energy consumption and emissions [3]. In recent years, shifts in customer demands have introduced new logistical challenges, as consumer behavior increasingly favors services like same-day deliveries and hassle-free returns, which are now standard expectations in e-commerce [4]. In the context of B2B operations, specific industries, such as automotive manufacturing, frequently rely on just-in-time or even just-in-sequence delivery methods [5]. These trends have collectively led to a substantial rise in freight volumes, creating a need for more efficient logistics strategies to manage them.

Figure 1.1 illustrates the marked increase in freight volume over recent decades. Moreover, Figure 1.1 highlights the modal distribution of intra-EU freight transport, where road transport dominates, accounting for just over 50% of freight movements. Maritime transport holds a significant share as well, approximately 30%. In terms of inland freight transport specifically, road transport's prevalence rises to around 75% [6], indicating that a large proportion of inland freight depends on road networks, contributing substantially to environmental impact. Projections indicate that environmental challenges related to transportation will continue to intensify in the coming decades, with road transport's share expected to increase even further [7]. This is particularly concerning due to road transport's significant negative impact compared to other transport methods, not only through emissions but also through additional external costs such as noise pollution, congestion, and accident rates. The Handbook on External Transport Costs [8] compares the external costs associated with different transport modes, revealing that road transport incurs external costs of 2.01 cents per ton kilometer. These costs are notably higher than those associated with rail transport (0.80 cents per ton-kilometer) and inland waterways (0.27 cents per ton-kilometer). Given these statistics and recent developments, it is clear that effective measures are necessary to ad-

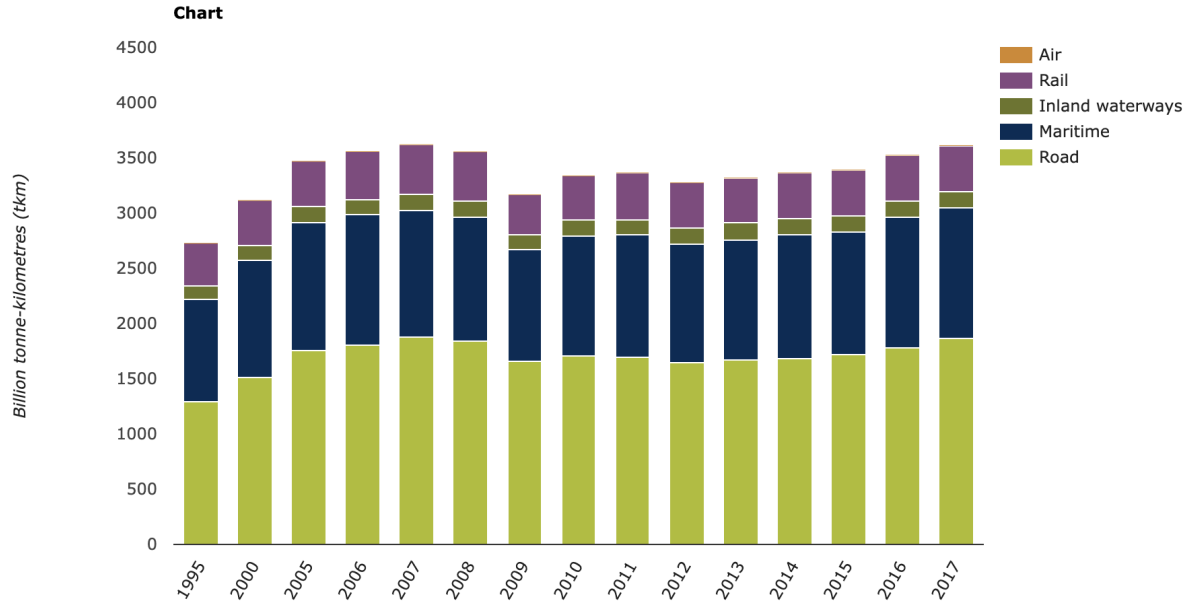


Figure 1.1: Freight transport volume and modal split within the EU [1].

dress the environmental challenges posed by freight transport. European governments have long recognized the environmental impact of the transportation sector and have committed to policies promoting sustainable development. These commitments have led to various national and international strategies, environmental agreements, and regional development initiatives [9]. At a global level, the Paris Agreement [10] represents a critical milestone for climate policy, adopted by the United Nations Framework Convention on Climate Change (UNFCCC) at the COP21 climate conference in Paris in December 2015. The Paris Agreement marks the first binding global accord to set a concrete limit on global warming, aiming to address climate change by restricting global temperature rise to well below 2°C (UNFCCC, 2016). Unlike the earlier Kyoto Protocol, which required commitments only from certain industrialized nations, the Paris Agreement represents a substantial advancement by involving 195 contracting parties in the effort. Under the Paris Agreement, each signatory is responsible for implementing strategies to meet established climate goals. Europe has taken on a prominent role, setting a target to become the world’s first climate-neutral continent. To achieve this, the European Green Deal was introduced, laying out an ambitious action plan designed to achieve net-zero greenhouse gas emissions by 2050. This plan promotes efficient resource use and a transition to a circular economy, aiming to restore biodiversity and significantly reduce emissions. Furthermore, to strengthen this commitment, the European Climate Law was proposed, seeking to legally mandate these climate targets and safeguard the Green Deal’s implementation. This law includes provisions for tracking progress and adjusting actions as necessary to meet objectives, aligning with the five-yearly global stock-taking outlined in the Paris Agreement. Achieving the objectives outlined in the European Green Deal will require a significant reduction in transport emissions. This goal is partic-

ularly challenging given that global demand for transport is projected to triple by 2050, which could lead to a doubling of carbon emissions (International Transport Forum, 2019). An ambitious roadmap proposed by the European Technology Platform ALICE outlines a strategy for achieving zero emissions in all logistics operations by 2050 [11]. This plan emphasizes optimizing transport capacity use and enhancing overall freight system productivity as key efficiency measures. Additionally, the adoption of sustainable vehicle technologies is expected to further support the decarbonization of freight transport [11]. While the ALICE roadmap represents a critical step toward environmentally sustainable logistics, the success of its implementation will ultimately depend on the willingness of stakeholders to adopt and enforce these measures.

Research Objectives

Despite the substantial political efforts described above, the environmental impact of the transport sector has yet to show meaningful improvement [3]. Current measures appear insufficient to incentivize transport users toward adopting sustainable freight transport practices. For policies to effectively promote sustainable freight transport, it is essential to understand both the demand for and the acceptance of these practices among transport users. Without a strong demand for environmentally friendly transport practices, the transition to sustainable freight transport is unlikely to succeed [12]. Thus, policy initiatives must be designed to align with the needs of transport users and actively foster their interest in sustainable freight solutions. Various alternatives are available for achieving sustainable freight transport, yet research on the demand for these options remains limited.

In this thesis, a comprehensive framework for sustainable freight transport has been developed, which is structured into two interconnected modules and will be thoroughly examined. The first module focuses on long-distance shipment using a strategy that supports the reduction of greenhouse gas emissions in freight transport through enhanced cooperation among various carriers. Horizontal collaboration minimizes transport demand by consolidating shipment flows and fully utilizing available capacity. Additionally, multimodal transport shifts freight toward more sustainable modes, balancing emissions reduction with cost-efficiency and operational effectiveness. The model combines road, rail, maritime, and air transportation, as illustrated in Figure 1.2, to identify the most cost-effective and environmentally friendly routes. By maximizing cargo utilization, it reduces vehicle numbers on the road, thus lowering CO₂ emissions and overall transport costs. This work highlights the benefits of cooperative logistics, demonstrating how carriers can jointly optimize resource and infrastructure usage.

The second module addresses the challenges of last-mile delivery in urban logistic networks. It introduces a variant of the classic multi-facility location-routing problem, where pickup and delivery stations (*pds*) are strategically connected to customers and a central warehouse. Customers are assigned to a *pds* based on minimizing sustainable costs and ensuring the distance does not exceed a predefined maximum. This module considers various means

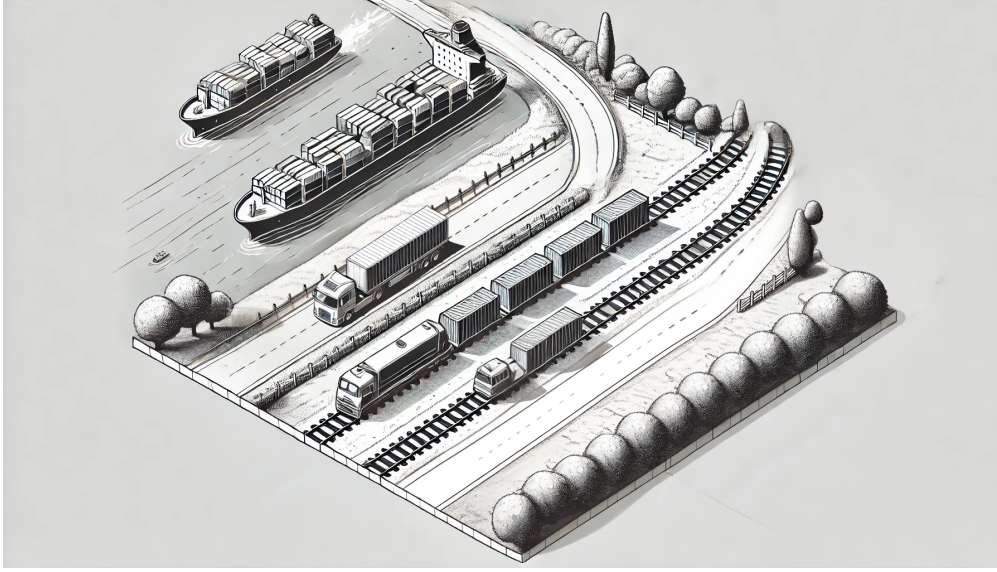


Figure 1.2: Graphical representation of horizontal collaboration among train, truck, and ship in a multimodal transport system. Generated using LLM.

of transport for customers to reach the *pds*, such as walking, biking, or using electric vehicles, further enhancing sustainability. Additionally, customers are categorized into subsets, with some being served directly from the warehouse while others utilize the *pds* network. By optimizing the number and location of *pds* and effectively assigning customers, this approach reduces emissions, alleviates urban congestion, and aligns with sustainable urban development goals. Together, these modules form a holistic framework that addresses both long-distance and last-mile logistics challenges, promoting a more sustainable and efficient freight transport system. The integration of multimodal transport with innovative last-mile delivery solutions exemplifies a comprehensive strategy to reduce environmental impact while maintaining operational effectiveness.

Research questions

The study papers presented in this thesis provide insight into the research questions underlying sustainable freight transport strategies.

- 1. Which determinants influence the acceptance of sustainable freight transport strategies?**

This research identifies several key factors influencing the acceptance of sustainable freight transport practices, including economic incentives, policy support, and customer demand. These determinants play a pivotal role in shaping the willingness of transport users to adopt eco-friendly solutions. Understanding these factors is essential to designing effective policy measures that align with both market needs and sustainability goals.

- 2. Which motives support horizontal collaboration in a freight transport network?**

Horizontal collaboration in freight transport networks is primarily motivated by the potential for cost savings, increased operational efficiency, and shared environmental responsibility. By consolidating shipments and optimizing shared resources, carriers can achieve economies of scale while reducing emissions and operational costs. This collaborative approach also fosters a competitive advantage by promoting service reliability and resource utilization.

- 3. How can the existing payload capacity of scheduled transport routes be maximized to meet new freight demands without necessitating additional vehicles?**

This question is addressed by exploring methods to enhance the utilization of existing payload capacities on scheduled transport routes. Strategies such as load consolidation, and improved real-time scheduling are examined for their potential to accommodate additional freight demands without deploying extra vehicles. This approach not only optimizes operational efficiency but also aligns with emissions reduction targets by minimizing the environmental footprint of freight transport.

- 4. What is the impact of different cost components, such as emissions, fuel, service, and consolidation costs, on the overall optimization of multimodal transport routes?**

The study evaluates how various cost factors, including emissions, fuel, service, and consolidation costs, influence route optimization in multimodal transport. By analyzing the trade-offs between these cost components, the research provides insights into selecting routes that balance economic and environmental considerations. This approach enables decision-makers to choose transport routes that are both cost-effective and environmentally sustainable.

Outline

This thesis is organized into seven chapters, each addressing different aspects of the development of a multimodal freight transport platform.

Chapter 1 lays the foundation for the research, discussing the motivation and background of the study. It introduces the significance of multimodal transport, particularly in the context of sustainable logistics. The chapter further defines the scope of the research, outlines the main objectives, and poses the key research questions addressed throughout the thesis. Additionally, it provides an outline of the overall thesis structure and the methodologies applied in the investigation.

Chapter 2 begins with a critical evaluation of the academic literature on multimodal transport systems, offering an in-depth analysis of studies related to optimization models and cost-effective routing in logistics. This section identifies significant gaps in the current body of knowledge and establishes the theoretical foundation for the models and approaches proposed later in the thesis. The chapter then shifts its focus to emerging technologies, such as the *Internet of Things (IoT)* and *Artificial Intelligence (AI)*, exploring their potential to transform multimodal transport systems. Definitions related to transport modals are provided, followed by an analysis of how these technologies impact efficiency, sustainability, and future trends. This discussion highlights both the opportunities and challenges associated with leveraging technological advancements for sustainable logistics.

Chapter 3 introduces the first module of the thesis, which proposes a mixed-integer model for path optimization. The chapter describes the problem of cost-effective routing in multimodal logistics, presenting a detailed mathematical formulation. Computational experiments are conducted, and the results are analyzed in terms of their efficiency and practicality in real-world applications.

Chapter 4 introduces a second module, focusing on optimizing the location of pickup-delivery stations to reduce emissions in urban logistics. The chapter presents an exact *Mixed Integer Linear Programming (MILP)* model and discusses the partitioning criteria used. Several computational experiments are conducted, and the results are analyzed, including tests on maximum distance, emission costs, and real-size case studies.

Chapter 5 provides an in-depth discussion of the architecture of the proposed multimodal transport platform. It describes the modular structure, detailing the main components of the system and their interactions. Additionally, the software architecture is outlined, covering the database structure, programming languages used, and tools such as mathematical solvers and middleware that were employed to implement the platform.

Chapter 6 summarizes the key contributions of the research and discusses its practical implications for the transport and logistics industry. It reflects on the main findings, acknowledging the limitations of the study and offering recommendations for future research. The chapter concludes by suggesting potential avenues for further investigation, particularly in the integration of additional services or technologies to enhance multimodal transport systems.

Chapter 2

Literature Review

2.1 Sustainable Multimodal Logistics

The logistics and transportation sectors are pivotal in global supply chains, supporting economic growth but simultaneously contributing significantly to environmental degradation. According to the *Intergovernmental Panel on Climate Change (IPCC)*, transport operations account for approximately 14% of *Global Greenhouse Gas (GHG)* emissions, representing a considerable share of the emissions driving climate change and air pollution. Freight transport, in particular, intensifies this impact, as road freight transport remains a primary source of emissions due to its heavy reliance on fossil fuels and its vast mileage in global supply chains [13]. With the rapid expansion of e-commerce and the globalization of trade, the demand for freight transport continues to grow, putting additional pressure on the environment. If current practices remain unchanged, CO₂ emissions from the logistics sector are projected to increase by nearly 50% by 2050, underscoring the urgent need for sustainable practices to mitigate these effects [14].

Multimodal logistics, which combines multiple transportation methods (such as rail, sea, and road), presents a promising alternative to unimodal approaches, potentially reducing environmental impacts while enhancing logistics efficiency [15]. Several studies highlight the environmental advantages of multimodal systems, noting that the combination of rail and water transport, for example, produces lower emissions than road transport alone, primarily due to higher fuel efficiency and fewer emissions per ton-kilometer transported [16]. Consequently, multimodal logistics is becoming central to sustainable logistics strategies aimed at reducing carbon footprints while still meeting operational demands.

The United Nations' *Sustainable Development Goals (SDG)* emphasize sustainable infrastructure and responsible consumption and production, which are essential elements of green logistics. Particularly relevant are *SDG 9*, focusing on resilient infrastructure and sustainable industrialization, and *SDG 13*, which advocates for urgent climate action [17]. *SDG 9* promotes resilient infrastructure development to foster sustainable industrialization and innovation, urging logistics sectors to adopt multimodal networks to optimize resource use

and mitigate environmental impacts [18]. By minimizing reliance on road transport, multimodal systems align with *SDG* 13's objectives by reducing emissions and promoting the use of cleaner transport modes like rail and waterway shipping, known for their lower carbon outputs [19]. In line with *SDG* 12 (Responsible Consumption and Production), sustainable logistics emphasizes reducing waste and optimizing resource utilization, achieved by consolidating freight loads and leveraging existing transportation capacities. For instance, research suggests that cooperative logistics models, which involve shared resources and capacities among logistics providers, can reduce vehicle empty runs by 20–30%, leading to significant emission reductions and cost savings [20]. Such approaches illustrate the broader potential of green logistics in advancing *SDG* targets and promoting responsible production and consumption in global supply chains. Multimodal transport systems represent a strategic shift from traditional road-based logistics models to those that integrate multiple modes of transport, such as rail, maritime, air, and road, for moving goods efficiently and sustainably.

The European Union (EU) has set ambitious goals within its Green Deal to transition at least 30% of long-distance road freight to more sustainable modes like rail and waterway by 2030, with a further increase to 50% by 2050, as part of its overarching aim to become climate-neutral by 2050 [21]. Such policies reflect the growing awareness that multimodal systems can curb the environmental impacts of logistics, particularly by reducing road congestion and lowering CO₂ emissions in densely populated or urban regions [22]. Studies reveal that multimodal systems achieve lower emissions by using modes like rail and waterways for long-haul segments, leaving road transport for short, last-mile deliveries. Research shows that integrating rail for the primary leg of the journey can cut greenhouse gas emissions by 70% compared to road-only routes, particularly for high-density goods like minerals and chemicals [23]. Additionally, intermodal transport—which emphasizes seamless transfer between different modes of transport—facilitates logistical efficiency by reducing handling times, optimizing capacity, and improving delivery accuracy, all of which contribute to a more sustainable logistics framework [24].

Technological advancements, especially in *IoT*, *AI*, and digital platforms, are transforming multimodal logistics. IoT-enabled sensors and GPS tracking devices are now commonplace across supply chains, allowing for real-time monitoring of goods' location, condition, and status. These technologies are particularly valuable for multimodal systems, where goods often transfer between different transportation modes, and consistent visibility is necessary to optimize cargo handling and scheduling [25]. For instance, IoT sensors enable temperature monitoring in refrigerated cargo, helping to avoid spoilage during transit, especially when goods are transferred from sea to road or rail transport [26]. *AI* and *Machine Learning (ML)* play an essential role in optimizing routes, managing logistics networks, and predicting demand patterns. For example, machine learning algorithms can analyze historical data to forecast peak demand periods, allowing companies to adjust transport schedules and consolidate shipments to maximize capacity and reduce trips [27]. *AI* also helps in adaptive

planning, such as adjusting routes based on real-time traffic conditions or weather forecasts, which enhances efficiency and lowers emissions [28]. These predictive capabilities contribute to fuel savings and emission reductions, positioning AI as a critical tool for sustainable logistics operations. Environmental sustainability in multimodal logistics is increasingly measured by emissions costs, factoring in both direct and indirect impacts on the environment. Advanced logistics models now incorporate emissions as weighted factors within their cost functions, which encourages the selection of lower-emission transport modes. Studies by Bouman et al., [29] demonstrate that CO₂ emissions can be reduced by a factor of 4 to 6 per transported unit of freight. By prioritizing modes with lower emissions (such as rail and waterways) over road transport, these models offer a practical approach to meeting regulatory emissions caps and achieving compliance with environmental standards [30]. Furthermore, the concept of "emissions per mile" has gained prominence, whereby logistics providers track CO₂ emissions per unit distance. This metric is particularly relevant in multimodal transport where different modes have vastly different emissions profiles. For example, air freight, while fast, has a significantly higher emissions output than rail or sea transport. By calculating emissions per mile, companies can make more informed decisions, such as limiting air freight to only the most time-sensitive deliveries, thus aligning operational efficiency with sustainability goals [31].

Cooperative logistics involves collaborative arrangements where different companies share logistics resources, such as vehicle fleets or warehousing facilities, to optimize operations and reduce environmental impacts. Cooperation can take many forms, from shared warehousing to collaborative transportation planning, where multiple companies consolidate shipments to improve load efficiency. Such arrangements have been shown to reduce CO₂ emissions by approximately 10–15% by maximizing vehicle utilization and reducing the frequency of empty or underloaded trips [32]. Logistics cooperation is particularly effective in multimodal transport systems, where goods frequently switch between transport modes. In these scenarios, cooperation can facilitate smoother transitions and reduce handling times, as companies align their schedules and pool resources [33]. This approach is especially valuable in regions with dense logistics networks, where frequent vehicle trips and tight delivery windows can exacerbate emissions and traffic congestion. Empirical research demonstrates the practical advantages of cooperative logistics. Xihan et al. [34] simulated logistics operations under cooperative models, showing substantial reductions in operational costs and emissions through optimized vehicle sharing. The simulation included various transport scenarios and demonstrated that cooperative logistics not only reduced emissions but also enhanced load efficiency, minimizing the number of trips and thus decreasing overall traffic congestion. These results highlight the efficacy of cooperative logistics in meeting both economic and environmental objectives, reinforcing its role in sustainable logistics strategies. The escalating global climate crisis necessitates immediate and effective sustainable practices across all industrial sectors, notably in logistics.

The Conference of the Parties (COP 21) underscores that climate change poses an urgent and potentially irreversible threat to human societies and the planet [35]. Consequently, there is a pressing need to expedite the reduction of global greenhouse gas (GHG) and pollutant emissions. In response, the move towards cooperative multimodal logistics has gained prominence as a strategy for companies to diminish their environmental footprint while sustaining efficient supply chains. This approach focuses on collaboration and resource sharing among various transportation modes—such as road, rail, maritime, and air—to establish a more sustainable and resilient logistics network. Addressing environmental challenges requires careful consideration of managerial implications and perspectives, particularly in aligning proposed methodologies with the global climate emergency. One significant aspect is optimizing the utilization of vehicles that are operating below full capacity, thereby contributing to a reduction in the total number of vehicles on the road in line with a green-oriented vision. This strategy aligns with the broader objective of minimizing the environmental impact of logistics operations. Subsequent sections will present experimental results indicating that even minor modifications to the multimodal network can lead to substantial decreases in pollutant emissions. These findings highlight the potential environmental benefits of optimizing existing transportation resources. Moreover, the sharing of information while maintaining confidentiality and integrity [36], as well as the sharing of resources throughout the supply chain, has become crucial for ensuring efficient and sustainable operations. Over the past two decades, there has been a growing recognition of the environmental and social impacts of logistics beyond traditional economic considerations.

The concepts of *green logistics* and *sustainable logistics* have emerged as pivotal in both industry and academic research [37, 38]. Previous studies suggest that the integration of Industry 4.0 technologies and the adoption of green practices can act as catalysts towards achieving a sustainable economy [39, 40]. These practices encompass a broad array of strategies designed to lessen the environmental and social burdens associated with logistics. Such strategies include efforts to lower emissions, cut down on waste, and uphold ethical labor standards [41]. Prioritizing the management of economic impacts, social responsibility, and CO₂ emissions serves a dual purpose: it safeguards the environment and contributes to a reduction in overall transport costs, thus supporting long-term sustainability [42], which is the primary aim of this study. In recent years, the logistics community and stakeholders have increasingly emphasized the importance of multimodal transportation, recognizing its varied sustainable benefits [43, 44]. This perspective is consistent with broader goals such as easing traffic congestion, cutting down on air pollution, and subsequently mitigating noise and physical wear on infrastructure [45]. Moreover, there is a growing focus on optimizing the organization of diverse cargo types within multimodal systems. It's worth noting that the multimodal transport of specialized cargo types demands substantial accountability, particularly given the distinct characteristics that such cargoes may possess. Since multimodal transport involves using at least two different modes of transportation, compliance with specific regulations related to cargo handling and transit is crucial to ensure both efficiency

and safety [46]. Additionally, the European Union (EU) has recognized the various external costs associated with road-based logistics, such as delays, congestion, and the environmental burden of CO₂ emissions [47, 48]. In response, the EU has set ambitious objectives to establish a competitive, resource-efficient transport network that encourages a transition to more sustainable modes of transport, particularly rail and waterways [49]. Achieving this shift in transport modes represents a vital step in minimizing the ecological footprint of the transport sector while maintaining effective and reliable goods movement [50, 51].

Another major issues in the delivery sector is in the last segment of the delivery chain, known as the last mile, which is both costly and environmentally impactful. Consequently, researchers and industry professionals are actively working on enhancing the efficiency and sustainability of this crucial phase in the logistics process. One promising innovation aimed at addressing these challenges is Out-of-Home Delivery (OOHD). This approach reimagines last-mile delivery by redirecting parcel drop-offs from direct home delivery to alternative collection points, such as nearby pickup stations. In contrast to the conventional method where packages are delivered to recipients' doorsteps, OOHD requires recipients to retrieve their items at their convenience from designated facilities. These facilities may include parcel lockers or shops specifically designed for secure storage and convenient retrieval of parcels. OOHD enhances last-mile efficiency in multiple ways:

- When recipients use eco-friendly modes of transport, such as bicycles or walking, to retrieve their packages, OOHD reduces the reliance on delivery vehicles. This, in turn, decreases both emissions and traffic congestion, particularly within densely populated urban areas.
- By consolidating deliveries to a single OOHD facility rather than multiple destinations, logistics providers can minimize the number of stops and the overall distance traveled per delivery route, thus improving route efficiency.
- OOHD offers increased flexibility in delivery route planning. Some recipients may be willing to pick up their packages from a variety of OOHD facilities, allowing for further optimization in route selection and delivery schedules.

Despite its advantages, OOHD does present certain challenges. Primarily, it depends on a dedicated infrastructure that requires substantial upfront investment. Establishing proprietary networks of OOHD facilities can be financially burdensome, making it less viable for smaller delivery providers with limited parcel volumes. In recent years, Out-of-Home Delivery has gained increasing prominence as a critical component of last-mile delivery strategies. A notable example is the German logistics provider DHL, which has made substantial investments to expand its network of parcel lockers. In 2019, DHL operated approximately 4,000 parcel lockers, a figure that grew to 8,500 by 2021. By the end of 2023, the company aims to reach a total of 15,000 parcel lockers [52]. This expansion aligns with the rising

adoption of parcel lockers in Germany. While only 3% of parcels were delivered to such facilities in 2019, it is projected that by 2025, 10% of the total parcel volume will be delivered via parcel lockers [53]. This shift highlights the growing relevance of OOHD as a solution to improve efficiency and sustainability in last-mile logistics. Optimization in the context of OOHD involves three primary decision-making components, namely location, routing, and assignment decisions.

- **Location decisions:** These involve identifying and selecting suitable locations for OOHD facilities, such as parcel lockers or pickup stations.
- **Routing decisions:** These pertain to the planning of delivery routes, specifically determining the sequence of delivery points that vehicles should visit.
- **Assignment decisions:** These relate to the allocation of final delivery locations for all customers, taking advantage of their flexibility in selecting pickup points.

It is important to note that not all optimization problems necessarily incorporate all three decision types. However, any problem addressed in this context will involve decision variables related to at least one of these components. The three types of decisions—location, routing, and assignment—are inherently interconnected. If these decisions were entirely independent, they could be addressed as separate optimization problems without compromising the quality of the solution. For instance, assignment options are directly influenced by the chosen locations of OOHD facilities, and the routing of delivery vehicles also depends on these locations. Conversely, the selection of facility locations is guided by their impact on both assignment flexibility and route efficiency. Boysen et al. [54] and Silva et al. [55] explore this topic in the context of various delivery approaches. These studies present a systematic comparison of methods for organizing and executing last-mile delivery, such as cargo bikes, drones, and crowd-shipping, among others. Several authors examine the stochastic interplay between open facility locations and customers' delivery location choices. Lin et al. [56], Lin et al. [57], and Lyu and Teo [58] apply discrete choice models to assess how the design of an OOHD network influences customer decision-making. Through this approach, location decisions are inherently linked to customers' selection of delivery points. A key explanatory factor in these models is the distance between the customer and the nearest parcel locker. Additionally, Lyu and Teo [58] identify the type of locker location—such as its proximity to shopping malls or metro stations—as another significant determinant. Beyond influencing customer preferences through facility placement, Lin et al. [57] further restrict the set of delivery options available to customers to guide their choices more effectively. However, due to the complexity and computational demands associated with discrete choice modeling, many researchers prefer deterministic approaches for modeling customer preferences. This often involves assigning customers to the nearest locker or a locker within a predefined radius. The conventional last-mile delivery process is notably cost-intensive due to the large number of stops, extensive distances traveled, and frequent failed delivery attempts. Delivery concepts

based on OOHD have the potential to significantly improve last-mile efficiency. This improvement is achieved by consolidating orders, wherein multiple customers in close proximity are grouped into a single delivery location. Moreover, since OOHD eliminates the need for direct handovers between the delivery personnel and the customers, the occurrence of failed delivery attempts can be nearly eliminated [59, 60].

An increasingly important area of interest within the community in last-mile delivery is the integration of *Unmanned Aerial Vehicles (UAVs)* into conventional truck-based delivery systems. This hybrid approach, often referred to as the drone-truck model, has attracted significant attention due to its ability to improve operational efficiency, lower logistical costs, and, most importantly, provide a more environmentally friendly solution. In particular, utilizing drones for small parcel deliveries has the potential to achieve notable energy savings and significantly reduce greenhouse gas emissions. Studies have shown that drones can consume up to 94% less energy per package compared to traditional delivery vehicles [61]. The idea of incorporating drones into logistics began to gain significant momentum in the early 2010s. Among the pioneering works, Murray and Chu [62] introduced the concept of a truck-drone delivery system, formulating the *Flying Sidekick Traveling Salesman Problem (FSTSP)* and the *Parallel Drone Scheduling Traveling Salesman Problem (PDSTSP)*. Their study highlighted the potential of drones to reduce the overall delivery completion time, defined as the moment when the last vehicle returns to the depot. They proposed a MILP model and developed a two-phase heuristic method capable of generating high-quality solutions for large-scale problem instances. Subsequent research has increasingly focused on heterogeneous fleets, taking into account variations in capacities, time constraints, and the operational ranges of both drones and trucks. These efforts aim to bridge the gap between theoretical models and real-world logistics applications.

2.2 Sustainable Multimodal Logistics through Advanced Technological Integration

In today's interconnected world, transportation is essential for facilitating the movement of goods and people across various regions. This industry constitutes a crucial element within the economic framework of any nation [63]. The transportation sector alone accounts for approximately one-third of total energy consumption and, in 2016, contributed to the emission of 946 million tonnes of Carbon Dioxide (CO₂) [64]. There is an acknowledged interplay between a company's environmental actions and its social impact [65]. In the case of multimodal transportation, certain practices with significant environmental footprints are adversely influencing the societal perception of the sector. Consequently, restructuring the multimodal logistics and freight transport network has become an increasingly prominent topic on the global agenda. Growing interest from governmental bodies at both national and international levels has driven efforts to establish innovative transport logistics models. These models aim to address system-wide changes while forecasting the future state of multimodal

logistics and freight transportation [66]. Multimodal transportation of goods has become increasingly common, utilizing various transportation networks such as sea, rail, road, air, and other routes. This approach to logistics is known for its advantages in reducing both delivery time and costs. A key characteristic of multimodal transport lies in the centralized control structure, where a single managing organization oversees the entire process. Currently, however, the operation of multimodal freight systems lacks cohesion and is segmented according to transport mode, such as rail from one station to another, maritime routes from port to port, and road transit from sender to destination. In the context of today's globalized trade, the delivery of international goods should not be assessed solely by traditional metrics like the chosen transport mode, distance, or transport costs. Instead, it must also consider other critical factors, including the duration of the main carriage, freight costs, customs clearance time, and other legal and certification requirements, along with state tax regulations [67]. In order to effectively address these complex parameters, a comprehensive approach is needed to increase the efficiency of the current system: one promising avenue is the integration of advanced digital technologies in the logistics sector. Digital technologies have become integral to modern life, making it difficult to envision a world without them. Considering the advancements in autonomous transportation and the extent of digitalization integrated into autonomous transport systems, it is reasonable to anticipate a growing presence of these technologies in the near future. This trend is expected to significantly enhance transportation infrastructure, improve service quality, and enable more effective management. However, as digitalization progresses, the logistics network becomes increasingly complex, creating a demand for more sophisticated data and information systems [68]. Consequently, the push for digital transformation within multimodal transportation intensifies each year, with the objective of boosting logistics and freight transport efficiency. This shift also underscores the role of digital data as a critical resource across all areas of socio-economic activity. The adoption of these technologies has catalyzed a paradigm shift toward Industry 4.0. Among the numerous advancements transforming the manufacturing landscape are technologies such as the Internet of Things (IoT), cloud computing, wireless sensor networks, embedded systems, and big data [69]. Manufacturers embracing these innovations are positioned to efficiently produce customized products while enhancing profitability. Examples of this digital transformation include the modernization of seaports to validate system efficiency and optimize operations [70], improved warehouse management and predictive accuracy through IoT integration [71], and the sustainable enhancement of smart mobility systems using big data analytics [72]. Kim et al. [73] and Kumar et al. [74] have examined the potential of the Internet of Things (IoT) to enhance decision-making within the multimodal transport and warehousing sectors. Their studies underscore the possibility of extending interaction modes beyond human-to-machine to include machine-to-machine communication. By leveraging IoT for these multi-level interactions, a comprehensive Multimodal Interaction (MI) system can be achieved. Additionally, research by Pournader et al. [75] and Perboli et al. [76] explores blockchain applications within supply chain, logistics, and multimodal transport management. Their findings highlight blockchain's ability to improve efficiency, capacity,

and reliability in supply chain operations. Further studies emphasize the importance of environmentally sustainable practices to achieve enhanced performance in multimodal node operations. In this context, the primary research question are outlined as follows:

- How do advanced digital technologies contribute to enhancing and scaling up existing multimodal node operations in logistics?

The research question aims to explore the impact of advanced and emerging digital technologies on enhancing multimodal node logistics operations. In the current landscape, the digital transformation of logistics requires a comprehensive approach that accounts for numerous influencing factors. Table 2.1 summarizes studies on various advanced digital technologies and their applications in the logistics industry.

Table 2.1: Papers dealing with digital technologies in the logistics sector.

Applications of Digital Technologies in the Logistics Industry	Authors and Year
Smart and Digital Technologies in Industry 4.0 Logistics	Fanti et al. [77], Zijm & Klumpp [78], Mar-Ortiz et al. [79], Wei et al. [80], D’Amico et al. [81], Sun et al. [82], Akkad & Bányai [83, 84], Levina et al. [68], Rasool et al. [85], Li et al. [86], Gupta et al. [87], Muradian et al. [88]
Internet of Things	Liu et al. [89], Zhao et al. [90], Yavari et al. [91], Tannady & Andry [92]
Blockchain	Meyer et al. [93], Arunmozhi et al. [94], Elmay et al. [95], Zhang [96]
Physical Internet	Dang Hoa & Kim [97]
Cloud & Big Data Computing	Neaga et al. [98]
Artificial Intelligence	Pinakpani et al. [99]

One key concept is the process of capturing data from the physical environment and bridging it to digital applications, commonly known as the ‘Digital Twin’. This technology facilitates the modeling of real-world entities in a digital format, often incorporating the Internet of Things (IoT). The main challenges in applying Digital Twin technology to logistics and multimodal node operations include operational costs and data validation in centralized scenarios. However, the integration of Blockchain technology, which provides a decentralized approach to data storage, could significantly enhance system robustness and efficiency. This combined architecture has the potential to develop an open-source framework for vehicle fleet management in logistics and freight transport, illustrating practical applications in real-world contexts [100]. To enhance logistics and integrated supply chain services, a robust tool is required to support effective decision-making. The Big Data Logistics Business Platform (BLDLP) serves this purpose by utilizing big data and cloud computing technologies,

enabling the processing of large volumes of data for logistical networks and various stakeholders [98]. Another promising technology is the Physical Internet (PI), which addresses the sustainability challenges facing current logistics services. By using PI containers, an algorithm can be developed to incorporate wireless sensors for monitoring both PI-containers and logistics operations.

For optimal results, this algorithm needs to be integrated with the industrial Internet of Things (IoT); without IoT, its effectiveness is limited. The use of wireless sensors is crucial, as desynchronization between physical and informational flows can occur in supply chain management systems without them [101]. Moreover, the Physical Internet system helps mitigate issues associated with centralized, data-driven models. A decentralized, blockchain-based approach offers a viable solution to address the core challenges of the Physical Internet, particularly regarding asset exchange in logistics networks and decentralized leadership structures [93]. Maritime trade plays a crucial role in the multimodal freight transportation industry but faces numerous complexities and inconsistencies in service. Many of these irregularities could be minimized by tracking maritime trade data and applying Artificial Intelligence (AI) models, which would not only optimize costs but also improve efficiency and reduce carbon emissions within the multimodal logistics sector. Through digital technology, key interstate transit routes across major hubs can be charted on transit maps, effectively managing the flow of cargo ships across different transport modes. Additionally, a collaborative Shapley Value approach could be implemented in this framework to enhance pollution control measures and support more effective decision-making [99]. In the process of digitizing the multimodal logistics industry, vehicle parking systems cannot be overlooked, especially when handling vehicles carrying hazardous chemicals. Advanced digital technologies now make it possible to implement IoT-enabled smart indoor parking systems for logistics vehicles, where a self-learning genetic tracking algorithm can ensure real-time vehicle tracking. This architecture and its algorithm have been validated for effectiveness in chemical logistics companies [90]. Furthermore, in multimodal logistics operations, the interplay between supply chain management and shipment consolidation is essential. For instance, when a carrier consolidates multiple smaller shipments into a single container, particularly over long distances, the cost efficiency of the supply chain is directly impacted. Traditionally, stochastic programming methods have been applied to design these systems; however, they often encounter limitations. By contrast, machine learning techniques that use historical data to predict stochastic parameters demonstrate significantly higher accuracy than traditional stochastic programming, thus providing valuable support for designing sustainable supply chain logistics [102]. Table 2.2 presents the characteristics and attributes of advanced digital technologies relevant to multimodal logistics services. An in-depth analysis of these attributes facilitates the investigation and decision-making processes, simplifying the selection of a digitally enabled framework for multimodal logistics operations.

Table 2.2: Characteristics and attributes of digital technologies.

Digital Technologies	Technologies	Characteristics and Attributes in Multimodal Logistics Services
Internet of Things		The Internet of Things (IoT) represents a modern advancement in human interaction with technology, enabling seamless data exchange between physical devices through wireless networks. IoT has a wide range of applications in multimodal logistics, such as warehouse management, where advanced data analytics increase productivity and picking accuracy. Moreover, IoT-enabled sensors can be utilized in logistics vehicles, allowing for the development of automated transportation systems that reduce logistics costs, energy usage, and resource consumption within multimodal logistics operations [103].
Blockchain		Blockchain technology allows parties to maintain a shared transaction database in a decentralized manner, ensuring transaction validation and authenticity through independent verification. In multimodal logistics, blockchain offers a secure approach for exchanging value and managing physical assets, addressing limitations of centralized systems. Additionally, it enables the use of smart contracts to improve supply chain operations, allowing users to track shipments transparently, which strengthens accountability and trust across the supply chain [76, 104].

Continued on next page

Digital Technologies	Technologies	Characteristics and Attributes in Multimodal Logistics Services
Physical Internet		The Physical Internet (PI) is an innovative approach aimed at enhancing the efficiency and sustainability of multimodal logistics operations. PI operates as a global logistics system, structured on interconnected networks of logistics that utilize standardized protocols, modular containers, and intelligent interfaces. This system facilitates collaboration and optimizes resource use. Unlike traditional supply chains, where companies focus on optimizing their individual logistics networks, PI envisions an integrated global open network. In a multimodal logistics context, PI containers—designed to be smart, eco-friendly, and modular—can be transported across a shared logistics infrastructure, with a wireless sensor algorithm monitoring the entire process. Within the PI framework, facilities and transport modes are shared resources, allocated according to user demand, allowing users to access inventory anywhere in the network and providing a multisource logistics solution [105, 106].
Cloud & Big Data Computing		Big Data and cloud computing encompass technologies for managing vast amounts of information that can be collected in real time. These systems handle data that is extensive in volume, high in velocity, and varied in structure, creating numerous opportunities for digital transformation in logistics and transportation. Through cloud computing, data can be manipulated, managed, and analyzed in real time, supporting operational improvements and enabling the development of new business models [107]. This infrastructure allows for advanced analytics and decision-making, providing a foundation for innovation in the logistics sector [108].

Continued on next page

Digital Technologies	Technologies	Characteristics and Attributes in Multimodal Logistics Services
	Artificial Intelligence	In the rapidly evolving landscape of computing and technology, Artificial Intelligence (AI) is defined as the science and engineering of creating smarter, high-cognition machines [109]. AI plays a critical role in multimodal logistics, where it can reduce traffic incidents by utilizing explainable AI systems that incorporate accident data to offer contextual advice to drivers, tailored to various risk levels [110]. Furthermore, AI combined with mathematical modeling is transformative for multimodal logistics, enhancing supply chain management by optimizing resource use. Additionally, AI supports other logistics functions, such as reverse logistics within the framework of a circular economy, demonstrating its broad impact [111, 112].

2.3 Transport modes

In the context of multimodal logistics, understanding the strengths and limitations of each transportation mode is crucial for optimizing operational efficiency and sustainability. This section examines the main types of transport —railway, road, waterway, air, and pipeline—and provides a balanced overview of their advantages and disadvantages. Each mode offers unique benefits in terms of speed, capacity, cost, and environmental impact, yet each also presents specific challenges. By assessing these factors, we can better understand the complex decision-making involved in selecting the most suitable transport solutions for different types of cargo and logistics needs. This analysis is particularly important for designing sustainable, flexible, and cost-effective logistics networks that can adapt to the demands of a globalized economy.

Railway transportation

Railway transportation stands as a primary method for cargo movement across various nations. It is intricately linked with major waterway transportation systems and numerous short-haul transport methods, creating a comprehensive transportation network where railways serve as the core component. In most countries, railway infrastructure is funded and administered by the government, facilitating transportation services across all societal sectors [113].

Advantages

- High carrying capacity.
- Faster speeds compared to other modes of transportation.
- Lower pollution levels: Unlike road transport, railway transport benefits from dedicated tracks, eliminating congestion issues.
- Minimal impact from weather conditions, ensuring safety and reliability.

Disadvantages

- Limited flexibility: Railway transport is confined to fixed routes, which prevents door-to-door service.
- Requires more rigorous packaging.
- Risk of cargo theft.
- High initial investment costs for railway infrastructure development.

Road Transportation

Road transport infrastructure includes highways, roadside stations, and vehicles that operate on these roads.

Advantages

- The global road network boasts the highest density among all transport modes.
- High flexibility: The extensive road network and the smaller capacity of individual vehicles allow for adaptable operations, often enabling direct door-to-door delivery from the shipper to the recipient.
- Speed and control over transit times.
- Freight vehicles are relatively low-cost, with the capability to operate on multiple routes and carry diverse cargoes.
- Enhances adaptability in freight transport.

Disadvantages

- Lower transportation capacity.
- Higher per-unit freight costs.
- Elevated risk of cargo theft.
- Issues with road congestion and pollution.

Waterway Transportation

Advantages

- High transport capacity and efficient in fuel and energy consumption.

Disadvantages

- Slow transit times.
- Indirect transportation routes.
- Susceptibility to weather conditions.
- Higher incidence of damage to bulk cargo.
- Long delivery times and challenges in maintaining schedules.
- High loading and unloading costs.
- Waterway transport (particularly inland waterways) is limited by natural waterways, making it difficult to use the most direct routes. The distance between points tends to be greater than with other modes. Moreover, shipping is highly susceptible to adverse weather conditions, such as wind and waves, complicating the assurance of timely deliveries.

Air Transportation

Advantages

- Rapid transport speed.
- Minimal restrictions due to terrain.
- High-quality service with a reputation for safety and reliability.
- Shorter transit times and greater operational flexibility.

Disadvantages

- High transportation costs: Due to the expense of aircraft and substantial fuel consumption, air transport remains the most costly transportation option.
- Limited carrying capacity with restrictions on cargo size and weight.
- Certain goods are prohibited from air transport.
- Highly impacted by weather conditions.

Pipeline Transportation

Pipeline transport has emerged as a novel method over the past few decades. At global gas pumping stations, goods are transported directly via pipelines, eliminating the need for vehicles such as cars and trains. When using pipeline transport, cargo moves through the pipeline under the force generated by a high-pressure pump until it reaches its destination. There are two primary types of pipelines: liquid pipelines (primarily for oil and its products), and gas pipelines (primarily for natural gas) [114].

Advantages

- Pipeline transport is unaffected by surface weather conditions, allowing for 24-hour operation throughout the year, maintaining continuous service for 365 days. Goods do not require packaging; the cargo moves safely within the pipeline, resulting in a very low damage rate. It is energy-efficient, occupies less land, is safe, and produces minimal pollution. The system is also relatively simple to operate and manage, with low operational costs due to the minimal labor required only a few maintenance workers at the gas pump stations are needed.

Disadvantages

- Pipeline transport is limited to the conveyance of liquids, gases, and a few homogenous solid materials. It lacks versatility, being confined to fixed pipelines and only permitting one-way transport. Additionally, the initial construction costs of pipelines are high. Due to these characteristics, pipeline transport has a very specific and limited scope of application.

Chapter 3

Module 1: Cost-Effective Routing in Multimodal Sustainable Logistics Collaboration

3.1 Introduction

In this section, we define a multimodal logistics problem where the paths of different carriers intersect to transport units of goods from a given origin to a destination. The optimization of the route, when a customer needs to ship goods, is based on a set of multimodal routes offered by various carriers. The optimal choice considers several parameters oriented towards cooperative logistics and environmental impact. The scenario applied concerns the first module of the framework, that gathers information on a series of transports carried out by vehicles of different types—trucks, trains, ships, and airplane. These scheduled journeys from an origin to a destination pass through several stages. For each transport, the framework collects information on travel times, the type of transport mode and related vehicle, and the payload capacity that is unoccupied and can be made available for other transports. The purpose of this study is threefold:

1. Verify whether the available payload capacity of already scheduled journeys can be utilized to satisfy a new request to transport goods from an origin to a destination without requiring additional vehicles.
2. Determine the number of transshipments from one vehicle to another necessary to reach the destination.
3. Compute the transport cost, including both direct and indirect costs related to the environmental impact of the defined routes.

Therefore, the overall objective of sustainable logistics is pursued not only by minimizing the number of vehicles on the road—and thus reducing traffic—in multimodal transport networks but also by offering shippers the least polluting mode of transport for their deliveries.

In the proposed approach, we assume that the list of routes offered by various transportation companies and their operative vehicles for each transport mode is known. We then compute the minimum-cost origin-destination paths in a multimodal logistic network model specifically designed for this problem.

3.1.1 Literature Review

By adopting a multimodal approach and fostering sustainable logistics practices, the transportation sector can play a pivotal role in fostering a resilient and sustainable economy [115]. Numerous studies have examined challenges in this area and proposed various solutions. Vosough et al. [116] address the critical issue of road traffic, which is a major source of urban air pollution, through the use of a dynamic traffic network simulator. This simulator models decisions regarding transportation mode, departure times, and route selections to reduce traffic-related pollution. Similarly, Comi and Polimeni [117] explore the potential of short-sea shipping (SSS) as an eco-friendly freight transport alternative that fulfills economic, social, and environmental needs. They propose an evaluation system to analyze the capabilities of SSS, particularly in terms of reducing external costs and promoting a shift from road-based freight transport to more sustainable SSS alternatives. In Ghana, Okyere et al. [118] assess the feasibility of a multimodal freight delivery model that combines road, rail, and waterway modes. Using a genetic algorithm model, they devise an optimal framework aimed at addressing economic, social, and environmental challenges, thereby supporting policymakers in choosing suitable transport options. Zheng et al. [119] focus on the integration of cold chain logistics (CCL) within multimodal transport systems in China, merging land and sea transport modes into a cohesive chain. They employ an enhanced particle swarm optimization (IPSO) algorithm to efficiently select optimal routes for cold chain food (CCF) distribution, concluding that railway transport is preferable to highway options for medium to long-distance shipments. Additionally, Dong et al. [120] illustrate that multimodal distribution offers both environmental and economic benefits, particularly when various industrial stakeholders work collaboratively to achieve economies of scale. This strategy has the potential to alleviate air pollution and reduce road congestion in India by proposing a modal shift that replaces a portion of road transport with roll-on/roll-off (RoRo) vessels. Garrido et al. [121] provide a framework for evaluating different hypothetical transportation scenarios to address logistic performance challenges in Colombia. Their approach includes a balanced linear transshipment (BLT) model that estimates the optimal configuration for a multimodal freight transportation network, taking into account issues such as high truck traffic volumes and the sparse network of active railways. Lin et al. [122] addresses the railway network design problem, which proposes a bi-level programming model to minimize the sum of carbon emissions costs, opportunity costs, transportation costs, and annual investment. The study highlights how railway construction can significantly reduce overall transportation emissions and demonstrates how decision-making is influenced by environmental considerations. Similarly, Truden and Hewitt [123] introduces the Service Network Design Problem with Fleet

and Emissions Management (SNDFEM), which integrates fleet acquisition decisions (diesel, electric, hydrogen) with regional emissions considerations. The study applies a Mixed Integer Programming (MIP) formulation and emphasizes the Well-to-Wheel (WtW) emissions framework, showcasing the potential of novel powertrain technologies in reducing both costs and emissions. On a more granular level, Bektaş and Laporte [124] extends the classical Vehicle Routing Problem (VRP) by incorporating pollution-related factors, formulating the Pollution-Routing Problem (PRP). This approach considers not only travel distance but also greenhouse gas emissions, fuel consumption, travel times, and costs, offering insights into trade-offs between vehicle load, speed, and total cost. The study highlights the complexity of solving PRP optimally while demonstrating its potential for significant environmental and economic savings. The shortest path problem, a fundamental and widely studied optimization challenge in logistics, plays a crucial role in enhancing operational efficiency. In this research, we investigate a variant that integrates temporal constraints, facilitating the coordination of multiple vehicles and incorporating activation costs for selected routes. This approach fits within the category of constrained shortest path problems [125], with specific relevance to the time-constrained shortest path problem [126] and the k-color shortest path problem [127]. Transportation remains a primary application area for shortest-path algorithms due to its significant impact on multiple environmental factors.

3.2 The problem Description

The context for this research focuses on a scenario with multiple carriers who carry out shipments often without using their full cargo capacity. This opens up the possibility for these carriers to share some of their available cargo space, thus optimizing their routes and enhancing efficiency. Carriers can provide information on their planned routes and available cargo space, enabling a more efficient use of capacity and increased profitability. Specifically, when goods are transported from an origin to a destination, the goal is to take advantage of the option of not relying solely on dedicated transport vehicles, but instead making use of the spare cargo space on routes already operated by active carriers. This approach offers three primary benefits: (i) reducing transportation costs, (ii) minimizing environmental pollution, and (iii) maximizing the efficiency of the fleet's assets. Let us consider the set R as repre-

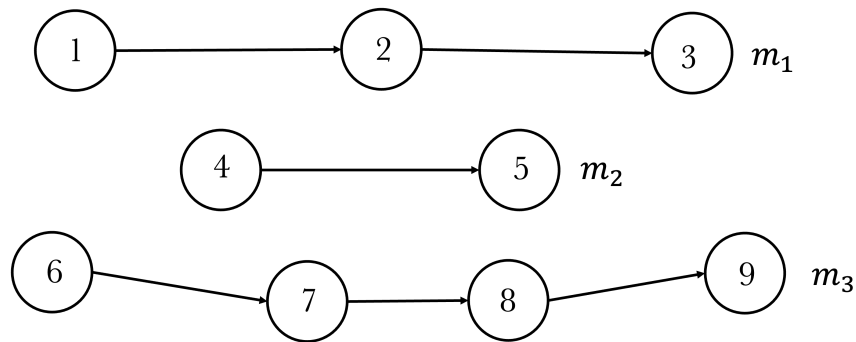


Figure 3.1: An example of a graph R with three different routes.

senting the routes that the carriers need to traverse. This set $R = (R_v, R_e)$ forms a directed graph where R_v represents the collection of nodes, indicating the physical locations included in the routes, and R_e refers to the set of arcs representing the available connections between these locations. Each arc $(i, j) \in R_e$ is linked to a vehicle $k \in M$, indicating that vehicle k travels along the path from node i to node j , denoted as e_{ijk} . The set M includes all the vehicles participating in the delivery schedule. From Figure 3.1, we can see that the paths offered by different carriers always have an initial node (nodes 1, 4, and 6, respectively, in Figure 3.1), a final node (nodes 3, 5, and 9, respectively, in Figure 3.1), and possibly several intermediate nodes that represent the stops made by the carriers before reaching their destination (nodes 2, 7, and 8, respectively, in Figure 3.1). Each arc e_{ijk} has an associated weight tt_{ijk} , which represents the travel time of that segment. Furthermore, each arc must account for several cost factors: emission cost generated by vehicle k (ce_{ijk}), fuel transportation cost (cf_{ijk}), service cost (cs_{ijk}) (which includes handling and maintenance), and the cost of consolidating goods between nodes i and j (cc_{ijk}). A novel issue of this multimodal logistics network is the incorporation of an additional set of arcs labeled D , representing potential detours that can occur between nodes. Figure 3.2 illustrates an example of a multimodal network that includes such detours.

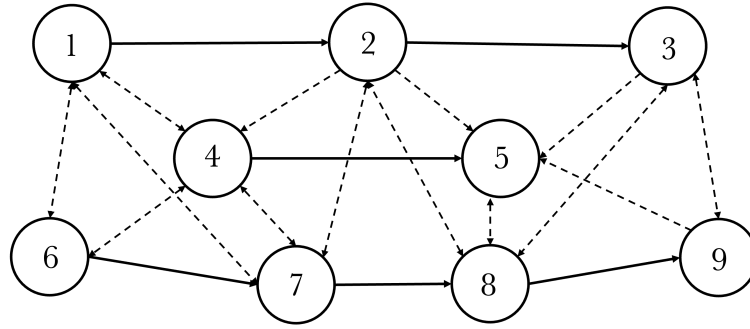


Figure 3.2: Example of a multimodal graph with potential detours in dashed lines.

Definition 1. A detour refers to a deviation from the primary route that a vehicle might undertake to either collect or deliver goods to a location not originally part of its itinerary.

Note that each carrier can specify the level of allowed detour for each route. For example, a truck could be willing to deviate a few kilometres from its route to pick up an item. The maximum number of kilometres within a detour offered for each route is an integral part of the input of the problem and is defined by the carriers providing the routes. The cost per kilometre of the detour is also part of the problem input.

Figure 3.3 presents a multimodal network displaying only the feasible detours. In this example, vehicle m_1 allows a maximum detour of 40 km, vehicle m_2 up to 20 km, and m_3 can deviate up to 50 km. It's noteworthy that there are four edges between nodes 4 and 7, signifying that both vehicles m_2 and m_3 can provide detours between these points. It is also crucial to recognize that not all vehicles are capable of offering detours. The following definition clarifies the concept of admissible detours:

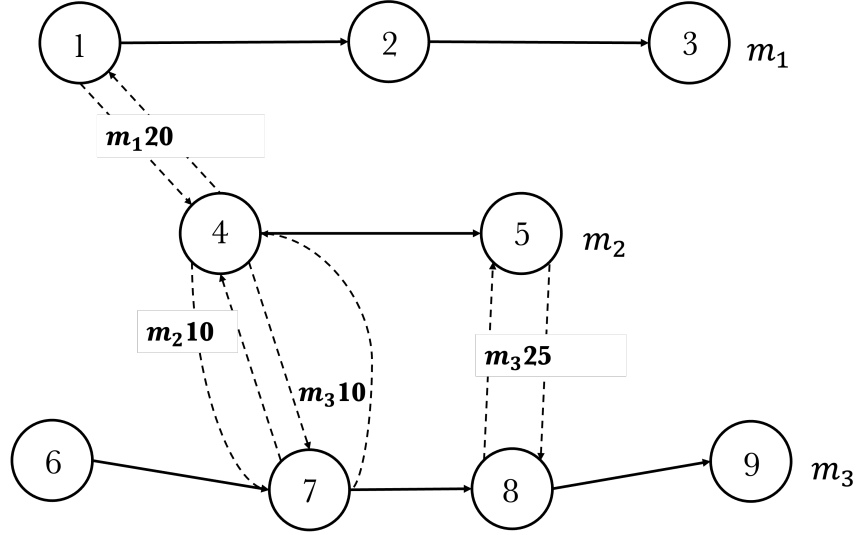


Figure 3.3: Example of a multimodal graph with admissible detours.

Definition 2. Admissible detours are those alternative routes that are offered by carriers who have confirmed their willingness to accept a deviation from their original path, which overall length does not surpass the predefined maximum limit.

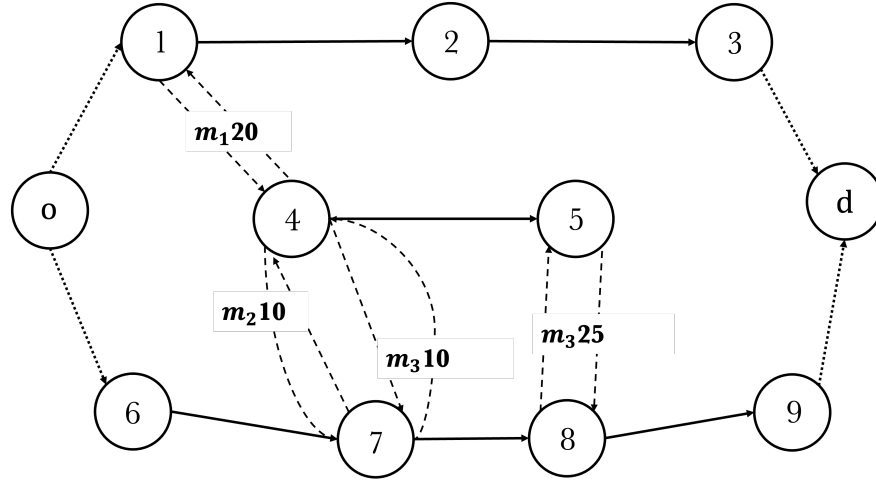


Figure 3.4: Example of a multimodal graph to which origin and destination nodes associated with the customer's transport request have been added

Figure 3.4 depicts the same three routes with admissible detours shown in Figure 3.3, incorporates the nodes o and d , which belong to the set A and represent the origin and destination of a customer's transportation request within the graph R . When determining a multimodal route for a specific shipment request, these nodes (o and d) must be included in the carriers' set of routes. Moreover, two additional subsets of arcs must be added to R . More precisely, let A_{out} be the set of outgoing arcs from node o , indicating that the customer is willing to travel the corresponding distances to deliver the goods to a carrier node. Analogously, let A_{in} be the set of arcs entering the destination node d . The model for this problem is represented by the digraph $G = (V, E, M)$, where $V = (R_v \cup A)$ constitutes the set of nodes

that contains all stops from the carrier routes, the origin of the goods to be shipped and their destination. The set $E = (R_e \cup D \cup A_{out} \cup A_{in})$ includes all the arcs in the graph, and all possible movements of the goods using the vehicles in the set M .

3.3 Mixed-Integer model for path optimization

To represent the main features of multimodal route problems, we must deal with models capable of including all the parameters that can affect the corresponding decision process. Thus, the digraph $G = (V, E, M)$ defined above with the following specifications is considered as the underlying network model. All cost parameters $(ce_{ijk}, cs_{jk}, cf_{ijk}, cc_{ijk})$ are expressed per kilometer.

- V : set of nodes.
- E : set of oriented arcs.
- M : set of vehicles.
- $o \in A$: origin node.
- $d \in A$: destination node.
- q : quantity to be transported.
- $q_k \geq q$: available capacity for each vehicle $k \in M$.
- TC : truck capacity.
- ta : maximum time to arrival at node d .
- tt_{ijk} : travel time for vehicle k to move from node i to j .
- ce_{ijk} : CO_2 emissions cost of vehicle k from node i to j .
- cs_{jk} : service cost of vehicle k .
- cf_{ijk} : fuel transportation cost of vehicle k from node i to j .
- cc_{ijk} : cost of load consolidation of vehicle k from node i to j .
- $t_{ik} \in \mathbb{R}$: departure time of vehicle k from node i , $\forall i \in V$.

Furthermore, we use the multiplier $\delta \in \mathbb{R}$ associated with the cost ce_{ijk} to weight the role played by the emissions cost in the overall cost differently. In fact, throughout the article, we will explore how the variation of δ influences the performance of our approach and analyse the practical implications of this choice in the proposed system design. This problem has been modelled using *MILP*. As a result, the proposed solution will require, in

the worst-case scenario, an exponential amount of time dependent on the input size, the *MILP* being classified as NP-complete problem [128]. Our *MILP* model has the following decision variables:

$$x_{ijk} = \begin{cases} 1, & \text{if vehicle } k \text{ is in the route from } i \text{ to } j \\ 0, & \text{otherwise} \end{cases},$$

$$y_k = \begin{cases} 1, & \text{if vehicle } k \text{ is activated} \\ 0, & \text{otherwise} \end{cases}.$$

As already mentioned, the objective function (*of*) of the problem aims to minimise the following four cost components:

- a. Costs associated with CO_2 emissions. These costs represent the financial impact of carbon dioxide emissions generated during transportation activities. They account for the environmental externalities linked to CO_2 , reflecting the growing emphasis on sustainability and the reduction of greenhouse gas emissions in logistics operations.
- b. Service cost of the used vehicle. This refers to the operational expenses directly associated with the utilization of a specific vehicle for transportation. These costs may include maintenance, depreciation, insurance, and other service-related expenditures required to ensure the vehicle's functionality and reliability during its operation.
- c. Transportation cost. This encompasses the expenses incurred for fuel consumption during transportation. It is a fundamental component of logistics costs and directly influences the overall efficiency of the transport operation, particularly in multimodal systems where fuel costs can vary significantly depending on the mode of transport.
- d. Consolidation cost. This cost applies exclusively to road-based transportation and pertains to the expenses involved in consolidating goods into a single truckload. Consolidation enhances efficiency by optimizing vehicle utilization, reducing the number of trips required, and minimizing empty truck movements, thereby contributing to cost savings and environmental benefits.

Consolidation of the load in transportation involves optimising the available space to transport the maximum amount of goods while avoiding under-utilisation of capacity. To encourage our mathematical model to generate solutions that prioritise load consolidation, we have introduced the concept of *consolidation cost* as a penalty to be applied when the load is not well consolidated. We have defined the function (3.1) to calculate this cost. The cost is associated with each arc used in the solution and can have a maximum value equal to one-tenth of the transportation cost. Specifically, we compute the percentage of unused load capacity, which ranges from zero (when the cargo capacity is filled to 100% capacity)

to one (when a truck travels with an empty load). To consider this percentage, we use the parameter TC , which represents the capacity of the trucks. The parameter is calculated based on the trucks' capacity because load consolidation applies only to trucks. The consolidation cost cc_{ijk} is then computed as a fraction of the transportation cost cf_{ijk} , scaled by the percentage of unused capacity. In particular, the term $\frac{(q_k - q)}{TC} \times \frac{cf_{ijk}}{10}$ acts as a multiplicative factor, ensuring that the penalty increases with higher unused capacity.

$$cc_{ijk} = \frac{(q_k - q)}{TC} \times \frac{cf_{ijk}}{10}. \quad (3.1)$$

Then, the problem can be formulated as follows:

$$MIN \ z = \delta \sum_{(i,j) \in E, k \in M} ce_{ijk} x_{ijk} + \sum_{(i,j) \in E, k \in M} cf_{ijk} x_{ijk} + \sum_{k \in M} cs_k y_k + \sum_{(i,j) \in E, k \in M} cc_{ijk} x_{ijk}, \quad (3.2)$$

subject to the constraints

$$\sum_{(i,j) \in E, k \in M} x_{ijk} - \sum_{(j,i) \in E, k \in M} x_{jik} = 0 \quad \forall j \in R_v, \forall k \in M, \quad (3.3)$$

$$\sum_{(o,j) \in E, k \in M} x_{ojk} = 1, \quad (3.4)$$

$$\sum_{(j,d) \in E, k \in M} x_{jdk} = 1, \quad (3.5)$$

$$x_{ijk} \leq y_k \quad \forall (i, j) \in E, \forall k \in M, \quad (3.6)$$

$$t_{jk} + ta(1 - x_{ijk}) \geq t_{ik} + tt_{ijk} \quad \forall (i, j) \in E, \forall k \in M, \quad (3.7)$$

$$x_{ijk} \in \{0, 1\} \quad \forall (i, j) \in E, \forall k \in M, \quad (3.8)$$

$$y_k \in \{0, 1\} \quad \forall k \in M. \quad (3.9)$$

The objective function (3.2) consists of the four previously defined cost components. The costs associated with CO_2 emissions, these costs refer to the expenses incurred due to the emission of CO_2 during transportation. Service cost of the used vehicle, this cost represents the expenses associated with the use of a specific vehicle for transportation. Transportation cost, this cost includes fuel costs. Consolidation cost, this cost is considered only for the road mode of transportation. It refers to the expenses incurred to consolidate goods into a single truckload for more efficient transportation. Constraint (3.3) ensures that if a vehicle reaches a node j that is not the origin or destination, it must also leave that same node. Constraint (3.4) ensures that exactly one vehicle departs from the origin node o . Constraint (3.5) ensures that exactly one vehicle arrives at the destination node d . Constraint (3.6) allows the use of the arc (i, j) with vehicle k only if vehicle k is active in the solution. Constraint (3.7) is formulated so that if the variable x_{ijk} is equal to zero, the left-hand side of the inequality takes a value greater than the arrival time at the destination, thus always satisfying the constraint. However, when the arc (i, j) is traversed by vehicle k and the

corresponding x_{ijk} is active, in order to satisfy the constraint, the departure time from node j must be greater than the departure time from node i plus the corresponding travel time. Finally, in (3.8) and (3.9), the decision variables are defined.

3.4 Computational Experiment

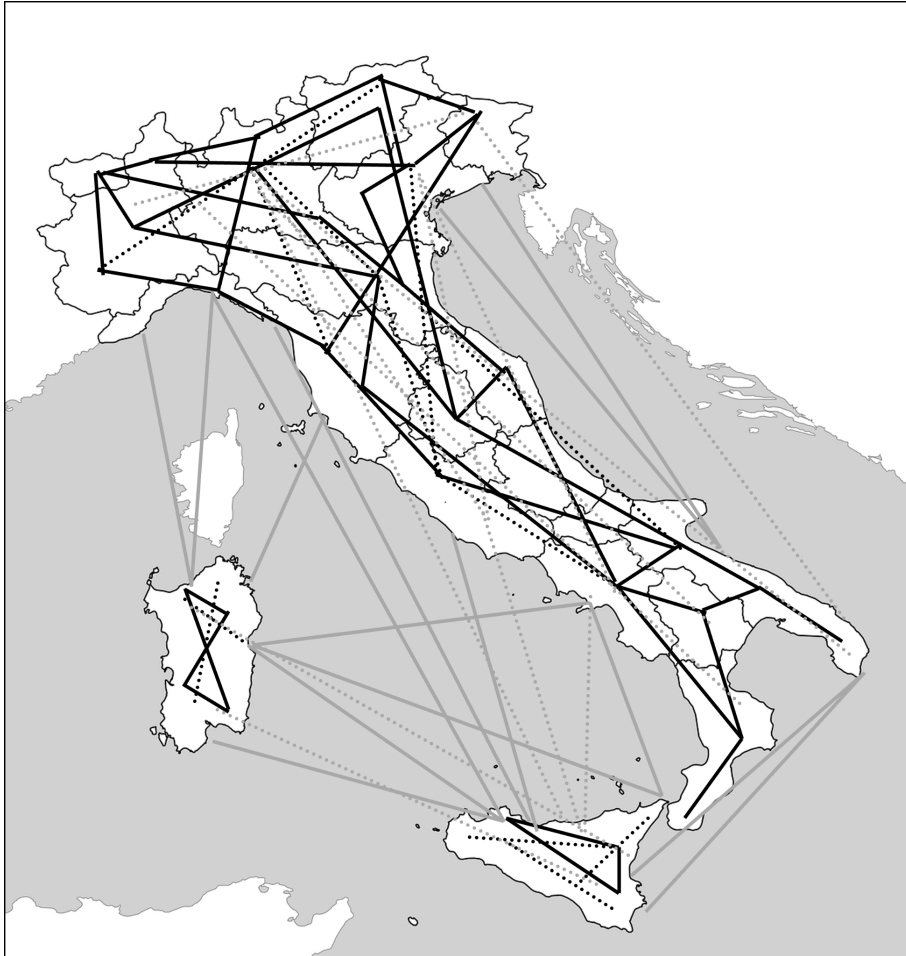
This section presents the experimental findings from the conducted tests. We begin by detailing the process used to generate the test instances and how the corresponding costs were established. Following this, we will present the experimental outcomes along with a comprehensive analysis. The code was developed in Java, and the mathematical models were solved using the CPLEX solver, version 20.1.0. The primary focus of these tests was not to evaluate the performance of the mathematical model itself, but rather to investigate the problem to assess whether a multimodal approach utilizing the available load capacity of traveling vehicles offers tangible benefits in a practical context. To accomplish this, we created realistic scenarios and conducted experiments by varying the key generation parameters. We did not conduct tests related to the computational performance of the model, as our problem is based on identifying a single multimodal route, and for this problem, the integer linear programming model did not require more than ten seconds to produce the optimal solution for any of the 648 instances.

3.4.1 Test Scenarios

This subsection outlines the process used to generate the 648 test instances applied in this study. The experiments were carried out by adjusting the parameter δ and either including or excluding the consolidation cost, resulting in a total of 3,240 computational experiments. Initially, 18 different multimodal example graphs were developed. The generation of these graphs involved the systematic variation of three key parameters: the total number of routes offered by the carriers, the percentage distribution of different vehicle types (truck, train, plane, and ship) and three different random seeds. Comprehensive details of the test instances are summarized in Table 3.1, where the column headings are defined as follows: **Vehicles** represents four values indicating the percentage distribution of routes offered by the carriers for trucks (**Trk**), trains (**Trn**), airplanes (**Pln**), and ships (**Shp**); **R** denotes the total number of routes offered; and **# Routes** specifies the number of routes generated for each vehicle type. The route generation was implemented realistically across all provinces in the Italian territory. Each of the 107 Italian provinces used the city center as the starting point for route generation. The **R** routes were established between randomly selected pairs of provinces, with the type of vehicle assigned according to the probability distribution specified in the **Vehicles** parameter. To ensure accurate vehicle compatibility, a search was performed for each Italian province to identify the presence of a railway station, airport, and seaport, allowing the generation of routes only when both provinces could accommodate the same type of vehicle. The resulting multimodal routes are illustrated in Figure 3.5. The

Table 3.1: Input parameters of the test instances.

Vehicles	R	# Routes			
		Trk	Trn	Pln	Shp
25-25-25-25	200	50	50	50	50
	300	75	75	75	75
50-20-15-15	200	100	40	30	30
	300	150	60	45	45
70-10-10-10	200	140	20	20	20
	300	210	30	30	30

**Figure 3.5:** Set of routes offered by carriers.

routes are differentiated by the type of line, with solid black lines representing truck routes, dotted black lines representing rail routes, dotted grey lines representing air routes, and solid grey lines representing sea routes. Additionally, the algorithm was implemented to prevent land vehicles from connecting provinces located on the islands of Sardinia and Sicily. As can be observed in Figure 3.5, only sea routes (solid grey lines) and air routes (dotted grey lines) connect the islands with the rest of the Italian peninsula. In these graphs, only trucks are allowed to take detours, and the detour distance for each truck varies randomly within the range of 20–80 km. For each of the 18 multimodal scenarios outlined in Table 3.1, a total of 36 instances were generated, resulting in 648 test cases in total. Each instance varies in terms of the number of items q shipped (**Items**), the selected origin-destination routes (see Figure 3.6), and the shipping radius, as detailed in Table 3.2. The shipping radius (**RaDis**) refers to the maximum radial distance that the customer who needs to ship their goods is willing to travel. The tests were carried out considering three different requests with the following origin and destination cities: Reggio Calabria to Terni (**RC-TR**), Roma to Bolzano (**RM-BZ**), and Taranto to Torino (**TA-TO**). We selected these three requests to represent different Italian regions, allowing us to assess the model’s performance across various geographical contexts. As shown in Table 3.2, variations in the generation parameters (Items, RaDis) can cause some instances to be infeasible. This occurs when it is impossible to establish a multimodal connection between the origin and destination, either because the available vehicles lack sufficient space to transport the required items (Items) or because no suitable multimodal path reaches the destination. Specifically, it becomes apparent that as the quantity of items to be transported increases, the number of available multimodal routes decreases due to the limited residual capacity of certain transportation modes, which leads to an increase in the number of infeasible solutions. Similarly, when the customer’s delivery radius (RaDis) is set to 0, feasibility is significantly constrained. In this case, the optimal route can only utilize carriers that either pass directly through the shipment’s origin or allow for a detour to pick up the items. If no such carriers exist, the instance becomes infeasible. Otherwise, feasibility depends on whether the permitted detour by the carrier allows for a valid connection. Naturally, the detour permitted by the carrier influences the objective function, leading to significantly higher costs in feasible cases. Conversely, as RaDis expands, a greater number of routes become accessible, including those further from the demand origin, resulting in an increased number of feasible solutions.

The costs applied in our experiments were obtained through a small market survey conducted with a group of small transport operators working in Italy. These operators provided cost estimates, noting that costs could fluctuate considerably as the number of requests increased. For each transportation mode, both a cost per kilometer (transport cost) and a cost per usage (service cost) were considered. The service cost encompasses expenses related to the loading and unloading of goods, as well as any potential reorganization of cargo. These costs are summarized in Table 3.3. Naturally, the costs vary based on factors such as the type of vehicle used, the load being transported, and the technology implemented. It’s worth mentioning that these figures represent average values, and the actual costs may differ sig-

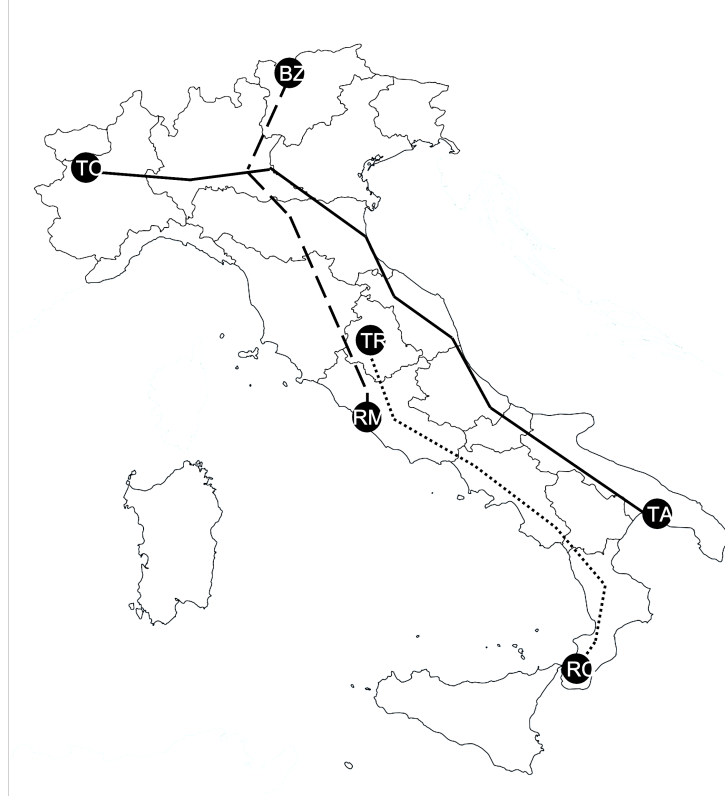


Figure 3.6: The routes Reggio Calabria-Terni, Roma-Bolzano, and Taranto-Torino are represented by dotted, dashed, and solid lines, respectively

nificantly depending on the vehicle specifications and operational conditions. Additionally, the conversion of CO_2 emissions into euros is influenced by the carbon emission value set by the European Union Emissions Trading System, as indicated in [129]. The consolidation cost, on the other hand, was determined using equation (3.1), with the truck capacity set at $TC = 24$. Throughout the study, the pallet was chosen as the load unit. For this load unit, it was decided to calculate the consolidation cost only for trucks, as shipments of a few pallets would not significantly impact ships, airplanes, or trains considering their high carrying capacity. However, for trucks, the goal is to maximise their load capacity. Formula (3.1) calculates the ratio between the remaining space in the truck after loading the goods and the total capacity of the truck. This ratio is then multiplied by one-tenth of the transportation cost.

3.4.2 Evaluation of Results and Effectiveness

This subsection presents the outcomes of the analysis of the proposed multimodal transportation framework. The focus of our evaluation was on assessing the system's performance in relation to cost, environmental impact, and efficiency. The findings offer valuable insights into how various mode combinations can effectively meet transportation demands, highlighting the most advantageous options for reducing costs, lowering carbon emissions, and enhancing overall performance. Table 3.4 outlines the average costs related to the objective

Table 3.2: Number of feasible solutions grouped by Items, *RaDis*, and Origin-Destination.

Items	RaDis	RC-TR	RM-BZ	TA-TO
1	0	6	11	6
	10	14	17	14
	50	14	18	18
	100	18	18	18
2	0	6	8	6
	10	7	16	13
	50	7	16	18
	100	18	18	18
4	0	6	8	8
	10	5	16	11
	50	5	16	17
	100	18	18	18

Table 3.3: Costs per item.

	Emissions cost (€/km)	Transport cost (€/km)	Service cost (€)
Truck	0.00165	0.5	50
Train	0.00066	0.1	75
Plane	0.00495	0	300
Ship	0.00011	0.1	100

function for each of the scenarios described in Table 3.1. In these scenarios, both the number of items to be shipped and the maximum delivery radius the customer is willing to accept for carrier delivery have been varied. A clear observation is that when the customer's delivery radius (*RaDis*) is set to 0, the costs are significantly higher. This is due to the fact that, in this case, the optimal route can only utilize carriers that either pass directly through the shipment's origin or allow for a detour to pick up the items. Naturally, the detour permitted by the carrier influences the objective function. On the other hand, when *RaDis* is set to 100 km, we observe a considerable reduction in costs across all routes and for all quantities of shipped items. This occurs because, with a larger delivery radius, customers have access to a wider selection of carriers, allowing them to choose the most cost-efficient option. Notably, in the case of a shipment from Reggio Calabria to Terni, increasing *RaDis* to 100 km resulted in savings of over 57%. It is also important to note that costs rise proportionally with the number of items to be shipped. These findings underscore the significant influence that *RaDis* has on overall shipping costs. Since the *RaDis* parameter is directly determined

Table 3.4: The average value of the objective function for the proposed scenarios.

Items	RaDis	RC-TR	RM-BZ	TA-TO
1	0	622.28	547.09	628.28
	10	539.31	454.49	679.13
	50	515.57	437.57	503.26
	100	270.68	242.53	361.47
2	0	1,225.97	940.34	1239.62
	10	1,036.98	904.65	1,341.74
	50	1,024.57	829.71	1,072.65
	100	683.26	482.18	861.36
4	0	2,348.30	2,009.91	2,584.75
	10	1,898.41	1,798.48	2,549.66
	50	1,864.05	1,727.35	2,103.56
	100	1,396.25	959.63	1,717.85

Table 3.5: Average values of the objective function components for the route Reggio Calabria-Terni.

Items	RaDis	Emi	Serv	Tra	Con
1	0	1.28	191.67	413.69	15.65
	10	2.53	310.71	219.30	6.76
	50	2.32	298.21	208.86	6.17
	100	1.06	181.94	87.19	0.49
2	0	1.28	383.33	827.37	13.99
	10	1.12	378,57	649.66	7.62
	50	1.10	378,57	637.48	7.42
	100	0.47	327.78	351.13	3.88
4	0	1.55	400.00	1,928.85	17.91
	10	1.34	460.00	1,430.63	6.44
	50	1.32	460.00	1,396.51	6.22
	100	0.51	666.67	724.77	4.31

by the customer requesting transportation, it is crucial to inform them about the impact of this choice when implementing a multimodal logistics system. While the number of items to be shipped also significantly affects costs, this parameter is a fixed input to the problem and cannot be modified. The details of the individual cost components of the objective function are presented in Tables 3.5, 3.6, and 3.7, respectively, for the Reggio Calabria-Terni, Roma-Bolzano, and Taranto-Torino routes.

Table 3.6: Average values of the objective function components for the route Roma-Bolzano.

Items	RaDis	Emi	Serv	Tra	Con
1	0	1.09	150.00	385.33	10.67
	10	0.82	198.53	249.05	6.09
	50	0.80	187.50	244.80	4.47
	100	0.65	98.61	178.13	4.55
2	0	0.97	275.00	655.47	8.91
	10	0.85	368.75	527.49	7.56
	50	0.77	331.25	491.47	6.22
	100	0.51	258.33	221.39	1.96
4	0	1.04	575.00	1,424.08	9.79
	10	0.87	737.50	1,053.63	6.49
	50	0.83	687.50	1,032.91	6.11
	100	0.56	466.67	490.42	1.99

Analysis of the results in Table 3.5 reveals notable cost variations in different scenarios for the Reggio Calabria-Terni route. The table presents the individual components of the objective function: Emissions, Service, Transportation, and Consolidation. All values are averages across the 18 test scenarios. These variations emphasize the importance of considering factors such as the number of items shipped and the maximum delivery radius customers are willing to accept. In general, as the number of shipped items increases, there is a gradual reduction in emissions costs (**Emi**). This can be explained by the possibility of consolidating goods, which leads to more efficient and environmentally sustainable transportation. The service cost (**Serv**) shown in Table 3.6 shows that a moderate increase in the *RaDis* parameter does not lead to a noticeable reduction in this cost. However, a substantial increase in *RaDis* to 100 km results in a significant reduction in service costs, by approximately 20%. On the other hand, the consolidation cost (**Con**) shown in Table 3.5 and Table 3.6, decreases progressively as the parameter *RaDis* increases. For example, in Table 3.6, when sending a single item with *RaDis* equal to 10, 50, and 100, compared to *RaDis* equal to 0, we observe reductions in the consolidation cost (*Con*) of 34%, 57%, and 80%. The behaviour of the consolidation cost with increasing *RaDis* shows a slightly different pattern in Table 3.7. A reduction in the consolidation cost is observed for *RaDis*

Table 3.7: Average values of the objective function components for the route Taranto-Torino.

Items	RaDis	Emi	Serv	Tra	Con
1	0	1.38	150.00	462.47	15.14
	10	1.41	228.57	432.94	16.21
	50	1.53	237.50	256.41	7.82
	100	1.59	231.94	126.24	1.69
2	0	1.38	300.00	924.93	13.31
	10	1.39	473.08	850.68	16.60
	50	0.96	438.89	624.83	7.98
	100	0.73	416.67	440.49	3.47
4	0	1.55	625.00	1,943.52	14.68
	10	1.35	827.27	1,705.89	15.15
	50	0.97	847.06	1,249.32	6.20
	100	0.76	805.56	907.82	3.71

values exceeding 10 km. However, a moderate increase in costs occurs when transitioning from a *RaDis* of 0 to 10 km. This can be primarily attributed to the presence of the port and the Taranto train station. At *RaDis* = 0, the initial use of ships or trains is highly favored, which leads to a reduction in the consolidation cost, as these modes of transport do not incur consolidation-related expenses. Table 3.8 shows the average distance traveled by each vehicle type, grouping instances based on the average types of vehicles present in the scenario.

Table 3.8: Average kilometres travelled for each type of vehicle in different scenarios.

Vehicles	Trk	Trn	Pln	Ship	Total
25-25-25-25	345.67	248.95	69.31	292.38	956.31
50-20-15-15	393.93	384.07	41.24	128.93	948.17
70-10-10-10	380.35	370.82	39.81	124.48	915.47

Considering a uniform distribution of vehicle types (25-25-25-25), with an equal number of routes for each type, it becomes immediately clear that road vehicles are the most frequently used mode of transport. This observation holds true across other scenarios as well. In the 50-20-15-15 scenario, where the number of truck routes doubles (a 100% increase), there is only a 14% rise in the kilometres travelled by road vehicles. Similarly, in the 70-10-10-10 scenario, despite a 180% increase in truck routes, the distance travelled by trucks only rises by 10%. Consequently, the increase in available truck routes leads to a decrease in the kilometres covered by other transportation modes. A wider range of truck routes enables

more direct paths to be identified, which reduces the total mileage and lessens the need for additional vehicles.

Table 3.9: Average costs grouped based on the percentage of transportation modes per vehicle type.

Vehicles	Obj	Emi	Serv	Tra	Con
25-25-25-25	1,027.67	1.05	454.13	566.64	5.84
50-20-15-15	1,037.59	1.08	390.63	638.51	7.38
70-10-10-10	1,001.81	1.04	377.16	616.49	7.12

Tables 3.9, 3.10, and 3.11 show the average cost values associated with the solution and its components, with the 648 instances grouped differently in each table. Specifically, Table 3.9 groups the instances based on the distribution of vehicle types. In Table 3.10, the grouping is done according to the number of items being transported, while Table 3.11 groups the data based on the *RaDis* values. Analysing Table 3.9, it is noteworthy that as the percentage of truck-operated routes rises from 25% to 50%, there is a slight increase in both the objective function and the emissions cost. However, when the proportion of truck-operated routes reaches 70%, both the total solution cost and the emissions cost decrease significantly. Table 3.10 provides valuable insight into the influence of the number of items transported on the final cost of the solutions. As expected, the overall cost increases with a higher number of items, yet emissions either remain constant or show only a slight increase. Table 3.11 confirms that as the value of *RaDis* increases, the average cost of the solutions drops significantly. This suggests that if the customer needing to ship their items is willing to travel further, they can access more competitive and cost-effective transport options.

Table 3.10: Average costs grouped by the number of transported items.

Items	Obj	Emi	Serv	Tra	Con
1	454.69	1.33	210.61	236.28	6.47
2	912.12	0.87	363.58	540.47	7.20
4	1,802.78	0.92	669.86	1125.01	6.99

Table 3.11: Average costs grouped by the parameter *RaDis*.

RaDis	Obj	Emi	Serv	Tra	Con
0	1333.68	1.26	338.46	981.03	12.93
10	1152.87	1.27	432.08	709.63	9.89
50	1059.12	1.15	429.26	622.22	6.49
100	775.02	0.74	387.19	384.46	2.63

Table 3.12: Average kilometres travelled by each type of vehicle, grouped by the parameter *RaDis*.

RaDis	Trk	Trn	Pln	Ship	Total
0	714.61	110.91	0	26.15	851.67
10	465.97	412.52	51.01	35.55	965.06
50	386.33	302.43	65.26	210.66	964.68
100	168.65	418.67	52.32	293.58	933.22

Table 3.12 presents the average kilometres travelled per instance for different modes of transportation, varying the parameter *RaDis*. This table is crucial, mainly when analysed together with Table 3.11. As *RaDis* increases, the cost of the solution decreases significantly, but at the same time the kilometres travelled do not decrease significantly. This is because, with a wider search radius to select the initial mode of transportation, the choice is often made to use ships, trains, or planes. The increase in kilometres travelled by ship or train justifies the reduction in costs, particularly in terms of associated emissions. As illustrated in Figure 3.7a, with the increase in *RaDis*, more cost-effective transportation modes than trucks can be selected. It is also noteworthy that when *RaDis* = 100 km, trains and ships are preferred over planes. Table 3.13 presents the results in which the multiplier δ associated with emission costs was adjusted to evaluate its impact on the choice of transportation modes. As defined in Section 3, $\delta \in \mathbb{R}$ is introduced as a multiplier for the cost ce_{ijk} . As previously mentioned, δ is used to vary the weight of emission costs within the overall analysis. In practice, the parameter δ allows for modulation of the relative importance of emission costs compared to other components of the objective function. A higher δ value increases the emphasis on emissions costs, whereas a lower value reduces their influence. This weighting mechanism offers flexibility in configuring the model, enabling more tailored customization based on the specific needs of the application or context. The values of δ considered were 1, 50, 100, and 150. Given that the emission costs used in this study were derived from [130], applying the parameter δ to amplify the impact of emission costs is highly valuable for exploring the possibility of more sustainable solutions to the problem. The results, reported in Table 3.13, demonstrate that as δ increases, the model shifts away from the use of trucks and planes, favoring trains and ships instead. Specifically, the average kilometres travelled by trucks (**Trk**) decrease as δ rises. The graph in Figure 3.7b illustrates that the average kilometres travelled by trains (**Trn**) remain relatively stable or show a slight increase. Additionally, the use of planes (**Pln**) decreases significantly, while the use of ships (**Ship**) increases substantially. These results suggest that the rise in emissions costs influences the selection of transportation modes, with a stronger preference for more sustainable options like trains and ships. This highlights the importance of factoring in emissions costs when optimizing transportation routes to reduce the overall environmental impact.

To assess the impact of consolidation costs on the solution, we conducted tests on the 648 instances, setting the consolidation cost to zero. Table 3.14 presents the results by

Table 3.13: Total kilometres travelled with different types of transportation as the δ parameter is varied.

δ	Trk	Trn	Pln	Ship
1	375	220	71	302
50	371	228	45	314
100	363	224	45	332
150	355	224	40	342

comparing scenarios with and without the consolidation cost. We focused on two specific parameters: **Load90**, which indicates the number of transports using trucks loaded to at least 90% of their capacity, and **Fullness**, which represents the average truck occupancy. Table 3.14 shows the computational results obtained by varying the parameters (Vehicles, RaDis, Items). In particular, three scenarios for Vehicles, four scenarios related to *RaDis*, and three scenarios associated with the number of items transported were considered. As shown, the number of trips with trucks filled to at least 90% capacity increases from seven, when the consolidation cost is not applied, to 20 when it is considered, effectively tripling this type of route. In the same cases, the fill percentage increases from 58% to 63%, reflecting a 5% improvement in load occupancy. Additionally, it is noteworthy that the fullness rises from 59% to 67% as the *RaDis* parameter increases, indicating that when customers are willing to travel longer distances to choose optimal starting points, the consolidation of transports can be significantly enhanced.

Table 3.14: Impact of consolidation cost on vehicle occupancy.

		With Consolidation Cost		Without Consolidation Cost	
		Load90	Fullness	Load90	Fullness
Vehicles	25-25-25-25	4	64%	4	61%
	50-20-15-15	8	62%	1	59%
	70-10-10-10	8	62%	2	55%
RaDis	0	0	59%	0	57%
	10	2	59%	0	57%
	50	8	65%	1	59%
	100	10	67%	6	60%
Items	1	15	64%	5	59%
	2	4	62%	1	56%
	4	1	62%	1	60%

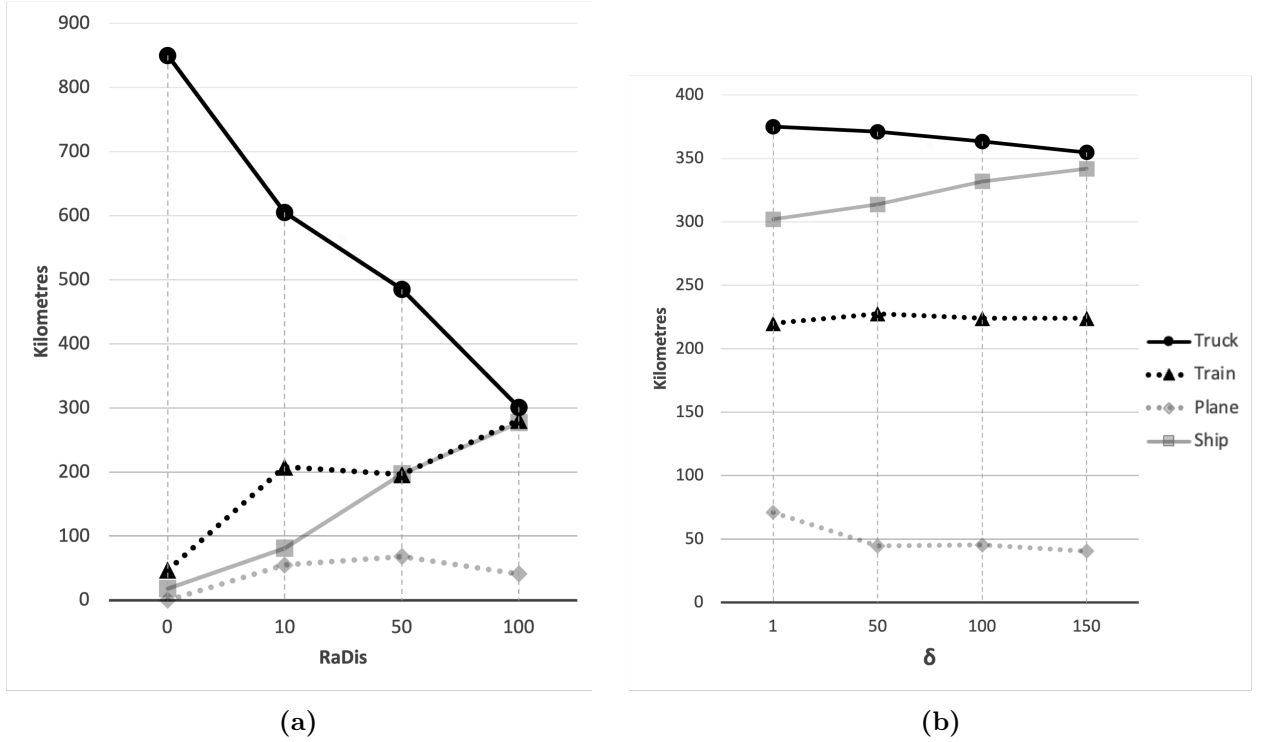


Figure 3.7: For each type of transportation, a line shows the average kilometres travelled as the considered parameter increases: 3.7a based on $RaDis$, and 3.7b based on the emission cost.

3.4.3 Insights

The results from the first module highlight the effectiveness of the proposed MILP framework in optimizing multimodal transport routes by balancing cost efficiency and environmental sustainability. This module, implemented as a Java component within a larger scalable and modular framework, demonstrates its capability to integrate various transportation modes while addressing cost and environmental constraints. Key findings include the significant impact of collaborative logistic practices, the role of consolidation in reducing road kilometers and emissions, and the strategic shift toward greener transport modes when prioritizing environmental costs. These insights underline the framework's potential to enhance logistics resilience and sustainability. A more detailed discussion and analysis of these results are presented in Chapter 6.

Chapter 4

Module 2: Optimize Pickup-Delivery Station Locations to Minimize Emissions in Urban Distribution

4.1 Introduction

This chapter addresses a critical problem in the context of last-mile logistics, where sustainable urban distribution solutions are increasingly necessary. As online shopping continues to grow, the environmental impact of last-mile deliveries must be reduced by minimizing the use of polluting vehicles in urban areas. To achieve this, the strategic use of Pick-up and Delivery Points (*pds*) is proposed as an alternative to traditional door-to-door deliveries. The second module of our modular platform addresses a distinct challenge in supply chain management. Using *pds*, carriers can deliver goods to centralized locations, significantly reducing the need for individual home deliveries. This approach not only improves logistic efficiency, but also supports sustainable urban mobility by encouraging customers to access *pds* via walking, cycling, or using electric scooters. The objective of the module is twofold: to minimize the number of active *pds* that cover the majority of customers and to reduce the total travel and emission costs across the urban network. For customers who cannot access *pds* efficiently, direct home delivery remains an option, ensuring service inclusivity. Furthermore, the module integrates the optimization of *pds* locations and delivery routes, enabling the assessment of incentive policies or discounts to promote *pds* pickup, as will be elaborated in subsequent sections. By presenting this module, we explore a last-mile logistics approach that aligns with the growing demand for sustainable and customer-centric e-commerce solutions.

4.1.1 Literature Review

Minimizing costs is a key objective in distribution logistics, prompting extensive research on strategies that help businesses reduce delivery expenses while also mitigating environmental

impact [131], [132]. In recent years, growing awareness of the social and environmental consequences of urban freight distribution has led to an increasing focus on sustainable urban mobility solutions, particularly within the smart city framework. One critical aspect of sustainable logistics is the optimization of last-mile deliveries, where several factors—such as depot location, fleet composition, and routing decisions—significantly influence emissions. Koc et al. [133] investigated the combined impact of these factors, employing an Adaptive Large Neighborhood Search (ALNS) metaheuristic to solve instances involving up to 100 customers. Their findings indicate that while circuitous routes may appear inefficient, they can actually result in higher travel speeds, lower costs, and reduced CO_2 emissions. Several studies have proposed advanced metaheuristic algorithms to tackle the challenges of sustainable logistics. Zhalechian et al. [134] introduced a multi-objective Mixed-Integer Nonlinear Programming (MINLP) model for a closed-loop Location-Inventory-Routing Problem (LIRP), incorporating stochastic and possibilistic approaches to manage uncertainty. To efficiently handle large problem instances, they developed a hybrid self-adaptive Genetic Algorithm (GA) combined with a Variable Neighborhood Search (VNS) algorithm. Similarly, Karakostas et al. [135] focused on a Pollution Location-Inventory-Routing Problem (PLIRP) and proposed a Basic VNS (BVNS) algorithm, which proved effective for solving medium-sized instances. This problem was further explored in an NP-hard combinatorial optimization study, where General Variable Neighborhood Search-based metaheuristics demonstrated their efficiency in handling larger-scale scenarios. The proposed approaches were tested on 30 newly generated instances, highlighting their ability to achieve high-quality solutions with minimal computational effort. Consumer behavior plays a significant role in the development of sustainable distribution strategies. Tilk et al. [136] introduced a Vehicle Routing Problem with Delivery Options (VRP-DO), where customers specify preferred delivery methods. Their model aims to minimize routing costs while adhering to constraints such as delivery time windows, vehicle capacity, and minimum service levels. In a related study, Grabenschweiger et al. [137] explored consumer satisfaction by integrating heterogeneous locker stations into the vehicle routing process. Their model seeks to minimize both travel costs and compensation costs, incentivizing customers to use locker stations for parcel collection. Furthermore, Jiang et al. [138] examined cost and emission reductions in a Traveling Salesman Problem (TSP) with pickup costs, linked to consumers' willingness to use Collection and Delivery Points (CDPs). Their results suggest that in areas where locker systems are widely accepted, carbon emissions can be reduced by up to 51.2%. Unlike these works, which mainly rely on metaheuristic approaches to address sustainable logistics challenges, our work introduces a solution method based on a Mixed Integer Linear Programming model. In addition to optimizing routing and facility location decisions, we explicitly account for customer accessibility by assigning them to pickup-delivery stations based on sustainable travel options, such as walking or cycling. Furthermore, our research includes a real-world case study in Genoa, demonstrating the practical applicability of the proposed approach to urban logistics.

4.2 Problem Definition

This research addresses a variant of the classic multi-facility location-routing problem, focusing on optimizing urban logistics through the integration of pickup and delivery points (*pds*) within a city network. Specifically, customers must visit a node $p \in P$ to collect the goods they ordered. The primary objective is to determine the number and subset of *pds* to activate from the set P , in such a way as to minimize overall costs, which include both travel and emission costs. In this context, different means of transport (e.g., walking, bicycles, electric vehicles) and the fixed costs associated with operating each *pds* are taken into account. A customer $q_i \in C$ is assigned to pick-up and delivery points $p_j \in P$ based on minimizing their sustainable travel cost, provided the distance between them does not exceed a predefined threshold. The model dynamically decides the assignment of customers to either a *pds* or direct home delivery, based on cost considerations. Specifically, the customer set is divided into two subsets Q and Q' , such that $C = Q \cup Q'$. This partitioning is not pre-determined, but decided by the optimization model, based on delivery costs and distance constraints. The binary variable x_{iw} determines whether a customer q_i is served directly by the warehouse ($x_{iw} = 1$) or by a *pds* ($x_{iw} = 0$). A similar approach is explored by Bonomi et al., (2022) [139], although their work addresses a *Vehicle Routing Problem (VRP)* with unlimited locker capacity in a directed graph, differing in both problem constraints and objective function. To solve the problem, we propose a *MILP* model, which clusters customers in set Q based on their proximity to *pds*. For an efficient computational solution, the *MILP* model is embedded within a branching algorithm. This algorithm partitions the solution space according to how sets Q and Q' are defined. The cost of serving customers outside the *pds* network is estimated by solving a *Travelling Salesman Problem (TSP)* that originates from and returns to the central warehouse. Depending on the number and distribution of these customers, the company must decide whether a single delivery route or multiple routes, solved as a VRP, would be more efficient given the available fleet. This decision is part of the optimization process and is not determined as a post-processing step. Figure 4.1 illustrates a possible solution to the location-routing problem. Two delivery circuits can be seen: one, representing home deliveries, directly serves customers from the warehouse; the other, representing the *pds* network, allows customers to collect their goods using sustainable transportation methods. Non-selected *pds* are shown as isolated nodes.

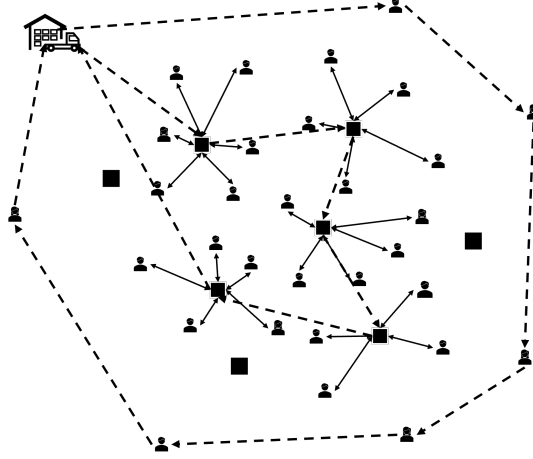


Figure 4.1: An example solution to the location-routing problem.

The proposed solution framework highlights the strategic value of optimizing the number and location of *pds* to maximize sustainable urban mobility. Once the transportation modes for both *pds* replenishment and direct customer deliveries are decided, the same approach can be adopted to solve a more comprehensive VRP, replacing the two separate circuits currently presented.

4.3 The Proposed Partitioning Approach

To find the solution to the present *pds* location-delivering problem that minimizes the total cost, given by the travelling and emission cost components, we propose an approach consisting of a *MILP* model presented in Section 4.3.1, and successive partitioning criteria described in Section 4.3.2. First, the required notation is here below reported.

- w is a node representing the warehouse from which all delivering routes depart.
- C is a finite set of customers.
- $\hat{Q} = C \cup \{w\}$ is a finite set of customer plus the warehouse.
- P is a finite set of *pds*.
- $P' \subseteq P$ is the subset of activated *pds*.
- $\hat{P} = P \cup \{w\}$ is a finite set of *pds* plus the warehouse.
- $r_j \geq 0$ is the capacity of p_j , $\forall j \in P$ defined as the maximum number of customers it can serve.
- $a_j \geq 0$ is the activation cost of p_j , $\forall j \in P$.
- D is the maximum distance that a user is willing to travel by nonpolluting means (e.g., on foot or bikes).

- f is the fuel cost per km.
- e is the air pollution emission per km.
- d_{ij} is the distance to customer i from pds j .
- d_{il} is the distance to customer i from customer l .
- d_{jk} is the distance to pds j from pds k .
- $c_{ij} = e \cdot 2d_{ij}$ is the air pollution cost of q_i from p_j , $\forall i \in C, \forall j \in P$.
- $c_{il} = d_{il} \cdot f \cdot e$ is the service cost of q_i from q_l , $\forall i, l \in Q$.
- $c_{jk} = d_{jk} \cdot f \cdot e$ is the service cost of p_j from p_k , $\forall j, k \in \hat{P}$.

All parameters are given by the benchmark problem instances. The mathematical programming formulation of the problem requires the following 4 decision variables, defined as:

$$\begin{aligned}
 x_{ij} &= \begin{cases} 1 & \text{if customer } q_i \in C \text{ is served by } p_j \in P \\ 0 & \text{otherwise;} \end{cases} \\
 y_j &= \begin{cases} 1 & \text{if } p_j \in P \text{ is activated} \\ 0 & \text{otherwise;} \end{cases} \\
 t_{il} &= \begin{cases} 1 & \text{if the path from } q_i \in \hat{Q} \text{ to } q_l \in \hat{Q} \text{ is selected} \\ 0 & \text{otherwise;} \end{cases} \\
 s_{jk} &= \begin{cases} 1 & \text{if the path from } p_j \in \hat{P} \text{ to } p_k \in \hat{P} \text{ is selected} \\ 0 & \text{otherwise;} \end{cases}
 \end{aligned}$$

u_i = continuous variable representing the position of node q_i in the tour, $\forall i \in \hat{Q}$.

u_j = continuous variable representing the position of node p_j in the tour, $\forall j \in \hat{P}$.

4.3.1 The Proposed MILP Model

The objective function of the model aims to minimize the overall distribution costs within an urban distribution network. In particular, it consists of the following 4 cost components (Equation (4.1)):

- a. pollutant emission from customers to pds,
- b. activation cost of the selected pds,
- c. cost of the distance traveled to serve customers not served by pds,
- d. and total distance traveled to supply the activated pds.

It is worth noting that in the computational tests that we present in Section 4.4, component (a) of the objective function (4.1) will have a zero contribution, setting the pollutant emission produced by customers walking or cycling to their reference *pds* at 0. In one experiment, however, this component will be taken into account by including the same pollutant coefficient as the vehicles used by the distribution company to supply *pds* and non-*pds* users. In the latter case, the relative cost can be seen as a "saving" value on the total cost of supply, which can then be taken into account as an incentive for customers to go directly to *pds* instead of opting for home delivery. This possible saving and its computation will be analysed in Section 4.4. Then, the proposed model for solving the problem under consideration is as follows:

$$MIN z = \sum_{q_i \in C} \sum_{p_j \in P} c_{ij} x_{ij} + \sum_{p_j \in P} a_j y_j + \sum_{q_i \in \hat{Q}} \sum_{q_l \in \hat{Q}} c_{il} t_{il} + \sum_{p_j \in \hat{P}} \sum_{p_k \in \hat{P}} c_{jk} s_{jk} \quad (4.1)$$

Subject to the constraints:

$$\sum_{p_j \in \hat{P}} x_{ij} = 1 \quad \forall q_i \in C \quad (4.2)$$

$$\sum_{q_i \in C} x_{ij} \leq r_j y_j \quad \forall p_j \in P \quad (4.3)$$

$$d_{ij} x_{ij} \leq D \quad \forall q_i \in C, \forall p_j \in P \quad (4.4)$$

$$\sum_{i \in C} t_{iw} \leq 1 \quad (4.5)$$

$$\sum_{l \in C} t_{wl} \leq 1 \quad (4.6)$$

$$\sum_{q_l \in \hat{Q} | l \neq i} t_{il} = x_{iw} \quad \forall q_i \in C \quad (4.7)$$

$$\sum_{q_i \in \hat{Q} | l \neq i} t_{li} = x_{lw} \quad \forall q_l \in C \quad (4.8)$$

$$u_i + (|\hat{Q}| - 1)t_{il} - (|\hat{Q}| - 2) \leq u_l \quad \forall i, l \in \hat{Q}, i \neq l \quad (4.9)$$

$$\sum_{j \in \hat{P}} s_{jw} \leq 1 \quad (4.10)$$

$$\sum_{k \in \hat{P}} s_{wk} \leq 1 \quad (4.11)$$

$$\sum_{p_k \in \hat{P} | j \neq k} s_{jk} = y_j \quad \forall p_j \in \hat{P} \quad (4.12)$$

$$\sum_{p_j \in \hat{P} | j \neq k} s_{kj} = y_k \quad \forall p_k \in \hat{P} \quad (4.13)$$

$$u_j + (|\hat{P}| - 1)s_{jk} - (|\hat{P}| - 2) \leq u_k \quad \forall j, k \in \hat{P}, j \neq k \quad (4.14)$$

$$x_{ij} \in \{0, 1\} \quad \forall i \in C, \forall j \in P \quad (4.15)$$

$$y_j \in \{0, 1\} \quad \forall j \in P \quad (4.16)$$

$$t_{il} \in \{0, 1\} \quad \forall i, l \in \hat{Q} \quad (4.17)$$

$$s_{jk} \in \{0, 1\} \quad \forall j, k \in \hat{P} \quad (4.18)$$

Constraints (4.2) ensure that each customer $q_i \in C$ is either served directly by exactly one pds $p_j \in \hat{P}$, to which it goes to pick up the goods it has ordered or is served in the home delivery route that starts from the warehouse w . Constraints (4.3) ensure that each pds $p_j \in P$ cannot serve more customers than its capacity r_j . Constraints (4.4) impose that the distance between each customer and each pds should not exceed the given maximum distance D . Constraints (4.5), (4.6), (4.10) and (4.11) ensures that from node w must leave/enter at most one outgoing ingoing edge, for each customer $q_i \in C$ and pds $p_j \in P$. The two different delivery tours of the goods are defined in the following constraints. Indeed, constraints (4.7) and (4.8) are the classical TSP formulation involving each customer $q_i \in C$ served by the warehouse and defining the partitioning between the set Q and Q' . Constraints (4.12) and (4.13) are the classical TSP formulation involving each $pds \in \hat{P}$. More precisely, these constraints guarantee that each node must have only one outgoing edge and only one ingoing edge, that is each node must have a predecessor node and a successor node in the circuit. Constraints (4.9) and (4.14) are the Miller Tucker Zemlin (MTZ) formulation for the subtour elimination constraints [140]. Finally, constraints (4.15)–(4.18) define the decision variables.

4.3.2 The Partitioning Criteria

To obtain solutions of the proposed *MILP* model in a computationally efficient way we embed it in a branching scheme in which its solution space is partitioned according to how the sets Q and Q' are determined. More precisely, we partition the set C of customers by dividing it into two disjoint (nonoverlapping) subsets according to the following conditions:

- e. at least one customer does not go to a pickup station and is served directly by w ;
- f. no customers are served by w , that is each customer has a reference pickup station close enough to pick up the ordered goods independently.

In the case (e) constraints (4.5) and (4.6) of the above model are modified as follows:

$$\sum_{i \in C} t_{iw} = 1 \quad (4.19)$$

$$\sum_{l \in C} t_{wl} = 1 \quad (4.20)$$

where constraints (4.19) and (4.20) ensure that there is at least one customer served by the warehouse.

In the case (f), instead, we eliminate from the objective function the costs relating to the customers served by w . Thus, we will have three cost components:

$$MIN z = \sum_{q_i \in C} \sum_{p_j \in P} c_{ij} x_{ij} + \sum_{p_j \in P} a_j y_j + \sum_{p_j \in \hat{P}} \sum_{p_k \in \hat{P}} c_{jk} s_{jk} \quad (4.21)$$

From the model described in the Section 4.3.1 we use the constraints: (4.3), (4.4) and (4.10)–(4.18) and we modify the constraint (4.2) as follows:

$$\sum_{p_j \in P} x_{ij} = 1 \quad \forall q_i \in C \quad (4.22)$$

Constraint (4.22) is defined $\forall p_j \in P$; in fact, having no customers to serve from w it guarantees that all customers go to a pds to pick up the ordered goods. Then, the optimal solution of the problem is the best between the solution of the model associated with the case (e), that is (4.1)–(4.4), (4.7)–(4.20) and the one associated with the case (f), that is (4.3), (4.4), (4.10)–(4.16), (4.18), (4.21) and (4.22).

4.4 Computational Experimentations

This section presents the outcomes of the computational experiments performed. The tests were conducted with the aim of assisting decision-makers in e-commerce companies to assess how the activation costs of pds , the distance between customers and their nearest pds , and the impact of vehicle emissions affect the choice of the number and location of pds and, consequently, the total cost of the pickup and delivery process. In the computational experiments discussed in the first four subsections, the instances were generated using a tournament method to create a higher density of customers in central areas compared to peripheral ones, considering the Euclidean distance over a 3x3 km city area. In Section 4.4.1, a case study is presented, based on data from a delivery problem involving customers in a district of the city of Genoa, Italy. All test have been run on a Windows Server 2019 Intel(R) Core(TM) i9-9820X CPU 10 cores, 20 thread, 3.30 GHz 3.31 GHz, 16 GB RAM (based in Italy). IBM ILOG CPLEX Optimization Studio 20.1.0 has been used as mixed integer linear programming solver. A time limit of 1 h have been set for solving each instance. We initially conducted tests by varying the number of customers from 10 to 150 and the number of pds from 5 to 30. For each set of instances, the activation cost of the pds ranged from 5 to 10, while their capacity ranged from 10 to 30. Detailed information about the customers and pds in the instances is provided in Table 4.1. The column headings in Table 4.1 are as follows: **Type** indicates the type of instance being considered; **C** represents the number of customers; **P** refers to the number of pds ; **Act** denotes the activation cost for each pds , and **Cap** represents the capacity of each pds .

Table 4.1: Definition of the instances of the problem for the first set of computational experiments.

Type	C	P	Act	Cap
1	10	5	5–10	10–30
2	20	5	5–10	10–30
3	50	5	5–10	10–30
4	50	10	5–10	10–30
5	100	10	5–10	10–30
6	50	20	5–10	10–30
7	80	20	5–10	10–30
8	100	20	5–10	10–30
9	120	30	5–10	10–30
10	150	30	5–10	10–30

In the first tests we estimated the cost of air pollution to be 2.27 €/vehicle per km, which represents the average air pollution cost for land freight transport. Naturally, this value can fluctuate based on factors such as the type of vehicle, its load or weight, the fuel used, and whether the area is urban or suburban [130]. For the purposes of this thesis, we assume that deliveries are made using light commercial vehicles (LCVs), in line with the European Union’s standards for vehicles with an authorized gross weight not exceeding 3 tons. Given the smaller size and reduced load capacity of LCVs, their fuel consumption averages between 8 and 10 liters per 100 km. Initially, we assumed the cost of fuel consumption of the vehicle used by the company to be 0.1 €/L. However, as mentioned in the previous section, we assume that the emission cost for customers traveling to and from *pds* is zero, and thus null the component (*a*) of the objective function. Lastly, the maximum acceptable distance for customers to travel to a *pds* for direct pickup of their ordered goods is set at 850 meters. Table 4.2 presents the results obtained by solving the model described in Section 4.3.2, using various problem instances configured with the parameters described above. Specifically, Table 4.2 provides, in each row, the average results generated from running 10 instances for each type defined earlier. Across these 10 instances, the variables that differ include the activation cost of *pds* (ranging from 5 to 10), the capacity of *pds* (ranging from 10 to 30), and the distance between customers and *pds*. Column headings of Table 4.2 are as follows. **Total Act Cost** is the average of the activation cost of the selected *pds*; **$\hat{Q}$ Cost** is the average total cost to serve customers not served by *pds*; **$\hat{P}$ Cost** is the average total cost to refill all the activated *pds*; **Obj** is the average value of the objective function (1) of the problem and **CPU** is the average computational time required to find the optimal solution, expressed in seconds.

Table 4.2: First computational test. Results of cost component values.

Type	Total Act Cost	$\hat{Q}$ Cost	$\hat{P}$ Cost	Obj	CPU
1	6.28	29.01	9.22	44.52	0.16
2	12.74	32.27	14.98	60	0.19
3	19.51	80.76	19.22	119.5	33.93
4	23.71	46.02	22.38	92.12	0.9
5	40.04	53.54	33.17	126.76	15.86
6	27.31	29.79	26.48	83.59	7.61
7	36.98	31.28	33.20	101.47	60.7
8	45.22	26.57	37.34	109.13	538.22
9	51.22	15.44	43.60	110.28	1744.06
10	52.89	19.86	45.58	118.33	2004.56

Looking at the results in Table 4.2, we consistently achieved an optimal solution within the predefined maximum time limit of one hour across all instance types. It is immediately evident that the 850-meter distance is ideal, as it results in the activation of a reasonable number of *pds*. More specifically, an average of 4.42 *pds* are activated, which successfully serve approximately 85% of the customers, as detailed in Table 4.3. This table reports the average number of activated *pds* and the percentage of customers served and not served by *pds* (see the columns "Selected *pds*", "PDS", and "W", respectively). Furthermore, with the remaining 15% of customers being served directly at home, we are able to strike an excellent balance between activation and transportation costs, while also containing the sustainability-related costs that are factored into the delivery process.

Table 4.3: First computational test. Results of the selected *pds* and served customers.

Type	Selected <i>pds</i>	PDS	W
1	0.9	55%	45%
2	1.8	74.5%	25.5%
3	2.6	70.6%	29.4%
4	3.2	84.4%	15.6%
5	5.3	90.7%	9.3%
6	4	90.8%	9.2%
7	5.3	93.75%	6.25%
8	6.1	95.9%	4.1%
9	7.3	98%	2%
10	7.7	98%	2%

After confirming that the method outlined in Section 4.3 successfully identified the op-

timal solution for all the instances considered, it is important to highlight the significant reduction in computational time achieved by the branching technique proposed in Section 4.3.2, compared to using only the model (4.1)–(4.18). Figure 4.2 shows the comparison of the computational time (second) required to find the optimal solution of the instances in Table 4.2 to the model alone (dashed line) and to the entire partitioning method (solid line), thus highlighting the efficiency of the proposed solution method. Additionally, Figure 4.2 demonstrates that for instances of type 1 and 6, the computational time is notably shorter compared to other instances, even as their size increases. This outcome is attributed to the favorable ratio between the number of customers and the number of available *pds* in these specific instances.

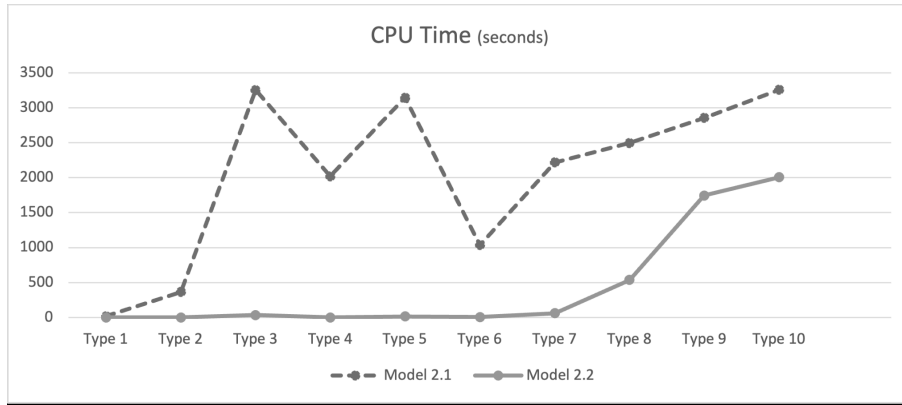


Figure 4.2: Comparison of the CPU time required by the model and the whole approach.

Tests with and without the Cost Component of Pollutant Emissions from Customer Mobility

In the next computational test, we selected the first instance from each type listed in Table 4.2, incorporating component (a) into the objective function, specifically equations (4.1) and (4.21), which account for the pollutant emission costs incurred by customers personally collecting their ordered goods. In this analysis, we assumed that customers use the same type of vehicle as the one the company uses to deliver goods directly from the warehouse. This approach enables a more meaningful comparison between the savings in activation costs of a *pds* and the delivery costs. Table 4.4 presents the optimal solution values for the selected instances when component (a) is excluded, i.e., when the emission cost is set to zero. The same results are shown in Table 4.5, but with the addition of a new column, **Served C Cost**, which reports the objective function component (a), alongside the columns from Table 4.4.

Table 4.4: Results of the first instance of each type considered in Table 4.2 without the cost component (a) of the objective function.

Instance	Total Act Cost	$\hat{Q}$ Cost	$\hat{P}$ Cost	Obj
1	5.49	16.18	11.16	32.83
2	5.01	26.56	10.92	42.49
3	21.31	36.97	21.29	79.56
4	18.42	36.97	21.36	76.75
5	50.14	62.00	37.07	149.22
6	25.91	21.76	26.64	74.30
7	43.07	26.76	36.89	106.72
8	47.34	15.90	37.08	100.32
9	40.85	37.45	36.64	114.94
10	56.93	0.00	41.97	98.90

It is evident that, up to instance 6, there is no difference between the values presented in Tables 4.4 and 4.5. In fact, when excluding the **Served C Cost** column from Table 4.5, the values in the **Obj** columns of both tables are identical and correspond to the same decisions regarding the activation of *pds*, as shown in Table 4.6. The column headings of Table 4.6 are the same as those in Table 4.3. However, in instances 7 through 10, differences arise between the results when the cost incurred by customers for collecting their goods is excluded or included in the objective function. Specifically, we observe that the model makes different decisions regarding the activation of pickup and delivery stations in the two scenarios, depending on the number of customers served. In fact, the model does not activate a *pds* if it serves a small number of customers relative to its capacity (Table 4.5), as doing so would be disadvantageous. We can observe the opposite behaviour in Tables 4.4 and 4.6, where the model activates a pickup-delivery station even if it serves only a limited number of customers relative to its capacity. A particularly notable case arises in instances 7 and 8, where the optimal solutions differ between the scenario without customer travel costs (Table 4.4) and the one that includes these costs (Table 4.5). Specifically, in the first case, one additional pickup-delivery station is activated compared to the second case. This occurs because it is more cost-effective to activate an additional *pds* (see Table 4.6), even if it serves only a few customers, as the overall cost remains more sustainable. An example of this can be seen in instance 7, depicted in Figure 4.3, where a pickup-delivery station is activated despite serving only two customers.

Table 4.5: Results of the instances of Table 4.4 with all the cost components of the objective function.

Instance	Served C Cost	Total Act Cost	$\hat{Q}$ Cost	$\hat{P}$ Cost	Obj
1	2.25	5.49	16.18	11.16	35.08
2	3.52	5.01	26.56	10.92	46.02
3	9.63	21.31	36.97	21.29	89.20
4	10.95	18.42	36.97	21.36	87.70
5	18.34	50.14	62.00	37.07	167.56
6	11.24	25.91	21.76	26.64	85.54
7	15.10	38.00	37.06	31.76	121.92
8	21.16	39.86	31.77	32.00	124.79
9	21.81	44.74	32.26	41.94	140.74
10	29.39	59.32	0.00	42.05	130.75

Table 4.6: Results of the selected *pds* and served customers.

Instance	Results Table 4.4			Results Table 4.5		
	Selected <i>pds</i>	PDS	W	Selected <i>pds</i>	PDS	W
1	1	80%	20%	1	80%	20%
2	1	80%	20%	1	80%	20%
3	3	88%	12%	3	88%	12%
4	3	88%	12%	3	88%	12%
5	6	89%	11%	6	89%	11%
6	4	94%	6%	4	94%	6%
7	6	95%	5%	5	92.50%	7.50%
8	6	98%	2%	5	95%	5%
9	6	95%	5%	7	95.83%	4.17%
10	7	100%	0	7	100%	0

The opposite situation occurs in the same instance presented in Table 4.5, where, after adding the transportation cost for customers traveling to and from the *pds*, it is no longer advantageous to activate an additional *pds* if only two customers are served. In this case, it is preferable to serve the customers directly from the warehouse along the route shown in Figure 4.4. Therefore, we can conclude that the proposed approach aims to serve as many customers as possible through the *pds*, within the constraints of maximum distance and capacity. Specifically, it assesses whether activating a pickup-delivery station is beneficial,

even if the number of customers it serves is significantly lower than its capacity, or if it is more efficient to serve them directly from the warehouse route. This explains why, in instance 9, an additional *pds* is activated when the cost component (*a*) is taken into account (see Table 4.6). For a more detailed analysis of the company's costs, we focus on instance 8, which involves a significant number of customers (100) and potential *pds* to be activated (20). In this instance, we also considered the extreme scenario where the company does not activate any *pds*, instead serving all customers directly at their homes through a delivery route starting from the warehouse. Based on Formula (4.23), the optimal solution in this scenario results in a total cost of $z = 509.50$ €, which corresponds to the customer service cost from the warehouse, represented by the third component (*c*) of the objective function (4.1).

$$\text{MIN } z = \sum_{q_i \in \hat{Q}} \sum_{q_l \in \hat{Q}} c_{il} t_{il} \quad (4.23)$$

It should be noted that in (4.23), $\hat{Q}$ represents $C \cup w$, meaning that $\hat{Q}$ includes all customers. However, the activation of pickup-delivery stations allows the company to achieve significant savings in the total cost. From the objective function (4.1), it is clear that these savings exceed 300% when accounting for the transportation costs between *pds* and customers (i.e., 124.79 €, as shown in Table 4.5) and more than 400% (i.e., 100.32 €, as shown in Table 4.4) when these costs are considered zero, due to sustainable and emission-free transportation methods. As a final consideration regarding the company's strategic location-routing decisions, based on the observations above, the company could incentivize customers to use *pds* for picking up their goods personally, using non-polluting means such as walking, cycling, or electric vehicles. To encourage this, the company could offer customers a discount on the purchase price, with the discount being up to 100% of the total cost savings, as seen in the case of instance 8. In this way, the company would still realize a cost saving while also promoting a sustainable urban distribution strategy.

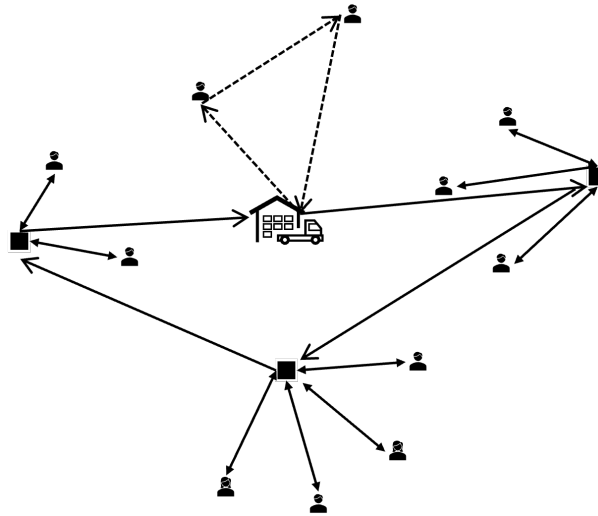


Figure 4.3: Example derived from Instance 7 from Table 4.4 without service cost of the customers.

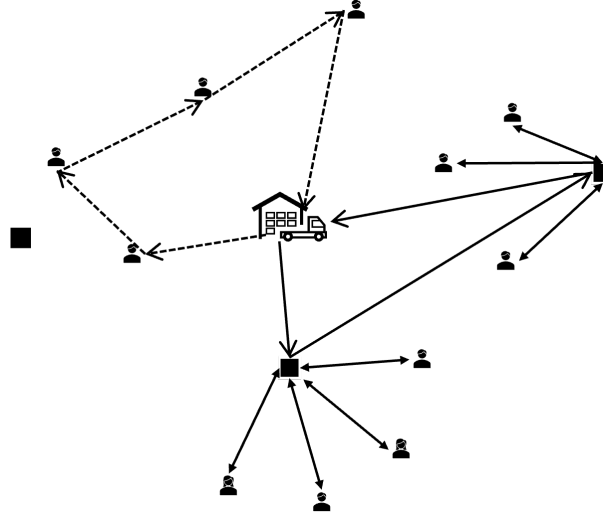


Figure 4.4: Example derived from Instance 7 from Table 4.5 with service cost of the customers.

4.4.1 A Real-Size Case Study

In this section, we present a case study that utilizes the method described in Section 4.3, following the computational tests conducted in the previous subsections. To analyze a realistic scenario, we consider a company specializing in distributing products ordered through electronic channels. With the rising volume of parcels to manage, the company aims to assess the effectiveness of integrating pickup-delivery stations to enhance service levels and minimize overall delivery costs. For this case, the customers involved in the service consist of 49 offices located within a district of Genoa, Italy, as depicted in Figure 4.5. Customer location data, as well as details on currently operational delivery points in this area (such as post offices), were extracted from OpenStreetMap to identify 19 viable pickup-delivery station candidates. In Figure 4.5, customers are shown as blue dots, the warehouse is indicated by a yellow diamond, and potential delivery points are marked as black diamonds.

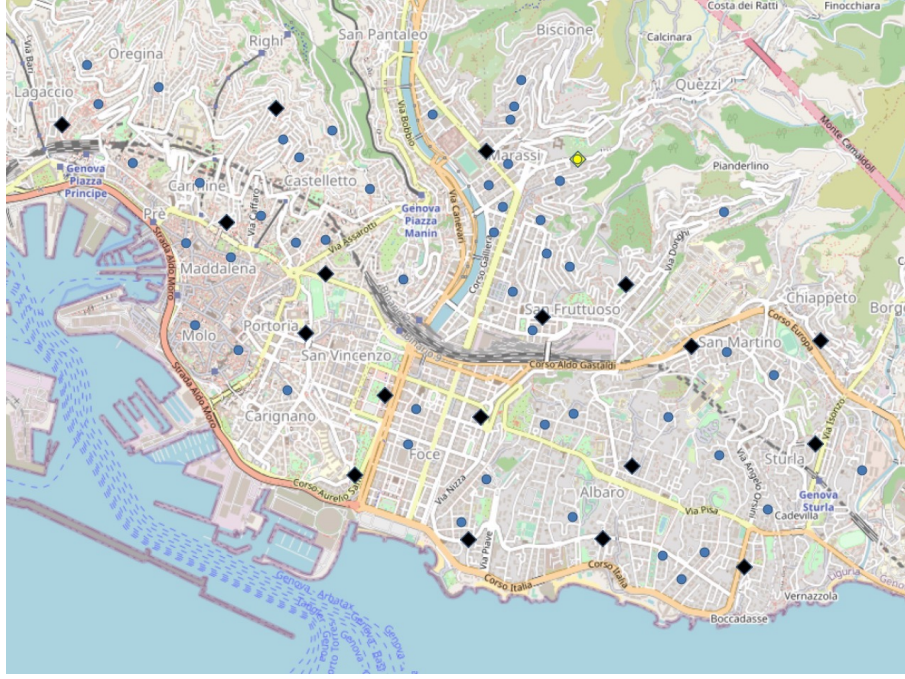


Figure 4.5: Urban area of the case study with the location of customers and *pds*.

The service costs associated with these active delivery points were derived based on their annual rental expenses, with the activation cost of each pickup-delivery station (*pds*) set at €1,000. Transportation costs remain consistent with those applied in previous tests. The distances between nodes were calculated using the urban transportation network for road vehicles and were obtained from OpenStreetMap via QGIS software, which facilitates access to and downloading of various types of geospatial data. As in previous instances, the maximum permissible distance between clients and *pds* was set to 850 meters.

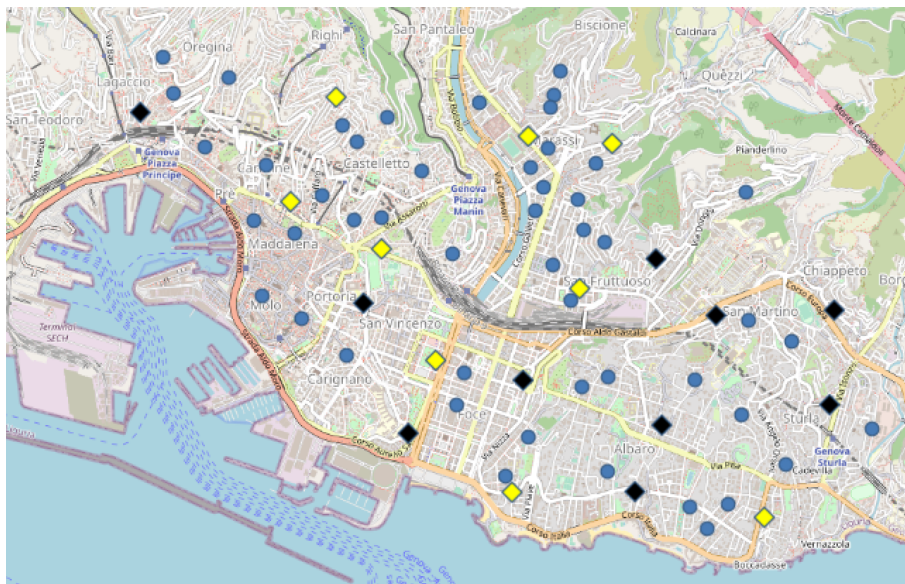


Figure 4.6: Activated pickup-delivery stations in the optimal solution.

Initially, we calculated the company's total delivery cost in a scenario where no pickup-

delivery stations (*pds*) are activated, meaning all customers are served directly from the warehouse. In this case, we applied the objective function presented in Equation (4.23), resulting in a total cost of €128,670.42. Table 4.7 presents the optimal solution obtained using the proposed method, in which eight *pds* are activated, shown in yellow in Figure 4.6. These activated *pds* cover 48.97% of the customers, while the remaining 51.02% continue to be served directly from the warehouse.

Table 4.7: Cost components of the objective function.

Act	$\hat{Q}$ Cost	$\hat{P}$ Cost	Obj
8.000	67,839.59	34,604.48	110,444.08

Additionally, the computational time required to determine the optimal solution was approximately 28 minutes. Although the costs used in this analysis were estimated based on publicly available information rather than the company’s actual costs, the findings enabled us to recommend the activation of specific *pds* at strategic locations within the district under study. Consequently, this setup provides customers with reduced wait times, faster delivery, enhanced sustainability, and lower overall costs.

4.4.2 Insights

The second module focuses on addressing the multifacility location-routing problem within an urban logistics context. Implemented as a Java component within the scalable framework, this module optimizes the placement and utilization of pickup-delivery stations while balancing home delivery services. Key findings include the identification of threshold values for customer walking distances and activation costs, beyond which home delivery becomes more cost-effective. Additionally, the results emphasize the potential of incentivizing customer behavior to achieve significant cost savings and reduce pollutant emissions. A more detailed analysis of these results is presented in Chapter 6.

Chapter 5

Platform Architecture

5.1 Modular Structure

The efficient management of multimodal logistics remains one of the most complex and significant challenges in modern supply chain management. A multimodal platform is designed to coordinate and optimize the transportation of goods using a combination of different transport modes, such as road, rail, sea, and air. This combination provides flexibility, cost optimization, reduction of carbon emissions, and overall enhancement of the supply chain's efficiency. To develop an effective multimodal platform, it is crucial to collect and integrate data from various sources, including transport providers, logistics terminals, IoT sensors, and fleet management systems. The need to integrate heterogeneous data and provide real-time information to platform users has necessitated the creation of a modular architecture. This architecture allows for the development of independent modules that can be easily updated or replaced without impacting the entire system, facilitating integration with external systems, and supporting platform scalability to adapt to changing market and customer needs.

5.1.1 Description of the main modules

A modular architecture allows the entire system to be divided into independent modules, each responsible for a specific function or component of the system. This approach offers several key advantages:

- **Maintainability:** Each module can be developed, tested, and updated independently of the others, reducing the time and effort required for system maintenance. If a module needs modification or updating, significant changes to other modules are unnecessary unless there are direct dependencies.
- **Scalability:** The modular architecture allows the system to scale according to the needs. New modules can be added to extend the platform's functionalities without compromising the stability or integrity of existing modules.

- **Reusability:** Developed modules can be reused in other projects or contexts, promoting a reuse-oriented development approach. This accelerates the development process and reduces the costs associated with duplication of development efforts.
- **Interoperability:** Thanks to the clear definition of interfaces and communication protocols between modules, the modular architecture ensures that different components of the system can seamlessly interoperate. This is particularly important in a multimodal context, where it is necessary to integrate data and functionalities from different systems and sources.

The adoption of a modular architecture has enabled the efficient integration of different technologies, such as MySQL for data management, Java for the backend, and CPLEX for transport route optimization, creating a cohesive and functional system. The following sections will describe in detail how each of these technologies has been used within the platform.

5.1.2 Platform Process Overview

The Deploy Class Diagram in Figure 5.1 illustrates the request handling process within the multimodal platform, simulating a scenario where a user interacts with the platform through Postman. **Postman** is a widely-used API development tool that enables users to create, test, and interact with APIs using *Hypertext Transfer Protocol (HTTP)* requests. It offers a user-friendly interface for sending requests to backend systems and receiving responses. In this simulation, Postman is used to demonstrate how a user submits a request to the multimodal platform via a REST POST method.

1. **Inserting the Request ID:** The user submits a request through Postman. The platform backend stores this request in the MySQL database and assigns it a unique request ID to ensure traceability throughout the process.
2. **Sending the Request ID to the Middleware:** Alongside the database storage, a `sent_ID_request` is triggered, sending the request ID to the middleware to initiate further processing.
3. **Middleware Fetching the Request:** The middleware retrieves the request from the database using the `get_request` function and updates the status of the request to "executing," indicating that the process is ongoing.
4. **Sending the Request to the Optimization Module:** The middleware forwards the request to the Optimization module (OPT) using the `sent_request_to_solve` method. The OPT module performs the necessary computations and solves the request based on predefined optimization algorithms.
5. **Solution Processing:** The OPT module generates a solution for the request and sends it back to the middleware.

6. **Saving the Solution and Marking the Request as Processed:** Once the solution is received, it is saved in the MySQL database, and the status of the request is updated to "processed". This marks the end of the request's lifecycle, and the user can be notified accordingly.

This workflow illustrates how the platform efficiently manages user requests, coordinating between the database, middleware, and optimization components to ensure the process runs smoothly.

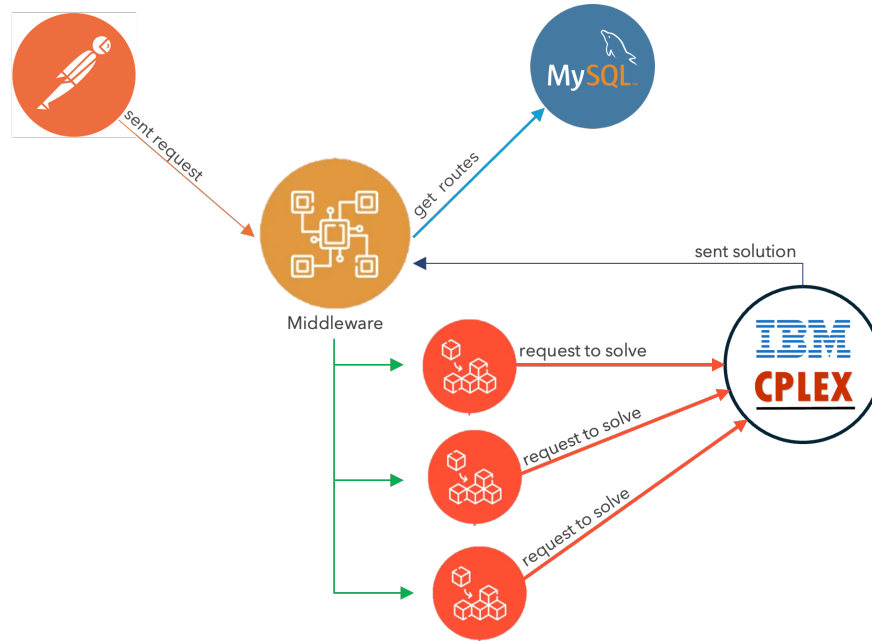


Figure 5.1: Deploy Class Diagram

5.2 Software Architecture

5.2.1 Class Diagram

Figure 5.2 illustrates the class diagram of the multimodal platform, showcasing the key entities and their relationships. This diagram provides a high-level representation of the system's structure, including its core components and their interactions. The platform is designed to support multimodal logistics operations through a modular architecture, ensuring scalability, flexibility, and interoperability.

The main elements of the diagram include:

- **Graph and Nodes:** Represent the multimodal transport network, where each node corresponds to a geographic location, such as a city or logistics hub. Nodes are connected by edges that store information about transportation costs, vehicle types, and environmental impacts.

- **Route and Solution:** The `RouteSupplier` class manages the transport routes offered by suppliers, while the `Solution` class represents optimized routes calculated by the platform.
- **TransportVehicle and GoodsType:** Define the types of vehicles available for transport, along with their capacities and environmental parameters, as well as the characteristics of goods being transported, such as whether they are hazardous or pollutant.
- **Address and PackingType:** Provide detailed information about the locations and packaging types used for the transportation of goods.

This class diagram serves as the foundation for understanding the logical structure of the platform and its implementation. It highlights how modular components interact to support complex logistics operations, enabling efficient and sustainable multimodal transport solutions.

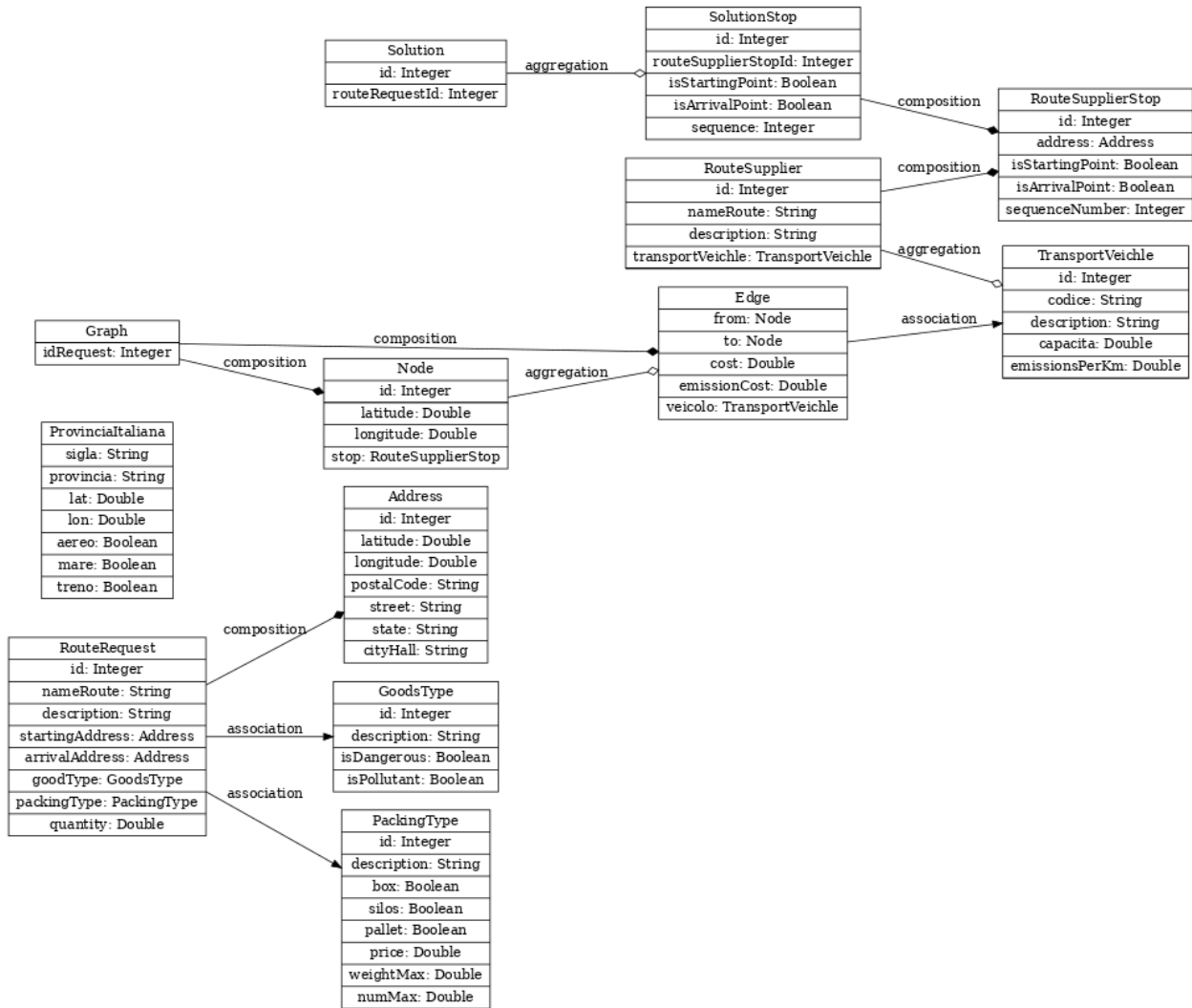


Figure 5.2: Class diagram of the multimodal platform.

5.2.2 General architecture of the Database

The database module is a fundamental component of the multimodal platform, being responsible for the persistence and efficient access to the data necessary for the system's operation. Choosing the type of database is crucial to ensuring optimal performance, scalability, and ease of maintenance.

Relational Databases

Relational databases are based on the relational model, which organizes data into tables composed of rows and columns. Each table represents a specific entity (e.g., User, Route-Supplier, GoodsType), and the relationships between tables are established through foreign keys. Relational databases are particularly appreciated for their ability to ensure data consistency, reliability, and integrity. They use the *Structured Query Language (SQL)* for querying and manipulating data, offering a high level of standardization and interoperability among different systems. They are suitable for applications that require complex transactions and referential integrity, such as financial systems, human resource management systems, and naturally, multimodal logistics platforms.

MySQL

MySQL is a widely used open-source relational database management system. It supports the SQL language and offers advanced features such as ACID transactions (Atomicity, Consistency, Isolation, Durability), access control through user management, and data replication to ensure system availability and resilience. Due to its versatility, MySQL is used in a wide range of applications, from small web applications to complex enterprise platforms.

Relational Database Schema

For the multimodal platform prototype, a relational database was adopted to efficiently manage structured data. The choice of MySQL as the database management system was motivated by its robustness, reliability, and broad community support. MySQL offers an ideal balance between performance, functionality, and ease of use, making it suitable for the platform's needs. The relational database schema presented in Figure 5.3 was designed to support the various functionalities of the multimodal platform, ensuring efficiency in data management, scalability, and maintenance of referential integrity. The following is a detailed analysis of the main tables and their relationships.

- **user**: represents the platform's users and contains the following attributes: `id`(primary key), `email`, `password`, `first_name`, `last_name`, and `profile_id`. The attribute `profile_id` is a foreign key that establishes a relationship with the `profile` table, indicating the type of profile associated with the user, such as administrator, customer, or supplier.

- **profile**: Defines the different types of user profiles available on the platform. It includes fields such as `id` (primary key), `is_supplier`, `is_customer`, `is_admin`, and `name`. Each record represents a specific profile, allowing differentiation of permissions and functionalities accessible by each type of user.
- **route_request**: Manages route requests from users. The main attributes include `id`(primary key), and `route_name`, `min_starting_date`, `max_starting_date`, `starting` and `arrival` address, `good_type_id`, and `user_id`.

Foreign keys, such as `starting_address_id` and `arrival_address_id`, establish relationships with the `address` table, while `good_type_id` connects to the `goods_type` table.

- **address**: Contains geographic information used to define the starting and arrival points of transport routes. This table is essential for accurately locating the geographic points necessary for route planning.
- **route_supplier**: Represents the suppliers that provide transportation routes within the platform. The attributes include `id` (primary key), `start date`, `arrival date`, `name route`, `transport vehicle id`, and `user id`. The foreign key `transport vehicle id` establishes a relationship with the `transport vehicle` table, indicating the vehicle used for the route.
- **transport_vehicle**: Describes the available transport vehicles. It contains attributes such as `id` (primary key), `code`, `description`, `volume`, `kg`, `emissions per km`, and `fuel cost per km`. This table is crucial for managing and optimizing the available transport resources.
- **transport_type**: Defines the different types of transport that can be utilized on the platform, such as `is_air`, `is_rail`, `is_maritime`, and `is_truck`. These fields are of boolean type and allow the categorization of transport modes based on their main characteristics.
- **goods_type**: Contains information about the types of goods that can be managed by the platform. The attributes include `id` (primary key), `description`, `is_dangerous`, and `is_pollutant`. This table enables the definition of specific handling and transportation requirements for different categories of goods.
- **packing_type**: Defines the types of packaging available for transporting goods. It includes fields such as `id` (primary key), `description`, `is_box`, `is_crate`, and `is_pallet`. This table is useful for optimizing vehicle loading based on the type of packaging used for goods.
- **transport_vehicle_packing_type_relation**: Manages the relationships between transport vehicles and the supported types of packaging. It includes attributes such

as `id` (primary key), `transport_vehicle_id`, `packing_type_id`, `price`, `weight_max`, and `num_max`. The foreign keys establish relationships with the `transport_vehicle` and `packing_type` tables, enabling optimized transport based on vehicle capacity and packaging type.

- **route_solution_stop**: Represents the stop points within route solutions. The attributes include `id` (primary key), `route_supplier_stop`, `date`, `arrival_point`, `departure_detour`, and `arrival_detour`.
- **route_supplier_stop**: Describes the stop points of route suppliers. It contains attributes such as `id` (primary key), `date`, `address_id`, `route_supplier_id`, `starting`, and `arrival` point, and `sequence_number`. This table supports detailed planning of supplier routes.
- **solution**: Contains data related to route optimization solutions. The main attributes include `id` (primary key), `solution_type` optimal or feasible, `objective_function_value`, `pollution_cost`, and `route_cost`. This table is fundamental for the analysis and optimization of routes within the platform.
- **Deltas**: Tracks changes in optimization parameters. The attributes include `id` (primary key), `value_double`, and `description`. This table is useful for monitoring and analyzing variations in input parameters during the optimization process.

The integration between different database modules enables efficient and scalable data management, which is essential for the success of the multimodal platform.

5.3 Data Standardization

Data standardization is a fundamental aspect in the development of complex information systems, such as the multimodal platform discussed in this thesis. Standardization ensures the consistency and compatibility of data exchanged between different system components and external systems. In our platform, data standardization facilitates the flow of information from the *Graphical User Interface (GUI)* to the mathematical model (solver) and vice versa, also allowing integration with external platforms. The main data standard used for the project is JSON.

5.3.1 JSON

JavaScript Object Notation (JSON) is a lightweight, text-based data format that uses a syntax based on key-value pairs. It is highly readable for both humans and machines and is independent of programming languages. JSON has become a de facto standard for data exchange in modern web applications due to its simplicity and flexibility. Unlike *eXtensible Markup Language (XML)*, JSON produces smaller file sizes and has a less complex structure,

making data analysis and manipulation easier. In our platform, JSON was chosen as the primary data exchange format, as it offers an optimal balance between readability, efficiency, and support from a wide range of programming languages and tools.

5.4 Programming Languages and Tools

In the context of developing complex systems such as the multimodal platform, the choice of programming language is crucial to ensuring performance, maintainability, and scalability. Different programming languages offer distinct advantages depending on the application. Among the languages used for developing web applications and enterprise software are Java, Python, C++, and JavaScript.

5.4.1 Java Enterprise

Java Enterprise was chosen as the main programming language for the development of the multimodal platform. Java is an object-oriented programming language known for its portability, robustness, and security. One of Java's main features is its ability to run on any platform that supports the *Java Virtual Machine (JVM)*, making it highly portable and versatile. Java also offers automatic memory management through garbage collection, reducing the risk of memory leaks and improving system stability. Moreover, Java has a rich ecosystem of libraries and frameworks, such as Spring and Hibernate, that facilitate the development of scalable and secure applications. In the context of our platform, Java was used to implement the backend, manage database connections, process requests from the GUI, and interact with the mathematical solver. The use of Java enables efficient workflow management and ensures a robust infrastructure for the multimodal system.

5.4.2 RESTful API

RESTful *Application Programming Interface (API)* represent a widely used communication architecture for developing scalable and interoperable web services. RESTful APIs are based on standard HTTP protocols and use HTTP methods such as GET, POST, PUT, and DELETE to perform data operations. RESTful APIs are designed to be stateless, meaning each HTTP request contains all the information necessary to perform the requested operation, thus improving scalability and session management. In our multimodal platform, the RESTful API architecture was adopted to facilitate communication between the GUI and the system backend, as well as to allow integration with external platforms. The data flow starts with the GUI, where the user enters transport route requests. These requests are sent to the back-end via RESTful API calls, using JSON as the data-exchange format. The back-end processes the requests, interacts with the relational database to retrieve and update the necessary data, and uses the mathematical solver to calculate the optimal routes. The calculation results are then sent back to the GUI via RESTful API calls, where they are displayed

for the user. This bidirectional data flow ensures a smooth and responsive user experience, minimizing latency and maximizing system efficiency. The use of RESTful APIs also allows easy integration of our platform with external systems. By using open standards such as JSON and HTTP, the platform can receive and send data to third-party services, facilitating collaboration and interoperability among different systems. This integration capability is essential for expanding the platform's reach and improving the ecosystem of multimodal logistics solutions.

5.4.3 Mathematical Solver

Mathematical solvers are computational tools used to find optimal solutions to complex optimization problems involving a set of variables and constraints. These tools are fundamental in many sectors, including logistics, engineering, finance, and operations research. In multimodal logistics and transport, mathematical solvers are employed to optimize transport routes, minimize operating costs, manage resources, and reduce environmental impact. Optimization problems can be classified into different categories, such as Linear Programming, Mixed-Integer Linear Programming, and *Non-Linear Programming (NLP)*. Mathematical solvers are designed to tackle specific types of optimization problems using advanced algorithms, such as the simplex method, branch-and-bound, interior-point methods, and stochastic optimization techniques.

Types of Mathematical Solvers

Mathematical solvers can be divided into different categories, depending on the type of optimization problem they solve:

- **Linear Programming Solvers:** Used to solve problems where both the objective function and the constraints are linear.
- **Mixed-Integer Linear Programming Solvers:** Used to solve problems where some or all decision variables must be integers. These problems are more complex than standard LP problems and require more advanced optimization techniques.
- **Non-Linear Programming Solvers:** Used to solve problems where either the objective function or the constraints are non-linear. These solvers are suitable for complex problems that require detailed modeling of non-linear behaviors.
- **Mixed-Integer Non-Linear Programming Solvers (MINLP):** Combine elements of MILP and NLP, used to solve problems with both linear and non-linear constraints and objectives with continuous and integer variables.

CPLEX

CPLEX is a commercial solver originally developed by IBM, specifically designed to solve Linear Programming, Mixed-Integer Linear Programming, and *Quadratic Programming (QP)* problems. CPLEX is renowned for its efficiency, scalability, and robustness, making it suitable for solving large-scale optimization problems in industrial and academic applications.

CPLEX offers several advanced features that distinguish it from other solvers:

- **High Performance:** CPLEX is known for its high computational performance, thanks to the efficient implementation of algorithms like the simplex and branch-and-bound. These algorithms are optimized to fully exploit hardware capabilities, including multi-thread parallelization.
- **Scalability:** CPLEX can handle optimization problems with millions of variables and constraints, making it ideal for large-scale applications such as optimizing multimodal transport networks.
- **Versatile Interface:** Supports various programming interfaces, including C, C++, Java, Python, and MATLAB, facilitating integration into existing development environments.
- **Support for Complex Problems:** In addition to LP and MILP, CPLEX also supports Quadratic Programming, *Quadratic Constrained Programming (QCP)*, and Non-Linear Programming, offering a wide range of tools to solve complex problems.

5.4.4 Middleware

Middleware is a software component that provides common services and functionality to facilitate communication and interoperability between different applications or software components within a complex system. In the context of the multimodal platform, it was necessary to create custom middleware to ensure effective and consistent communication between the various modules used. This custom middleware was specifically designed to integrate the GUI, the backend, mathematical solvers, and external systems, ensuring that data flows continuously and efficiently throughout the system architecture.

Multimodal Middleware

The implemented middleware provides several key services that enhance system efficiency, scalability, and security.

- **Communication between GUI and Backend:** To ensure smooth communication between the GUI and the backend, the middleware manages requests from the user interface and forwards them to the backend for processing. This architecture facilitates a responsive user interface and ensures that all operations are performed efficiently.

- **Integration with Mathematical Solvers:** The middleware is designed to facilitate integration with the mathematical solvers used in the system, managing communication between the backend and external solvers such as CPLEX. This approach allows for the optimization of transport and logistics operations using complex mathematical models.
- **Management of RESTful APIs:** To enable integration with external systems, the middleware handles RESTful API calls, allowing the interaction and management of incoming and outgoing requests. This facilitates the integration of the platform with other systems and external services, maintaining a high level of interoperability.
- **Security and Authentication:** Another fundamental role of the middleware is managing user authentication and authorization. This ensures that only authorized users can access the platform's functionalities, protecting sensitive data and maintaining the overall security of the system.

The custom middleware developed for the multimodal platform represents an essential component in ensuring efficient and secure communication between the various modules of the system, contributing to its overall scalability and reliability.

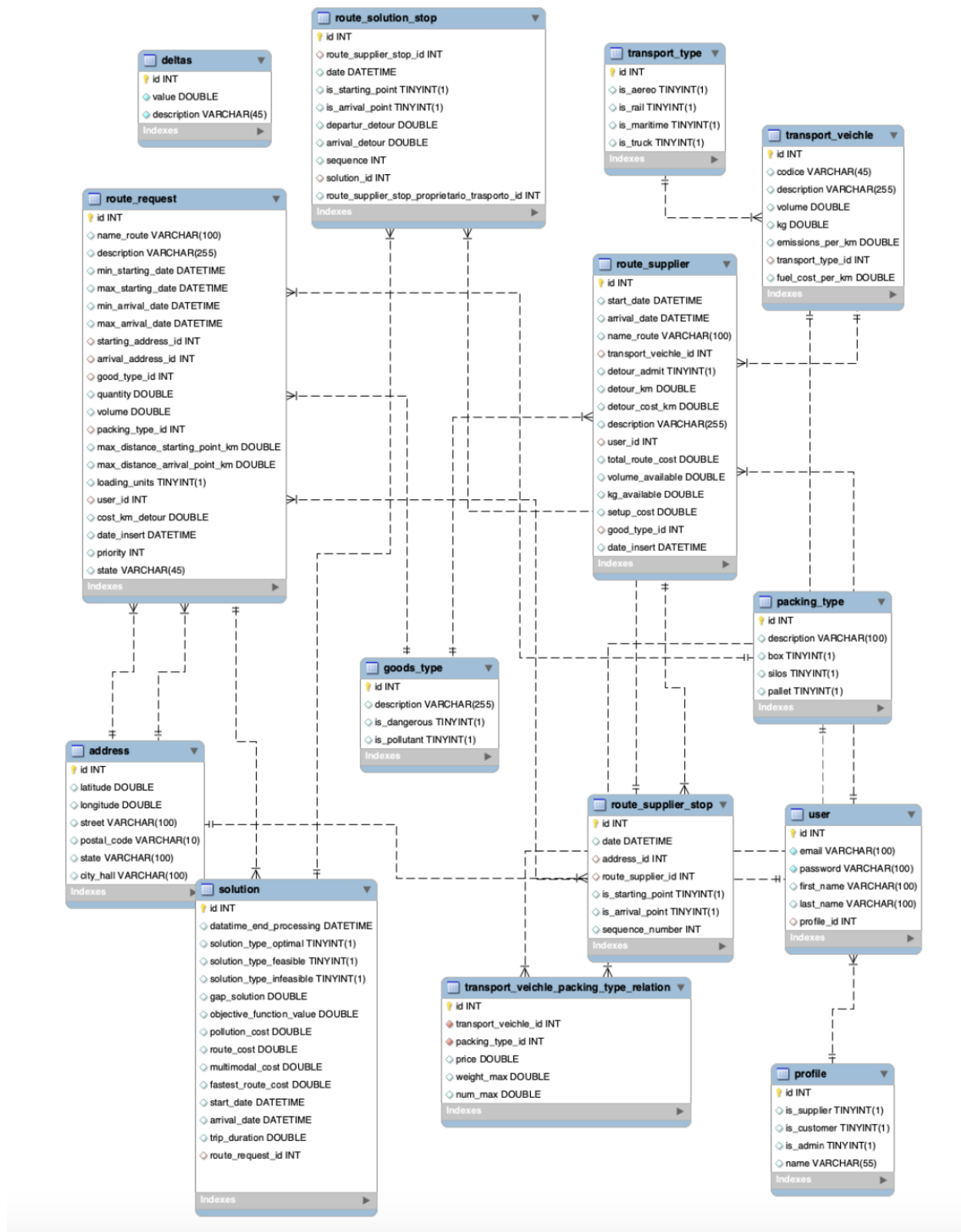


Figure 5.3: The Entity Relational Model

Chapter 6

Conclusions and Future Perspectives

6.1 Summary of Results

This thesis proposed and validated a framework for optimizing multimodal transport routes, aiming to minimize total logistics costs while reducing pollutant emissions. Through the use of a Mixed-Integer Linear Programming model, the framework incorporates key factors such as load efficiency, transshipment capabilities, and transportation costs, along with environmental considerations such as CO_2 emissions. The results from extensive computational experiments demonstrated the effectiveness of the proposed models, achieving significant reductions in both economic costs and environmental impact. Additionally, real-world case studies highlighted the model's applicability to complex urban logistics scenarios, confirming its potential for practical implementation. This dissertation presents a comprehensive study addressing two distinct but complementary modules aimed at optimizing sustainable logistics practices within multimodal transportation networks and urban distribution systems.

Module 1: Cost-Effective Routing in Multimodal Logistics

The first module focused on developing a framework to identify cost-effective origin-to-destination routes within customized multimodal transportation networks. The proposed MILP model, along with its associated data management procedures, has been incorporated into a unified system designed to identify routes that minimize the total transportation cost. This optimization aims to enhance logistics operations within multimodal transport systems, addressing the growing need for more sustainable logistics practices in response to the global climate crisis.

The framework optimizes route selection by considering several key factors, including vehicle load efficiency, transshipment capabilities, and transportation expenses. It incorporates not only traditional costs—such as those associated with route length and vehicle type—but also environmental costs, including pollutant emissions and vehicle occupancy levels. A novel contribution of this work lies in the introduction of a consolidation cost model within the objective function, which, as evidenced by the results, helps reduce the total kilometers traveled by road vehicles by prioritizing trips conducted by fully loaded trucks. The model also

aligns with sustainable logistics principles by incorporating environmental and collaborative logistics factors across different vehicle types, including trucks, trains, planes, and ships.

The effectiveness of the proposed MILP model was demonstrated through extensive testing on approximately 3,240 instances. These tests confirmed that the model, based on a specifically designed multimodal graph, accurately incorporates the aforementioned factors. For example, when the customer delivery radius was restricted to 100 km, the solutions provided a significantly lower average cost compared to longer routes, even though the total distance traveled remained nearly the same. This outcome highlights the advantages of offering customers more competitive transportation alternatives when optimizing for cost. An analysis of these results further emphasizes the importance of collaboration among different carriers within the multimodal network. Specifically, by allowing carriers to share unused cargo space on scheduled routes, the proposed system reduces the need for additional vehicles, maximizing existing capacity to meet new demands. This collaborative approach leads to fewer vehicles being required, resulting in lower transportation costs and reduced emissions, thus supporting the sustainability objectives of the framework.

A particularly important finding from an environmental sustainability perspective came from varying the weight placed on emissions costs in the objective function. The tests showed that as the importance of emissions costs increased, there was a notable shift away from the use of trucks and planes, with trains and ships becoming more favorable transportation options. Specifically, as the emissions cost coefficient rose, the total kilometers traveled by trucks decreased. Another key observation came from the analysis of the consolidation cost impact on optimal solutions. By introducing a penalty for trucks that were not fully loaded, it was found that nearly 90% load occupancy could be achieved for almost three times as many trucks. Additionally, there was an average increase of at least 8% in cases where slightly longer routes were taken to consolidate loads.

In conclusion, the results obtained from the proposed MILP model demonstrate that the framework provides a robust foundation for promoting sustainable logistics practices, offering valuable insights for decision-making in medium- to long-distance goods transportation scenarios. Overall, cooperation among carriers is essential for enhancing the resilience of logistics networks, reducing emissions, and achieving cost efficiency, making it a critical factor in the development of sustainable logistics strategies.

Module 2: Optimizing Pickup-Delivery Station Locations in Urban Logistics

The second module examined a variant of the multifacility location-routing problem within an urban context, targeting a business-to-consumer company. The objective was to minimize the overall costs of the pickup and delivery process while devising environmentally sustainable distribution plans that reduce pollutant emissions. This required finding an optimal balance between the number of pickup-delivery stations used for goods collected directly by customers and the number of customers served via home delivery.

Strategically, the research sought to analyze how the placement of pickup-delivery stations changes based on factors such as the maximum distance customers are willing to walk, as

well as the length and cost of delivery routes. The activation costs of these stations, along with the types of vehicles employed by the company, also influenced the determination of optimal solutions.

To address this problem, we proposed a novel exact solution method grounded in the partitioning of the solution space of a MILP model. Specifically, a branching constraint was introduced to divide customers into two groups: those served by pickup-delivery stations and those served via direct delivery. This partitioning enabled the formulation of routes for both pickup-delivery stations and home deliveries. Computational experiments conducted on randomly generated instances involving up to 150 customers and 30 pickup-delivery stations demonstrated the efficiency of the proposed method in terms of both solution quality and computational time. As shown in Tables 4.2 and 4.4, all tests achieved optimal solutions within 35 minutes. In tests evaluating the impact of varying the maximum distance customers were willing to travel for self-collection, a deviation of just 1% from the optimal objective value was observed in three instances within a computational time limit of 1 hour. These tests also revealed threshold values for both customer walking distances and the costs of pickup-delivery stations, beyond which home delivery becomes more cost-effective than establishing additional stations.

Furthermore, applying the proposed exact method to a case study based in an urban district of Genoa validated its applicability to real-world urban delivery scenarios. The method effectively minimized pollutant emissions while optimizing the distribution process.

Finally, the study assessed the potential for incentivizing customers to use pickup-delivery stations, demonstrating that this approach could generate significant cost savings for the company while promoting environmental sustainability.

6.1.1 Main Contributions of the Research

This research provides significant contributions to the field of sustainable logistics and transportation by addressing both theoretical and practical aspects of optimizing multimodal and urban logistics. These contributions can be summarized as follows:

- **Integration of Sustainability Metrics:** A pivotal aspect of this work is the integration of environmental sustainability metrics into logistics optimization. By including emission costs and penalties for underutilized vehicle capacity within the objective function, the research bridges the gap between economic efficiency and ecological responsibility. This dual focus ensures that the optimization process not only minimizes traditional costs, such as fuel and labor, but also aligns with global sustainability goals. The incorporation of these metrics allows decision-makers to quantify environmental impacts explicitly and consider them in the development of sustainable logistics strategies.
- **New Mathematical Approach:** A key methodological advancement presented in this research is the development of a MILP-based exact method. This approach enables

the framework to address complex challenges associated with multimodal logistics and urban delivery networks. The innovation lies in its ability to manage both the multimodal transportation of goods over long distances and the location-routing decisions needed for urban last-mile delivery, ensuring adaptability and robustness across different contexts.

- **Real-World Applicability:** The practical relevance of the proposed framework is demonstrated through its application to real-world scenarios. Notably, the study's application to urban logistics in Genoa validates the scalability and usability of the framework in addressing real-life challenges. By using detailed data and realistic parameters, the research highlights the framework's effectiveness in minimizing emissions, optimizing vehicle routes, and balancing pickup-delivery station operations. These case studies not only showcase the framework's applicability but also provide valuable insights for logistics companies and policymakers aiming to improve efficiency and sustainability in urban settings.
- **Promotion of Collaborative Logistics:** The research underscores the critical role of collaboration among carriers in achieving sustainable logistics goals. By optimizing shared capacities and leveraging unused cargo space, the proposed framework minimizes the need for additional vehicles, thus reducing costs and emissions. This collaborative approach aligns with the principles of cooperative logistics, promoting resource-sharing and operational efficiency. The results demonstrate how collaboration can enhance the resilience of logistics networks, reduce congestion, and support environmental sustainability objectives, offering a model for future cooperative practices in the logistics sector.

In summary, the contributions of this research go beyond theoretical advancements, providing actionable insights and practical tools to address the pressing challenges of sustainable logistics. By integrating environmental considerations, introducing innovative methods, validating real-world applications, and emphasizing collaboration, this study establishes a strong foundation for the development of efficient, sustainable, and resilient logistics systems.

6.2 Future Research Perspectives

As part of the ongoing collaboration with the Joint Research Centre (JRC) of the European Commission, the next phase of this research will involve an in-depth evaluation of the proposed model using datasets and case studies provided by the JRC. A primary objective of this evaluation is to ensure that the model aligns with the TRIMODE (TRansport Integrated Model of Europe) framework. TRIMODE is a sophisticated modelling system designed to address various scenarios, including infrastructure investments, pricing strategies, technological advancements, and regulatory policies. It integrates a detailed European transport network with advanced energy and economic models [141]. Our methodology mirrors that

employed by the European Commission, facilitating a systematic comparison between the solutions generated by our model and those produced by TRIMODE. This comparative approach aims to determine which model delivers superior results in terms of efficiency and accuracy. The findings will be instrumental in validating and refining our framework, identifying its strengths and potential areas for improvement. Additionally, benchmarking against an established model like TRIMODE provides valuable insights into the unique challenges and opportunities in the context of multimodal logistics across Europe. By analyzing and comparing the outcomes from both models, this study seeks to provide a comprehensive evaluation of the proposed approach. The results will help pinpoint areas for refinement and development, contributing to the advancement of a robust and effective framework for multimodal logistics optimization. This effort represents a significant step toward enhancing the model's applicability to real-world European transport and logistics scenarios. Future developments of this research will focus on several critical aspects to further improve the capabilities and applicability of the proposed framework:

- **Enhancing the model for simultaneous management of multiple transport service requests and freight types:** Expanding the model to accommodate concurrent requests for diverse transport services and freight types will enhance its scalability and adaptability, enabling it to tackle more complex and realistic logistics scenarios.
- **Validation with real-world data from multimodal logistics networks and data flows:** Conducting experiments with real-world demand data will bridge the gap between theoretical modeling and practical applications, validating the framework's relevance and identifying areas for improvement.
- **Simulating specific policy measures:** Integrating policy simulations, such as carbon pricing, road usage restrictions, or incentives for collaboration among carriers, will enable the framework to evaluate the implications of various policy decisions on multimodal logistics efficiency and sustainability.

An additional focus will be the further development of the second module, which addresses the integration of trucks and drones in last-mile delivery operations. This work aims to extend the Heterogeneous Drone-Truck Routing Problem, optimizing the collaboration between trucks and multiple heterogeneous drones to minimize total delivery completion time while considering uncertainties in drone flight times.

Future enhancements to this module will address the following key aspects:

- **Last-Mile Delivery with Truck and Drone:** Improving the model to ensure efficient coordination between trucks and drones, particularly in scenarios involving varying payload capacities, flight ranges, and operational constraints. This effort will tackle practical challenges associated with deploying drone-truck systems for real-world last-mile delivery.

- **Robust Optimization to Handle Drone Flight Time Uncertainty:** Developing robust optimization techniques to account for uncertainties in drone flight times caused by environmental conditions, payload variations, and technical limitations. This will ensure reliable and efficient delivery operations even in unpredictable scenarios.

This work represents a significant step forward in advancing the second module, with the potential to substantially improve the efficiency, sustainability, and resilience of last-mile logistics.

In conclusion, these future research directions aim to refine and expand the proposed framework further, ensuring its continued relevance in addressing both current and emerging challenges in sustainable logistics.

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