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Multi-criteria integration of passenger and freight transport for sustainable last-mile delivery logistics

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ABSTRACT

The first and last mile (FLM) transport for passengers and freight significantly contributes to overall pollution, transportation costs and energy consumption. Recent scientific reports at European level suggest that combining passenger and freight flows (commonly referred to as *integrated transport*) could be an effective strategy to promote sustainable and energy-efficient FLM transport. Public transportation usually covers most populated areas of the city, making it suitable for this kind of dual operation. Despite their potential, integrated systems have not been extensively explored. This study develops an algorithm that optimizes the location of dual-purpose stops within Bilbao's bus network in Spain to facilitate such integrated operations through a combination of evolutionary algorithms. The real multi-objective optimization scenario proposed as a case study formulates and solves the problem of balancing the benefits and inconveniences of incorporating such a combined service. The design of the system's operational aspects involves the integration of the real scenario service characteristics into the problem formulation, as well as an analysis of local planning documents. The system's performance is assessed and compared to existing public transport and freight systems, considering the Pareto trade-off of two key factors for the design of the service: the impact of the integrated transport service on the passengers' quality of service and the mileage required to deliver goods to their corresponding destinations. Our findings indicate that operational benefits and energy savings can be achieved gauging the level of inconvenience introduced in the passenger transportation service.

1. Introduction

The growing demand for passenger movement and the expansion of e-commerce have led to a general increase in travel and deliveries, resulting in more complex and fragmented logistics. These trends pose additional challenges for transport operations and have significant societal impacts. Short-haul passenger and freight transport, particularly the initial and final segments of longer journeys (known as the First-Last Mile, or FLM), is a critical aspect of transport operations due to their high costs and negative impacts relative to the entire trip. FLM is especially problematic in urban areas, where routes are often fragmented and uncoordinated, leading to low vehicle occupancy, excessive number of displacements, high environmental costs, community impacts, and increased system expenses (Kåresdotter et al., 2022; Charisis et al., 2018; Park et al., 2021).

One potential solution to improve FLM efficiency is the integration of passenger and freight transport into a single operational transportation framework. Authorities and policymakers have attempted to address inefficiencies in various ways, often resulting in uncoordinated strategies with limited success and some negative outcomes, such as reduced competitiveness and a more complex mobility system (Zubin et al., 2021; Pyrialakou et al., 2019). In contrast, operators have promoted integrated transport solutions. The 2007 Green Paper on Urban Mobility by the European Commission (European Comission, 2007) highlighted the potential benefits of integrating passenger and freight transport to enhance the environmental, social, and financial sustainability of FLM. This prompted further research into various forms of short-haul passenger–freight combined transport, referred to as freight-on-transit or IPFT (Integrated Passenger Freight Transport), in both

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urban and rural settings. Trentini and Malhéné (Trentini and Malhéné, 2010) identified three potential forms of integration: infrastructural (shared infrastructure for both freight and passenger vehicles), vehicular (transporting goods and passengers on the same vehicle), and nodal (using specific network nodes for both passenger and freight functions). While vehicular integration has been widely studied, infrastructural and nodal integrations have received less attention to date.

Evaluating the performance of IPFT for FLM is crucial to determine its practical applicability (Li et al., 2022; Melo and Costa, 2011). The practical implementation of this paradigm may face challenges such as ensuring passenger acceptance through dedicated surveys and pilot actions (Mohri et al., 2024), complying with regulatory and normative requirements (Gao and Zhao, 2017), addressing the limited knowledge of urban freight demand patterns (Cappelli and Nocera, 2006), and considering possible additional costs for adapting infrastructure (e.g., modifying bus stops or vehicles) and for training staff in freight handling (Baker et al., 2023). In addition to operational performance, the adoption of the proposed IPFT system depends on stakeholder acceptance. For freight transport clients, key considerations include cargo security, handling reliability, and competitive delivery costs. For bus passengers, acceptance can be influenced by comfort, safety, and the perception that freight handling does not compromise transportation service quality. Addressing these concerns through measures such as secure freight compartments, minimal-impact loading processes, and clear communication of broader environmental and societal benefits can significantly improve the likelihood of successful implementation. In urban areas, the primary goals are to reduce the number of circulating vehicles, thereby addressing congestion, noise, and environmental issues, and promoting more efficient use of urban space (Holcombe and Williams, 2010; Timilsina and Dulal, 2011) and public transport (Nocera, 2010). In rural areas, IPFT aims to improve the financial sustainability of transport and logistics operations, maintain the attractiveness and competitiveness of remote areas and businesses, and enhance opportunities and quality of life for residents (Feng et al., 2023). IPFT contributions for FLM can be classified into two main areas: (i) evaluating the performance of integrated systems using specific indicators (Bruzzone et al., 2023; Kashav and Garg, 2025), and (ii) developing mathematical models to optimize integrated systems (Machado et al., 2025; Pimentel and Alvelos, 2018). Most research aims to explore the benefits of IPFT compared to conventional transport, focusing on environmental, socioeconomic, and financial aspects. However, these studies often overlook the question of when to adopt IPFT versus independent delivery and transport, based on stakeholders' needs and preferences, and tend to emphasize environmental and social impacts over operational aspects.

Previous studies on IPFT have extensively explored optimal routing and scheduling models. However, to the best of our knowledge, only one study has specifically examined how conventional bus stops can be adapted to handle freight and transformed into dual-purpose stops (i.e., stops designed for both passenger transportation and goods delivery). The recent work by Yang et al. in Yang et al. (2024b) investigated parcel delivery integration within fixed-route public transport networks, aiming to improve urban logistics efficiency and sustainability. Their results highlight the feasibility of synchronized parcel flows through an arc-based metaheuristic algorithm combining Genetic Algorithms (GA) and Variable Neighborhood Search (VNS). However, their approach considers double stops only as a consequence of broader parcel delivery optimization strategies.

Differently and from a novel perspective, the study presented in this manuscript reverses that paradigm by proposing a mathematical model to identify scenarios where integrating freight into a conventional bus line is advantageous, focusing on the operational aspects of individual stops, and comparing IPFT with separate passenger and freight transport systems. Specifically, we propose a multi-objective optimization model to evaluate trade-offs between passenger service quality and freight delivery efficiency, emphasizing localized considerations such as urban planning, infrastructure adaptation, and operational strategies. The model employs Multi-Objective Evolutionary Algorithms (MOEAs) to determine optimal configurations for dual-purpose bus stops, incorporating variables like parcel unloading times, maximum freight load per bus, and walking distances for parcel collection. Particularly, we formulate a bi-objective combinatorial optimization problem and solve it using a multi-objective metaheuristic algorithm tailored to discrete search spaces. A case study in Bilbao, Spain, validates the utility of the designed algorithm in addressing the IPFT problem. The Pareto approximations generated by the solver illustrate trade-offs between mileage and passenger service quality impacts. This study advances the state of the art by designing and validating an evaluation framework for practical IPFT decision-making, allowing for the exploration of different scenarios. By addressing an open research gap with a context-specific mathematical model, it offers innovative solutions and insights for integrating passenger and freight transport, paving the way for more sustainable and efficient urban mobility systems.

The rest of the this paper is structured as follows: Section 2 reviews past contributions, Section 3 introduces the problem and formulates it mathematically. Section 4 describes the case study and the algorithms used to efficiently solve the formulated problem. Section 5 discusses the results obtained in the case study under consideration. Finally, Section 6 concludes the paper with a summary of our findings and an outline of future research lines.

2. Related work

In recent years, the academic interest in the integration of passenger and freight transport (IPFT) has grown significantly (Arvidsson et al., 2016; Kiba-Janiak et al., 2021; Cavallaro et al., 2023). In the literature, this concept appears under various names, including co-modality (Zhu et al., 2023), cargo hitching (Van Duin et al., 2019), systems with mixed passengers and goods (Masson et al., 2017), share-a-ride (Cheng et al., 2023), integrated passenger and freight logistics (Bruzzone et al., 2023), and collaborative passenger and freight transport (Li et al., 2021). The variety of terms reflects the complexity and multidimensional nature of the topic, which is studied across different disciplines and contexts. Its relevance is further emphasized by the recent release of a dedicated special issue in a prominent journal (Antoniou et al., 2023). Researchers have approached IPFT from diverse perspectives, adapting their analyses to specific mobility systems and operational conditions. This section discusses the general perspectives on IPFT, as well as concrete algorithmic proposals developed to address specific challenges in the field.

2.1. General perspectives on IPFT integration

The integration of passenger and freight transport has been examined from multiple angles, often adapted to the characteristics of specific mobility systems and contexts.

One prominent strategy involves vehicle sharing, where the same transport vehicles serve both passengers and freight. For example, several studies have demonstrated how local bus services can be optimized to carry goods alongside passengers, making use of existing public transport capacity to improve efficiency and lower costs. The works in Bruzzone et al. (2023) and Cavallaro and Nocera (2023) show that spare capacity on local buses can effectively be repurposed for freight transport.

Another approach focuses on the shared use of infrastructure. In Hörsting and Cleophas (2023), the authors investigate the operation of freight trams using existing urban tram tracks within regular passenger services. This model leverages established rail infrastructure, reducing the need for separate freight systems and helping to ease urban congestion. Hörsting and Cleophas introduce a linear mixed-integer program that optimizes the train schedule and allocates cargo, featuring a lexicographical objective function that prioritizes passenger transport while minimizing cargo delivery delay. Li et al. (2022) integrate the train unit scheduling problem with combined transportation of passengers and freight during off-peak hours, with the objective of fully utilizing the remaining capacity by allowing a flexible composition such that the capacity can better meet the demand. These authors explore the feasibility of integrating freight and passenger services within a high-speed railway system, enabling the sharing of transportation resources under multiple operational modes. They propose a sharing-carriage mode, used in combination with a sharing-train mode, to maximize the utilization of unused capacity within the existing railway schedule.

Integration can also extend to other transport-related assets. For instance, Fessler et al. (2023) proposes placing small consolidation centers or parcel lockers at transit stops, enabling more efficient last-mile delivery. This approach transforms public transport hubs into multifunctional spaces, optimizing urban land use while enhancing delivery efficiency.

All these strategies can be used at the same time, as in Liu et al. (2025). This paper explores the road–underground co-modality for urban freight transport (RUM4UFT) as a solution to urban traffic challenges, which includes three modal split strategies: mixed-use metro lines, metro freight–passenger integration, and purpose-built underground corridors.

There is also recent interest in the general planning of these systems, including the contribution in terms of externalities. Tapia et al. (2023) use disaggregated activity-based models for urban passenger transport and freight transport to save freight trips and thus alleviate urban transport congestion and environmental pollution. de Oliveira et al. (2024) note that the rapid expansion of e-commerce has intensified freight movements in urban areas, hindering progress towards sustainable cities. They argue that utilizing the spare capacity of public transport systems can help offset the negative externalities of urban freight and advance sustainability objectives. This article identifies and evaluates the key factors essential for developing integrated freight–public transport systems.

Finally, the literature shows increasing interest in the role of autonomous vehicles in facilitating the integration of passenger and freight transport. Several studies have explored scenarios ranging from autonomous buses delivering parcels during off-peak hours to shared autonomous shuttles designed for both passengers and goods, indicating a promising direction for future research and real-world implementation. An urban-based integrated automated public transportation system that serves both people and freight is examined in Sun et al. (2020), which leverages on emerging technologies such as information communication technology and automated vehicle, while Staritz et al. (2025) focus on user acceptance of systems that integrate passenger and freight flows.

2.2. Algorithmic proposals for IPFT integration

A substantial body of IPFT research focuses on mathematical modeling and operational strategies aimed at optimizing routing, scheduling, and resource utilization. Most studies employ heuristic, metaheuristic, or exact optimization approaches, with the choice of method often depending on problem size, data availability, and operational constraints:

- *Vehicle–hub-last-mile integration:* In Pimentel and Alvelos (2018), the authors propose a model that assigns origin loads (or requests) to inbound hubs (bus operator centers), transfers them to bus services, and finally to bus stops for collection by micro-logistics operators using environmentally friendly fleets. The objective is to minimize total service time while ensuring synchronization across the network and balancing loads with system capacities.
- *Share-a-ride models:* A mixed Integer Linear Programming (MILP) model was developed in Li et al. (2014) for the "share-a-ride" problem in taxi-based passenger–parcel services. This model optimizes both routing and scheduling to serve passengers and parcels jointly. Mo et al. (2024) offer a cost-efficient way to use existing capacity while reducing environmental impacts, presenting an integrated optimization model that coordinates freight train scheduling, package allocation, and passenger train rescheduling under dynamic passenger demand. Similarly, Ghilas et al. (2016, 2018) addressed pickup-and-delivery problem variants through heuristic methods, offering practical solutions that account for real-world constraints in mixed transport systems. For subway systems, Dong et al. (2018) proposed a MILP model to integrate passenger and freight services, improving capacity utilization and service efficiency.
- *Uncertainty handling:* The study in Machado et al. (2023) incorporates freight demand uncertainty, accounting for scenarios with varying demand volumes, delivery time windows, and last-mile constraints. They use an exact ILP method alongside two greedy randomized adaptive search procedures. Likewise, Mo et al. (2024) formulated an integrated model for freight train scheduling, package allocation, and passenger train rescheduling with dynamic passenger demand, applying linearization techniques to manage non-linear constraints within a warm-start MILP framework.
- *Simulation-based approaches:* In Fehn et al. (2023), an agent-based simulation framework integrates three heuristic parcel-assignment strategies into a ride-pooling control algorithm, enabling adaptive routing and scheduling in dynamic demand environments.
- *Mode-specific solutions:* For freight-by-tram, the research in Ozturk and Patrick (2018) applies approximation algorithms, pseudo-polynomial dynamic programming, and heuristic methods to address IPFT-specific constraints. On-demand IPFT routing was studied in Molenbruch et al. (2021) using a metaheuristic algorithm to optimize routes for combined passenger and freight demand. Petit and Ouyang (2022) use continuum approximation to reduce the computation burden by formulating the design problem with respect to a few decision variables.
- *Green and demand-driven routing:* A demand-driven MILP model based on the green vehicle routing problem was introduced in Yang et al. (2023) to maximize vehicle capacity usage for both passengers and goods. In rural contexts, Yang et al. (2023) used mixed-integer programming to evaluate taxi-based freight–passenger integration, optimizing for both profitability and labor feasibility.
- *Crowdsourced and long-haul integration:* In Yang et al. (2024a), the synchronized passenger–freight co-modality problem is addressed via a population-based variable neighborhood search, modeling scenarios where passengers volunteer to transport parcels for compensation. Long-haul IPFT is explored in Wang et al. (2023), where additional railcars are attached to passenger trains; the authors apply a binary integer model with Lagrangian relaxation and Tabu Search heuristics.
- *Urban rail and rural bus integration:* The urban freight transport problem tackled in Behiri et al. (2018) uses a passenger rail network as a backbone, combining MILP with heuristics for practical implementation. In rural public transit, He et al. (2023) develops an MILP model for electric buses transporting passengers and e-commerce parcels, optimizing both routing and scheduling to minimize system-wide costs.
- *Hybrid metaheuristics:* The study in Yang et al. (2024b) integrates parcel delivery schedules into public transport operations, using a hybrid genetic algorithm-variable neighborhood search to reduce average delivery times in a single-objective optimization setting. The paper explores the integration of parcel delivery schedules

with public transport networks, proposing a model to optimize this co-modality integration, focusing on reducing the average time to deliver individual parcels.

- *Game theory approaches:* There has been also late interest for game-theory applications to these models. For instance, Zheng et al. (2025) examine a scenario in which an intercity bus company leverages its surplus capacity to transport freight on behalf of a logistics company. The interaction between their decisions is modeled as a sequential game, and a backward induction approach is applied to derive optimal operational strategies for both parties given a specific freight volume. In addition, a multi-period optimization model is developed to determine the system-optimal freight volume allocation for the logistics company, supported by a tailored algorithm capable of producing near-optimal solutions.

2.3. Algorithmic trends and gaps

From the reviewed literature, classic integer programming remains dominant, particularly for small- and medium-sized problems. However, scalability issues arise in large, real-time systems. Metaheuristics such as Genetic Algorithms, Variable Neighborhood Search, Tabu Search, and Greedy Adaptive Procedures are better suited for complex, dynamic, or large-scale scenarios where speed and adaptability outweigh guaranteed optimality. Applying MOEAs offers additional flexibility by balancing competing objectives, enabling stakeholders to choose from a Pareto front of solutions. MOEAs have been widely applied in freight and last-mile logistics (Osaba et al., 2021), including drone integration (Lee and Wong, 2022), multi-carrier routing (Zhang et al., 2020), and urban safety considerations such asbike–freight interactions (Osaba et al., 2018). They are also used for strategic facility location problems, such as parcel locker placement (Che et al., 2022) and depot allocation in supply chains (Shankar et al., 2013). Emerging methods such as reinforcement learning, Large Neighborhood Search (LNS), and constraint programming hybrids are showing promise for adaptive, data-driven IPFT operations, especially under uncertain demand.

Despite extensive modeling of routing and scheduling problems, few studies address infrastructure adaptation, specifically, modifying conventional bus stops to support both passenger boarding and freight loading. Our work addresses this gap by developing a mathematical model to determine where freight integration into a bus network is most advantageous, converting selected bus stops into “dual-purpose” facilities that efficiently serve both passengers and freight.

3. Problem description and mathematical statement

Defining the passenger–freight bus problem in an urban environment requires establishing different aspects of the service in order to configure the problem at hand. First, Section 3.1 describes the scenario, *i.e.* the nature of the service, how it is going to operate in the regular line stops and how the freight management is going to be performed. Next, Section 3.2 focuses on the mathematical definition of the problem, elaborating on the variables and the objective functions.

3.1. Overall description of the scenario

Currently, it is common for logistic companies to rely on certain collection points, such as small businesses and shops with which they have agreements, to deliver part of the goods, which are then picked up later by their final recipients. These locations act as intermediate depots in the delivery operation, reducing the number of stops that delivery vehicles need to make. With the recipient’s acceptance, the delivery is sent to one of these collection points instead of directly to the final address. The freight–passenger bus concept aims to further reduce the number of delivery vehicles visiting collection points by replacing part or most of them with bus deliveries, using company vehicles only for home deliveries. This way, the traffic required to serve these locations could be replaced by vehicles that already operate along fixed routes. Our work hinges on the idea of reserving a certain space on buses to carry these goods alongside passengers. The buses available for this task will operate within a set of bus lines, each with a series of stops. The stops along a given bus route are traversed sequentially in time, meaning that the subset of nodes in its line follows a specific visitation order. Unless otherwise stated, we assume that the bus routes are cyclical. Among the stops on each line, some will serve as *double stops*, *i.e.*, stops that function as both freight and passenger stops.

To qualify as a double stop, a bus stop must be within a certain walking distance of a predefined collection point for the scenario under consideration. Consequently, only bus stops within range of at least one collection point can be considered as candidates for a double stop. The walking range influences the impact of unloading goods at a double stop: the longer the walking range, the greater the impact on the total journey time of the passengers. The double stops do not need any special feature beyond the proximity to available collection points, such as lockers or specific unloading zones. The parcels are picked by the collection point personnel, who should be at the stop when the bus arrives. Operationally, when a bus reaches a double stop, it takes longer than a usual stop because extra time is reserved for a worker from the associated collection point to retrieve the specific parcels. This delay is an inconvenience for passengers, and its severity depends on the distance between the double bus stop and the nearest collection point in the city. The unloading of parcels is performed by employees of the collection points (see Fig. 1), whose operations fall outside the scope of this analysis. In principle, the designated staff member is expected to be waiting at the bus stop upon arrival and is responsible for unloading the parcels during the stop. This process incurs a base time penalty (defined below). However, if the number of parcels exceeds what the agent can transport in a single trip from the bus to the collection point, the bus must wait for the agent to return and collect the remaining parcels. This necessitates the definition of a maximum operation time per batch and a maximum number of batches (determined by the barrow’s capacity), which in turn limits the total number of parcels a bus can carry per trip. Once unloaded from the bus, the subsequent transport of parcels to the collection point is not part of the bus operation and does not contribute to additional delay. All these aspects are formally defined in the following section.

Without loss of generality, parcel demand is assumed to be driven by census data and the spatial distribution of buildings in the study area. If fine-grained historical records of parcel demand were available, the demand could be projected geographically, leading to a more accurate estimation of spatial and temporal demand patterns. However, we adopt a more conservative modeling approach to account for the worst-case scenario where only aggregated demand rates at the city or district level are available. Given an aggregated city-level demand (parcels per inhabitant over a given time frame), the demand is distributed across the city based on population data. As later explained in detail in Section 4.1.3, all parcels delivered in the city within the time frame are assigned at random to buildings, weighting the chances of choosing a given building by its population, estimated using the population of its district and with replacement, so that inhabitants in a building can request more than one parcel.

Parcels can be delivered using different methods depending on the reachability of the delivery service defined in this manuscript. Service reachability depends on the distance between collection points and the locations where demand is generated. Intuitively, users will be less inclined to use the service if the distance between their location and the collection point is large, requiring them to traverse long distances to collect their parcels. As we will later define mathematically, service reachability is determined by the maximum walking time that users are willing to accept. This maximum walking time defines the total aggregated demand (parcels) assigned to each collection point, depending

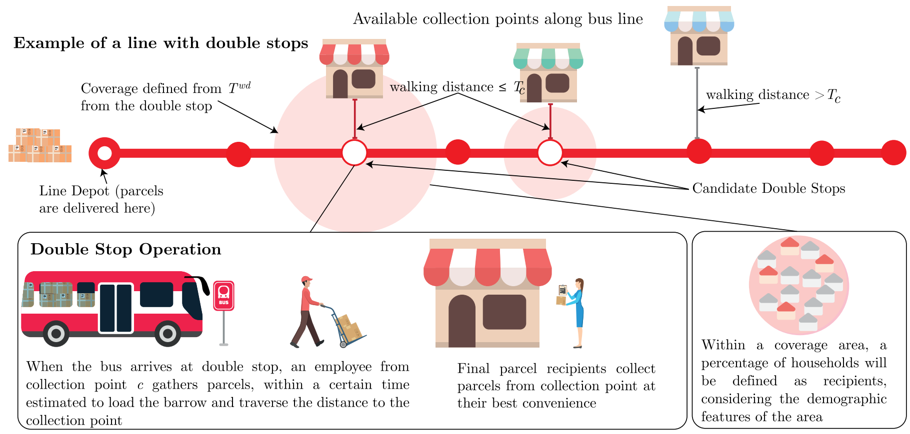

Fig. 1. Schematic diagram of the end-to-end operation of the considered IPFT system.

on the buildings within the isochrone area (Aranguren et al., 2023) centered on the collection point.

For each bus line, a maximum freight capacity is defined based on the nominal capacity of the bus and its scheduled stops at double stops. The total number of parcels a bus can carry must not exceed this capacity. In principle, buses provide freight service only during valley hours (periods of low passenger demand) to minimize the impact on passenger service quality and ensure sufficient space is available for freight. Since the freight load is known in advance, the expected delay can be estimated and displayed at bus stops and through the service app, allowing passengers to choose alternative routes if the delay makes their usual route impractical. Valley hours can vary between buses, so the number of complete round trips a bus can make during valley hours is defined as the number of times it can complete a full route within that time frame. This also determines how often the bus can stop for freight unloading at double stops. Computation of valley hours is grounded on real occupancy data of each line. Additionally, a maximum batch size for unloading parcels is established to prevent excessive delays, as buses carrying larger freight loads require longer unloading times and face greater penalties.

To facilitate loading parcels onto buses, our scenario assumes that each bus line's terminal includes a depot where logistic companies deposit the parcels designated for bus delivery. Servicing these depots incurs costs for the logistic company, but these costs should be lower than delivering the same parcels deeper into the city. Furthermore, because bus line terminals are often located on the outskirts, this system helps reduce delivery traffic in the city center. Finally, a *main depot* for the logistic company is designated as the starting point for routes that serve both the line depots and home addresses not covered by the integrated parcel–freight transport (IPFT) service. The complete end-to-end operation of the whole IPFT system is depicted in Fig. 1.

In this scenario, the optimization goal is two-fold:

- *Minimization of the traffic impact caused by delivery vehicles*: selecting the best double stops for the bus service should, in principle, reduce the distance traveled by traditional delivery vehicles, thereby minimizing the impact of parcel deliveries on traffic congestion, pollution, noise, and other urban issues. Although the model does not explicitly compute pollutant emissions, the total delivery distance is used as a proxy for environmental impact, which is consistent with most emissions estimation frameworks. Reducing vehicle kilometers traveled is strongly correlated with lower fuel consumption and emissions, especially in urban freight contexts. In the particular case of Bilbao, its sustainable urban mobility plan (PMUS)[1] establishes the estimated emissions for light vehicles in 350 g per kilometer (5.25 Kg. per 15 km trips), considering the topography and typical level of service in the central area roads. Considering that in the best emissions approach available, the relationship between traveled kilometers and emissions is linear, both metrics can be equally considered for practical use. This abstraction allows for tractable modeling while still supporting sustainability-oriented decision-making. Therefore, if, for a given maximum acceptable walking time, the demand coverage of selected double stops is maximized, it should lead to a reduction in traffic and emissions related to last-mile logistics. However, as observed in Fig. 2, solutions with similar coverage can have different implications in terms of the distance traveled by regular delivery vehicles. Thus, this objective depends not only on the demand coverage of the selected double stops but also on their location within the urban road network.
- *Minimization of the degradation of bus transportation service quality*: allocating part of the bus space for parcel deliveries creates an inconvenience for passengers by reducing available seating and increasing stop durations at double stops. This negatively impacts passenger service quality. While the model abstracts these impacts through time penalties, it does not yet incorporate localized urban features such as pedestrian congestion, stop-specific infrastructure readiness, or traffic bottlenecks. These factors could significantly influence the feasibility and efficiency of parcel handling at specific stops and are important considerations for future extensions of the model. Since the IPFT service is constrained to operate during low-demand time slots, the impact on service quality is measured primarily in terms of time delays. These delays stem from the additional time required to unload parcels at double bus stops and transport them to the nearest collection points. This second objective is quantified by the total additional time required for all buses stopping at double stops to unload parcels assigned to their nearest collection points, along with the extended completion time due to the unloading process.

These two objectives inherently conflict with each other, requiring a careful balance when selecting double stop locations. On one hand, maximizing coverage to reduce delivery vehicle traffic suggests choosing double stops that are widely spread across the city, ensuring that a large number of collection points are within an acceptable walking distance. However, this can lead to a higher number of double stops, increasing the total time buses spend unloading parcels and thus degrading passenger service quality. On the other hand, minimizing passenger disruption would favor selecting fewer double stops, ideally those located in areas with minimal impact on bus travel times. Yet, this approach may reduce the overall demand coverage, leading to more deliveries being handled by traditional freight vehicles and consequently increasing urban congestion. Therefore, an optimal double

[1] Bilbao's Sustainable Mobility Plan, https://pmus.bilbao.eus/wp-content/uploads/2016/10/PMUS-Plan-de-Movilidad-Urbana-Sostenible-de-Bilbao.pdf [acc. Dec 1st, 2025].

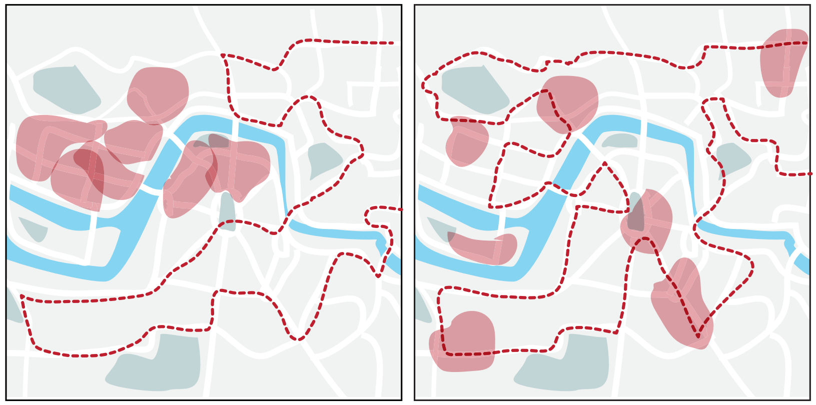

Fig. 2. Two examples of possible solutions. Red areas depict isochrone areas associated to different double stops each, while dotted line pictures the route a delivery vehicle will perform when attending the remaining parcel demand. While both solutions involve the same amount of double stops covering a similar % of the aggregate parcel demand, the distance to be traveled for the left case is lower.

stop allocation strategy must meet a balance between these opposing objectives, ensuring that enough demand is shifted to the bus system without imposing excessive delays on passengers.

3.2. Mathematical definition

The mathematical statement of the problem underneath the scenario described previously departs from the definition of the bus routes available in a city as $\{\mathcal{N}_l\}_{l=1}^{L}$, where $\mathcal{N}_l \subseteq \mathcal{N}$ denotes the subset of nodes (*bus stops*) of the lth bus line with respect to the overall set of nodes in the graph $\mathcal{G} = \{\mathcal{N}, \mathcal{V}\}$ that models the public transportation network of the city. Such routes may not be independent of each other, *i.e.* it may occur that $\mathcal{N}_l \cap \mathcal{N}_{l'} \neq \emptyset$ for $l, l' \in \{1, \dots, L\}$ such that $l \neq l'$. We also define as $\mathcal{B}$ the set of all buildings of the city, part of which will be covered by the IPFT service. Typically, stops in the center areas of the city share multiple lines while neighborhood stops are covered by single lines. Each bus stop of a bus line is therefore a node of the trajectory of the line $\mathcal{N}_l$. Double stops are defined as a subset $\mathcal{N}^{\text{ds}} \subseteq \mathcal{N}^{\text{all}} \subseteq \mathcal{N}$, where $\mathcal{N}^{\text{all}} = \bigcup_{l=1}^{L} \mathcal{N}_l$ denotes all bus stops in the city under consideration.

A collection point is defined as c, whereas the set of all collection points in the city is denoted as $\mathcal{C}$. We refer as T_c to the maximum walking time allowed to reach the collection point c from its closest double bus stop $n_c^{\text{ds}} \in \mathcal{N}^{\text{ds}}$. The time needed by a person to unload the parcels in double bus stop n_c^{ds} is given by $T^{\downarrow}(n_c^{\text{ds}})$. On the other hand, the aggregated demand is given by H (number of inhabitants demanding the delivery of a single parcel during a day), whereas the overall daily demand is denoted as D (total number of parcels to be delivered in a city per day). A selection of buildings are sampled uniformly throughout the whole city, considering the overall demand D that is computed applying the generated demand per inhabitant ratio H to the whole population of the city. This results in a set of individual demand points (buildings). The level of reachability provided by each of the double stops of the IPFT service can be defined based on the amount of demand points that have access to at least one of the collection points in $\mathcal{C}$ within a specified walking time T^{wd}. The computation of T^{wd}-isochrones centered on each collection point $c \in \mathcal{C}$ results in a coverage area associated to c, which computes which demand points can be serviced by c and, ultimately, a total number of parcels $D(c)$ serviced by collection point $c \in \mathcal{C}$.

The maximum freight quantity $q_l = r_l \cdot Q^{\max}$ is computed based on the nominal bus capacity $Q^{\max}$ and the number r_l of complete round trips of a bus in line $\mathcal{N}_l$. The total number of parcels that a bus can deliver cannot exceed q_l. Besides, when considering the process of unloading parcels from the bus to the collection point $c \in \mathcal{C}$, a maximum batch of parcels $D^{\max}$ can be unloaded at a time. The depot in the header of each bus line that has double stops is denoted as $n^{l,\circledcirc} \in \mathcal{N}$.

As explained previously, the goal is to determine a subset of all bus stops $\mathcal{N}^{\text{ds}} \subseteq \mathcal{N}^{\text{all}} \subseteq \mathcal{N}$ that will serve for the *double purpose* of passenger and parcel transportation. Essentially this can be modeled as a combinatorial optimization problem driven by $|\mathcal{N}_{\text{ds}}|$ decision variables. Assuming $|\mathcal{N}_{\text{ds}}| = L$ (i.e. as many double bus stops as bus lines in the scenario), solutions to this problem can be numerically encoded as an L-length solution vector $\mathbf{x} = \{x_l\}_{l=1}^{L}$, such that $x_l \in \{-1, 1, \dots, |N^{\text{all}}|\}$. Here, $x_l \in \{1, \dots, N\}$ indicates the index of the node in $\mathcal{N}^{\text{all}}$ selected to be a double bus stop, whereas $x_l = -1$ denotes the case in which line l does not have a double stop. Fig. 3 exemplifies this solution encoding strategy and the confluence of two conflicting objectives in the selection of which bus stops should be used for both passenger transportation and parcel delivery.

The quality (fitness) associated to a certain value of this vector $\mathbf{x}$ will be a result of computing the impact of delivering all parcels not covered by the IPFT service via regular delivery, as well as the degradation of the quality of service of the bus passengers caused by the unloading of parcels at the double bus services. The impact of delivery vehicles is defined as $f_{dist}(\mathbf{x}; \mathcal{G}, \mathcal{C}, \mathcal{B})$, which is given by the sum of (i) the distance that needs to be traveled by regular delivery vehicles to deliver the parcels to those buildings in $\mathcal{B}$ with demand that is not covered by any double stop (given by T_c, T^{wd}, H and D); and (ii) the distance required to transport the freight from the logistic company depot to the bus line header depots $n^{l,\circledcirc}$ (only for those lines with assigned double bus stops as per $\mathbf{x}$). As argued in Section 3.1, $f_{dist}(\cdot)$ serves not only as a logistical cost metric but also as a proxy for environmental impact, under the assumption that emissions scale proportionally with the distance traveled by regular delivery fleets.

The other conflicting objective, the impact on the quality of the transportation service perceived by the passenger of the bus lines in the city, is given by $f_{qos}(\mathbf{x}; \mathcal{G}, \mathcal{B}, \mathcal{C})$. Currently, this function models delay based on unloading time and batch size, but does not explicitly account for localized urban factors such as pedestrian flow, stop-level infrastructure constraints, or traffic conditions. As discussed in Section 3.1, these elements could be integrated into future extensions of this problem formulation to refine the estimation of service disruption and improve location-specific decision-making. Hence, this quality degradation $f_{qos}(\mathbf{x}; \mathcal{G}, \mathcal{B}, \mathcal{C})$ is gauged by the time $T^{\downarrow}(n_c^{\text{ds}})$ needed for unloading the parcels at a double bus stop n_c^{ds} given by $\mathbf{x}$, and for carrying them to the nearest collection point in $c \in \mathcal{C}$. Importantly, this delay accounts only for the time the bus remains stationary while the worker from the collection point retrieves the parcels directly from the vehicle. It does not include the time required to transport the parcels from the bus stop to the collection point, as the bus resumes its itinerary immediately after unloading. The worker is expected to be

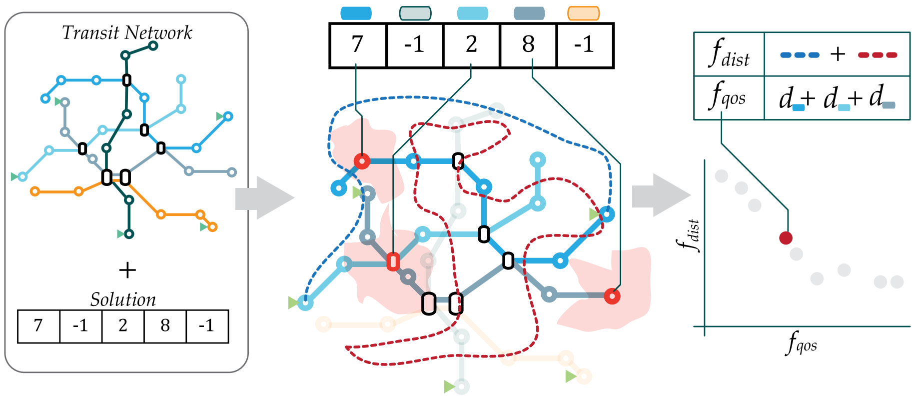

Fig. 3. Given a transit network and a defined solution, the scheme at the center depicts in red circles and areas the selected double stops and covered areas respectively. The blue dotted line represents the route a delivery vehicle will perform to reach the line headers of affected lines (green triangles), while the red dotted line showcases the delivery route for the remaining parcels. The impact of the selected solution is illustrated on the right diagram, being f_{dist} the sum of the traveled distance in both delivery routes and f_{qos} the sum of the delays associated to each double stop.

present at the stop upon arrival and handles the transfer independently once the parcels are retrieved. The unloading process consists of a fixed setup time and a per-batch unloading time, with the total delay capped according to the bus's freight capacity. This objective can be computed as:

$$f_{qos}(\mathbf{x}; \mathcal{G}, \mathcal{B}, \mathcal{C}) = \sum_{l=1}^{L} T_{\boxdot} \cdot \left\lceil \frac{D(c)}{W_{\boxdot}} \right\rceil + \lambda \cdot \left\lceil \frac{D(c)}{Q^{\max}} \right\rceil, \tag{1}$$

where $\lceil D(c)/Q^{\max} \rceil$ is the number of round trips that the bus needs to stop in the double stop closer to collection point c to satisfy the demand $D(c)$ considering its maximum capacity $Q^{\max}$; λ is a fixed independent unloading penalty that is computed in each round trip in which the bus stops to unload; $T_{\boxdot}$ denotes the time required to unload a batch of $W_{\boxdot}$ parcels from the bus, which is multiplied by the number of batches that will be needed to unload the complete demand along all the round trips. As explained before, the *typical* demand $D(c)$ of each collection point c is characterized statistically based on H (demand per inhabitant ratio), D (total aggregate demand), the set of buildings in the city $\mathcal{B}$, and the maximum admissible time T^{wd} for a user to collect their demanded parcels from a collection point $c \in \mathcal{C}$.

By considering these two conflicting objectives, the overall bi-objective optimization problem can be formally stated as follows:

$$\mathcal{X}^* = \arg_{\mathbf{x}} \left[\min f_{qos}(\mathbf{x}; \mathcal{G}, \mathcal{B}, \mathcal{C}), \min f_{dist}(\mathbf{x}; \mathcal{G}, \mathcal{B}, \mathcal{C}) \right], \tag{2}$$

where $\mathcal{X}^*$ denotes a set of choices of double bus stops that best balance between the two objectives. Intuitively, lower total distances to complete the overall demand of D imply more double stops, hence higher delivery delays at the *double* stops established by $\mathbf{x}$ may occur, so the impact in the time that defines $f_{qos}(\cdot)$ could be higher. Conversely, the higher the quality of service (reducing the time spent at double stops) for the bus passenger is aimed to be, the lower the number of double stops to be allocated in the public transit network will be, ultimately increasing the total driven distance to deliver the parcels not covered by the IPFT and therefore, detrimentally impacting on $f_{dist}(\cdot)$. This observation motivates that the above problem seeks not single solutions, but rather a set $\mathcal{X}^*$ of $\mathbf{x}$ solutions (a Pareto front approximation) that optimally balance, in the Pareto sense, between the two objectives. This approximated Pareto front provides the decision maker with a set of different IPFT deployments, so that it becomes possible for the decision maker to understand the relative gains that can be achieved in one of such objectives and its penalty in the other.

4. Case study

We particularize the IPFT problem defined in the previous section in a use case conducted over the city of Bilbao (Spain), for which the IPFT system will be evaluated based on real data. Bilbao operates a metropolitan bus service, known as *Bilbobus*, which provides efficient passenger transportation to all districts. The service has three types of lines: regular service, night special services and neighborhood lines. A solution for the problem stated in previous section should consider the following boundaries that have been defined as design parameters or constants:

- A maximum walking time T_c equal to 30 s is set to reflect the operational constraints of small, single-staffed establishments, which are common in the area of study. Larger values may cause business owners (particularly those operating alone, such as tobacco shops, haberdasheries and shoe repair stores) to avoid participating in the IPFT system, as they would need to leave their business unattended for longer periods. While shops may have multiple employees and could accommodate longer walking times, this constraint is designed to ensure inclusivity of smaller businesses that might otherwise opt out. Moreover, T_c is a configurable parameter within the proposed framework and can be adapted to different urban contexts. In regions where shops are typically staffed by more than one person, this value could be increased to several minutes without compromising operational feasibility.
- The maximum walking time $T^{\mathrm{wd}} \in \{5, 6, \ldots, 10\}$ that defines the coverage of an isochrone area is limited between 5 and 10 min. Lower values imply an irrelevant impact on $f_{dist}(\cdot)$ and $f_{qos}(\cdot)$, given the small number of buildings $b_{\boxtimes}$ that would be covered by a double stop. On the opposite side, above 10 min, the number of trips $\lceil D(c)/Q^{\max} \rceil$ needed to satisfy the demand to be served in each area would exceed those established for the bus line during the valley hours.
- Generated demand per inhabitant and day H. As explained in Sections 3.1 and 4.1.3, the demand is generated randomly giving more weight to the buildings in districts with more population. The overall demand established for the city has been set to $H = 0.01$, *i.e.*, 1 parcel per 100 inhabitants a day.
- Available volume per bus in terms of parcel fitting capacity, defined as $Q^{max} = 100$ units of freight (it is assumed that all parcels or units of freight have the same size).
- The maximum freight batch to unload at a time $W_{\boxdot} = 25$, leading to a maximum of 4 unloading actions if the bus is traveling at full freight capacity.
- The fixed penalization time for making a single double stop is set to $\lambda = 30$ seconds, which accounts for the procedural overhead required to prepare the bus for the unloading process. This includes actions such as opening the freight compartment,

ensuring safe access for the collection point staff, and initiating the handover. This time is incurred regardless of the number of parcels to be unloaded and reflects a constant setup cost per stop.
- The time required to unload a batch of parcels is set to $T_{\boxdot} = 60$ seconds, representing the estimated duration needed to physically transfer one batch of parcels from the bus to the collection point. This time scales with the number of batches, which depends on the total parcel load and the barrow capacity used by the collection point staff. By modeling this component separately from λ, the framework captures both fixed and variable aspects of the unloading process, allowing for more accurate estimation of passenger delay and service impact.
- The maximum number of double stops per line has been fixed to 1. This simplifies the calculation of f_{qos}, but specially the definition of $\mathbf{x}$, which will be an L-length tuple, as each line $\mathcal{N}_l$ (with $l = 1, \dots, L$) can only have a double stop.
- Stops that share multiple lines can only be a double stop of one of the lines, which means that only one line can serve a given double stop, in order to avoid solutions in which several lines cover the same area.

It is important to highlight that these considerations have been adjusted considering the particularities of the city of Bilbao and its bus service. Thus, a maximum delay time of 4 min and 30 s at a double stop (as a result of adding λ to $T_{\boxdot}$ times the maximum unloading actions) could be deemed completely impractical in some cities or too short for others. The computation of parcel demand ratios can behave very differently depending on the regions (Courier Parcel Statistics, 2025). This work uses a simplistic computation of the parcel demand based on the number of inhabitants and a uniform distribution, since the estimation of real world parcel demand would require having access to historic data from delivery companies, such as DHL, SEUR, NACEX, UPS or GLS, among others. Nevertheless, tweaking the design parameters would only result in different shapes and dispositions of the solutions in the results, being our main contribution the conception of the IPFT system and not so much its perfect adaptation to the case study, reason for which they have been fixed to focus the analysis in the aspects mentioned above.

The defined scenario only considers the regular service lines, as night services occur outside business hours and neighborhood lines operate small buses that are not suited for freight transport. This results in $L = 28$ lines. The coverage of these lines is depicted in Fig. 4.

Each bus route encompasses multiple bus stops, which may be utilized by various bus lines. For a bus stop to be considered for conversion into a double stop, it must first meet the $T_c = 30$ constraint. A selection of potential collection points has been performed to conform C, considering all businesses listed within T_c of the bus stops. Given the specific nature of the services offered at each establishment, certain types of businesses, such as law firms and pharmacies, are excluded from consideration. Only convenience and retail stores, along with restaurants and supermarkets, have been deemed suitable. All data concerning the establishments of Bilbao has been collected from (BilbaoDendak: promoting city's commercial and tourist activity, 2025). After considering the business type and their proximity to each bus stop, from a grand total of 430 stops, the amount of them that can be configured as double stops is $|\mathcal{N}^{\text{all}}| = 88$. The final selection of double stops is represented in Fig. 4 as red dots. From the exploration of these data, all the line headers $l_{\circledcirc}$ and their locations are also obtained and stored for subsequent usage in the optimization process.

A baseline scenario in which there is no passenger–freight service is defined, allowing to compute the cost of visiting a sample of buildings that satisfy the demand D, prior to the adoption of the proposed freight-sharing system. Considering the same freight demand D, the goal is to find a configuration of double stops that reduces the baseline pollution emission levels. Customers are expected to choose a sustainable travel mean to the collection point c, considering that driving is actually slower when covering the range defined for T^{wd}. As a result, an area of the city will not need to be serviced by the regular delivery service for every double stop that is placed, lowering pollution in comparison to the baseline scenario.

4.1. Methodological approach

The methodology to obtain solutions $\mathbf{x}$, *i.e.*, disposition of double stops along lines that is based upon the scheme depicted in Fig. 3 consists essentially in the application of different multi-objective solvers to the formulation of the problem described in previous section. This depends on the measurement of some distances and computation of different variables described in Section 3.

4.1.1. Computation of different distances

We recall that the objective function f_{dist} requires computing two distances: (i) the distance that needs to be traveled by regular delivery vehicles to those buildings in $\mathcal{B}$ with demand not covered by any double stop; and (ii) the distance required to transport the freight from the logistic company depot to the bus line header depots $n^{l,\circledcirc}$. Both of them are obtained by solving respective instances of the Traveling Salesman Problem (TSP), in which optimal routes that connect all buildings with demand not covered by the IPFT service and all line headers $n^{l,\circledcirc}$ involved in a particular solution, are computed for each solution $\mathbf{x}$. To approximate the solution for each of the TSP problems, a greedy algorithm has been implemented. Although this solution method only finds an upper bound to the real minimum, this discrepancy can account to the fact that in real life the delivery would be performed by means of several vehicles which implies larger distances and some other of the inefficiencies of a real delivery service.

4.1.2. Isochrone areas and buildings inside them

The isochrone lines that define an area around a collection point c are computed once a given set of double stops is defined. For each double stop, isochrones corresponding to $T^{\text{wd}} = 5$ and $T^{\text{wd}} = 10$ are obtained using Open Trip Planner (OTP) (OpenTripPlanner, 2025), a routing machine that, based on a OpenStreetMap (OpenStreetMap, 2025) graph, provides the distances that can be reached from a certain point. Once an area is defined, the buildings inside it are pre-computed so that the optimization process can access them as a look-up table.

4.1.3. Demand and fitness computation

The task of estimating the total volume of freight to be delivered daily is complex and influenced by various factors (van de Riet et al., 2007). Even when focusing solely on e-commerce (Jain et al., 2020), historical data serves as the most reliable predictor for accurate forecasting. In this context, estimating the total volume and spatial distribution of freight demand in urban areas is a complex task, often constrained by limited access to granular historical delivery data. In this study, we adopt a simplified yet conservative modeling approach to simulate parcel demand, which assumes (i) the density of population to be constant among all the buildings within a district and the demand of packages to be constant among the population; and (ii) a uniform random assignment of parcels to buildings, weighted by district-level population. The total population of each neighborhood and the number of buildings are obtained from Eustat (2025) and Bilbao Open Data (buildings) (2025), respectively. These parameters enable to compute the average number of residents per building, which will be used, along with the data presented in Fig. 6, to calculate the estimated parcel demand. These assumptions are motivated by three considerations:

- *Data availability*: In many urban planning contexts, especially during early-stage feasibility assessments, detailed parcel delivery records are either unavailable or remain proprietary. By relying on publicly accessible census data and assuming an uniform demand distribution, our framework remains applicable even in data-scarce environments. This ensures that the proposed IPFT framework can be applied even when only aggregated demand rates are known.

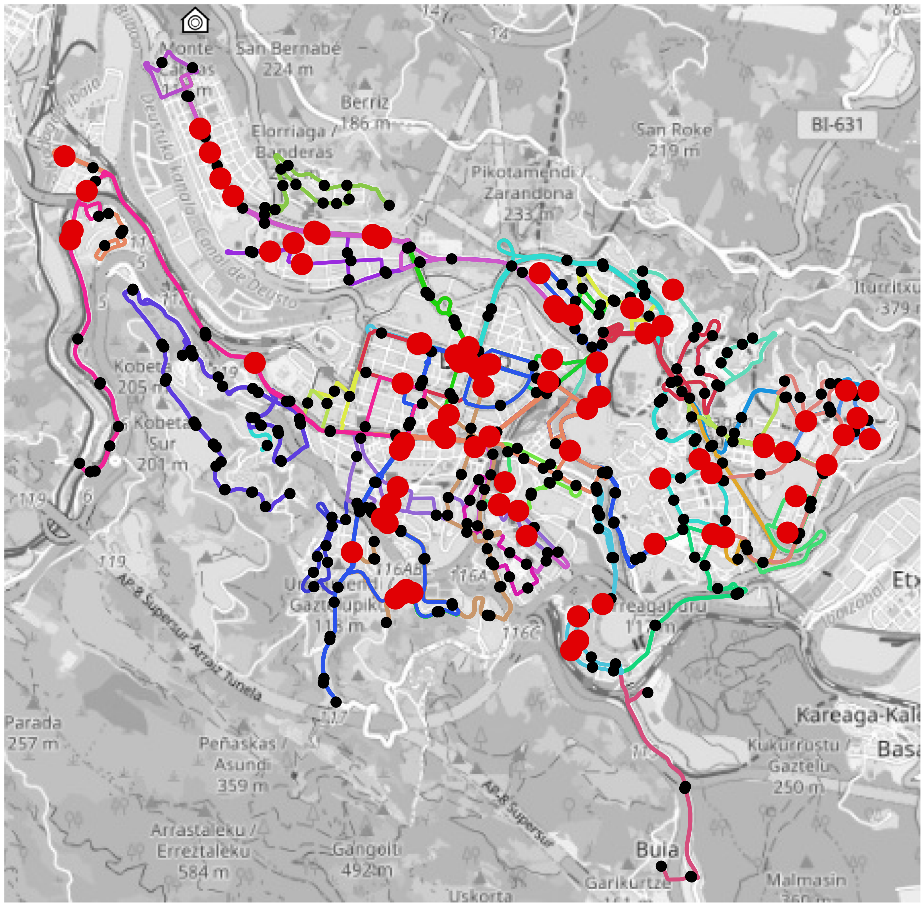

Fig. 4. Bus lines of the Bilbobus public transportation service available in the city of Bilbao (Spain), with all stops of each line (black and red dots). Red dots represent the stops enabled to be treated as double stop. The main depot is represented by a *house* icon.

- *Scenario diversity*: To mitigate the limitations of uniform assignment, we evaluate each candidate solution against ten randomized demand distributions sampled from a discrete probability distribution defined on the set of residential buildings in the study area, where the probability of selecting a building is proportional to its estimated population based on district-level census data. This evaluation strategy ensures that selected double stop configurations are not overly sensitive to any single demand realization. Solutions that perform consistently well across multiple demand scenarios are considered more robust and generalizable.
- *Modularity and future adaptability*: While the current model uses a simplified demand generation process, it is designed to be modular. Should fine-grained historical data become available, the demand assignment mechanism can be readily replaced with more realistic spatial and temporal demand models. This flexibility allows the framework to evolve alongside improvements in data availability and quality.

Although uniform random assignment may not fully reflect real-world parcel demand patterns, the approach for estimating freight volume demand described above yields a conservative baseline for evaluating the operational feasibility and trade-offs of IPFT systems. Furthermore, the assumptions made in our approach can be relaxed considering actual data from delivery companies should be available.

To ensure that the optimization process does not overfit to a single demand realization, we extend the evaluation of each candidate solution to a set of 10 parcel demand estimations. These distributions are generated using the same population-weighted random assignment method described above. During the multi-objective optimization process, the function $f_{dist}(\cdot)$ is computed as the maximum delivery distance observed across these 10 sampled scenarios. This conservative approach ensures that each solution in the Pareto front is robust against variability in parcel demand and remains feasible under multiple plausible demand configurations.

4.1.4. Optimization algorithms under consideration

The size of $L = 28$ bus lines and $|\mathcal{N}^{\text{all}}| = 88$ bus stops that can potentially be double bus stops lead to a vast number of combinations to be evaluated in search for solutions that minimize both $f_{dist}(\cdot)$ and $f_{qos}(\cdot)$. An efficient way to explore the solution space is using MOEAs Deb et al. (2016). The jMetalPy library (Benítez-Hidalgo et al., 2019) has been selected for designing the optimization problem, given its extensive collection of meta-heuristics, parallel computing capabilities, multiple encoding options and variety of operators, among other features.

Solutions $\mathbf{x}$ to the problem stated in Section 3.2 are encoded as vectors of length L, where each position corresponds to a candidate bus stop. The value stored in a position indicates the bus line ID (selected from the set of $|\mathcal{N}^{\text{all}}|$ bus lines) that is assigned to be converted into a dual-purpose stop. If a candidate stop is not designated as a dual-purpose stop, the corresponding position in $\mathbf{x}$ takes the value -1. A dictionary structure is used to keep track of the bus lines associated with each candidate stop. To guarantee solution feasibility, each bus line ID can appear at most once in $\mathbf{x}$, thereby ensuring that every bus line includes no more than one dual-purpose stop.

In the context of evolutionary metaheuristics, crossover is an operation that involves generating new $\mathbf{x}$ from an original population $\mathcal{X}_p$ by exchanging information between two or more $\mathbf{x}$. The outcome, referred to as offspring $\mathcal{X}_o$, allows the exploration of the search space by sharing beneficial traits found in previous solutions, promoting the creation of potentially better ones. For the problem at hand, an ad-hoc crossover operator has been designed. The double stops assigned by the selected $\mathbf{x} \in \mathcal{X}_p$ are randomly combined between the same $l \in \{1, \ldots, L\}$. By forcing this constraint, the crossover operator can only produce valid solutions. On the other hand, the mutation operation is used to introduce diversity in $\mathcal{X}_p$. Given a certain $\mathbf{x}$, the designed mutation operation involves assigning a different double stop to a route $\mathcal{N}_l$ that has already an assigned double stop. Only those bus stops in $\mathcal{N}_l$ that are not assigned to other routes can be exchanged under this mutation operator.

The optimization process, as illustrated in Algorithm 1, departs from the selection of a random set of buildings demanding parcels. This selection is made such that the quantity of packages slated for delivery matches D. The postal addresses of buildings in this set of buildings and their mapping to the nodes in $\mathcal{G}$ serve as the basis for solving the TSP and hence influence the computation of $f_{dist}(\cdot)$. A population of valid solutions $\mathcal{X}_p$ is randomly generated and then evaluated using $f_{dist}(\cdot)$ and $f_{qos}(\cdot)$. Subsequently, an iterative process is initiated, where new populations are generated and evaluated, until a number of evaluations $eval_{\max}$ is achieved. Within each iteration, an offspring $\mathcal{X}_{\text{off}}$ is derived from solutions inside the population $\mathcal{X}_{pop}$ by applying crossover and mutation. After evaluating $\mathcal{X}_{\text{off}}$, these solutions are appended to the overall population. To finish, which solutions are kept or discarded for the next generation is defined by the meta-heuristic implemented by the MOEA and the Pareto-wise obtained metrics.

Algorithm 1 `Multi-objective Optimization Process`

Require: Objectives $f_{dist}(\cdot)$ and $f_{qos}(\cdot)$, solution $\mathbf{x}$, population of generated solutions $\mathcal{X}_{\text{pop}}$, its offspring $\mathcal{X}_{\text{off}}$, number of evaluations to perform $eval_{max}$
Ensure: Pareto optimal solutions
Randomly sample 10 different spatial demands (see Section 4.1.3)
Initialize $\mathcal{X}_{pop}$ with random yet feasible solutions
Evaluate each $\mathbf{x} \in \mathcal{X}_{pop}$ using $f_{dist}(\cdot)$ and $f_{qos}(\cdot)$
Set $t = 0$
while $t < eval_{\max}$ **do**
    Select solutions from $\mathcal{X}_{pop}$ based on their objective function values
    Perform crossover and mutation to generate $\mathcal{X}_{\text{off}}$
    Evaluate each $\mathbf{x} \in \mathcal{X}_{\text{off}}$ using $f_{qos}(\cdot)$ and $f_{dist}(\cdot)$ of the solution with highest distance metric across the sampled spatial parcel demands
    Retain the best $\mathbf{x} \in \mathcal{X}_{\text{pop}} \cup \mathcal{X}_{\text{off}}$
    Update $\mathcal{X}_{\text{pop}}$ with the retained solutions
    Set $t = t + 1$
end while
$\mathcal{X}^*$ is given by the non-dominated solutions in $\mathcal{X}_{\text{pop}}$

How solutions are ranked and when to perform mutation and crossover, depends on the optimization algorithm to use. Specifically, four algorithms are considered and analyzed in the following section:

- `NSGA2` (Non-dominated Sorting Genetic Algorithm 2): an evolutionary algorithm that implements a non-dominated sorting procedure and an elitist strategy to maintain diversity among explored solutions (Deb et al., 2002).
- `NSGA3` (Non-dominated Sorting Genetic Algorithm 3): an extension of `NSGA2`, designed for many-objective optimization problems and to preserve diversity when exploring the solution space (Ishibuchi et al., 2016).
- `MOCELL` (Multi-Objective Cellular Genetic Algorithm): an evolutionary algorithm in which non-dominated solutions are stored so they can randomly replace individuals of future populations (Nebro et al., 2009b).
- `SMPSO` (Speed-constrained Multi-objective Particle Swarm Optimization): a particle-swarm based optimization algorithm designed for multi-objective optimization, with a speed constraint to control the exploration and exploitation trade-off (Nebro et al., 2009a).

These selected algorithms are well-established metaheuristics in the field of evolutionary multi-objective optimization. They are chosen for their complementary strengths in convergence speed, diversity preservation, and scalability, which are essential for exploring trade-offs in strategic transport planning. Additionally, their integration within the jMetalPy framework enable efficient implementation and parallel evaluation, making them suitable for the discrete and combinatorial nature of the formulated IPFT problem.

All MOEAs are configured as follows: an initial population composed by 100 valid solutions is generated by sampling double stop candidates following a uniform distribution. The offspring population size is set equal to the initial population size (100 individuals) to maintain a balance between exploration and exploitation throughout the evolutionary process. Using the same value ensures that, at each generation, the search space is explored by a sufficiently diverse set of candidate solutions, while also preserving a comparable selection pressure to drive convergence. The crossover probability is set to 90% as crossover is the primary mechanism for exploring the solution space and combining promising traits from parent solutions (Emmerich and Deutz, 2018). A 10% of the solution population is allowed to remain between evaluations of the algorithm (*elitism rate*), which provides stability to the optimization process. While the crossover operation consists of mixing information of valid solutions, the mutation operator can introduce less effective solutions, hence its application should be carefully controlled. In this case, the mutation rate is set to $1/L$ (namely, the inverse of the number of bus lines). This design choice ensures that mutations are limited to a single element of the solution vector $\mathbf{x}$, thereby preserving solution feasibility while still enabling local search.

4.2. Scenario parameters

An essential design parameter to be decided is the range T^{wd} of the isochrone areas. Two alternatives have been contemplated: 5 and 10 min, which represent the maximum duration a citizen within the isochrone area would require to reach the double stop on foot. Reducing the maximum time required to reach a double stop consequently reduces the number of buildings within that range, ultimately leading to a significant decrease in the number of parcels encompassed by each isochrone. An isochrone area of 10 min implies catering to the daily demand of hundreds of parcels, whereas isochrone areas of 5 min are an order of magnitude lower (*i.e.*, between 10 and 40 parcels). The areas of both values of T^{wd} are depicted in Fig. 5. Areas defined by $T^{\text{wd}} = 5$ leave a great part of the city uncovered by the IPFT service, which can lead with a higher probability to situations like the one depicted in Fig. 2: the fleet of delivery vehicles could potentially traverse a similar distance with or without the IPFT. Besides, as Fig. 5 shows, the totality of $T^{\text{wd}} = 10$ minute isochrone areas cover a great part of the city, while the 5 min approach would necessarily leave large areas outside the service.

These two factors seem sufficient to opt for the $T^{\text{wd}} = 10$ solution. In order to observe the impact of this decision in terms of covered population, Fig. 6 plots the number of inhabitants that would benefit from the freight sharing system given a double stop being implemented at a bus stop, depending on the T^{wd}. The figure shows that increasing the walking range of a double stop can increase considerably the coverage in some areas of the city, while others like stops 63, 64 or 81 have a very similar coverage. This can be explained by the local properties of each stop: they can be placed in low population areas, locations affected by slopes that reduce the distance walkable in a time frame, or near obstacles that cannot be avoided within the greater T^{wd}.

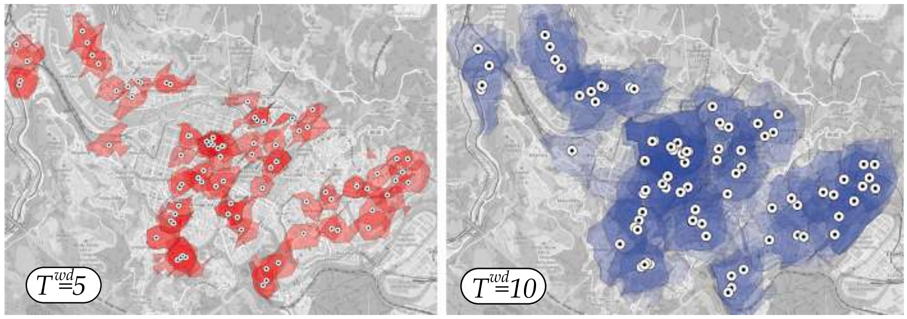

Fig. 5. Area coverage of all double stops with $T^{\mathrm{wd}} = 5$ and $T^{\mathrm{wd}} = 10$ minute isochrone areas (left and right respectively).

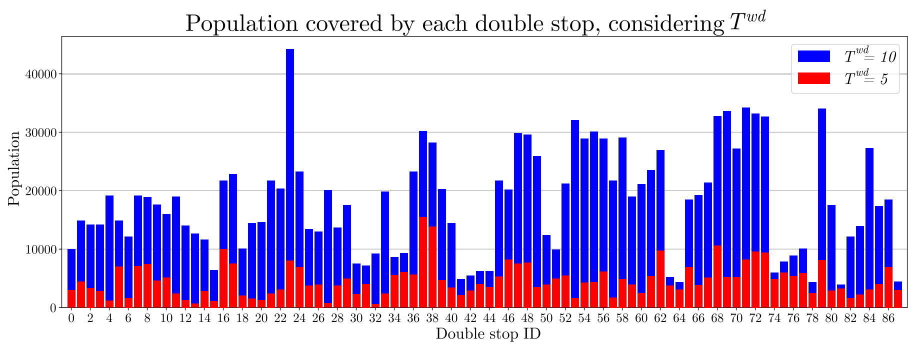

Fig. 6. Population covered by isochrone areas of 10 min. Population is computed from the buildings that falls within the isochrone range and the average population on each building for the corresponding neighborhood.

4.2.1. *Algorithm evaluation*

Due to the different solving capabilities of the considered algorithms, our experiment design proposes a set of evaluation techniques to assess which MOEA performs best in solving the formulated problem particularized for the city of Bilbao. This quantitative evaluation is made on the basis of several multiobjective quality indicators that examine the properties of the resulting Pareto front. Specifically, the following metrics are computed for every set of non-dominated solutions produced by every MOEA under comparison:

- HV (*Hypervolume*): HV measures the relative area of the space in the objective space that is dominated by the Pareto front estimated by a given solver, with respect to a reference point. The higher the HV value is, the larger the area of the estimated Pareto front w.r.t. the reference point will be, hence the better its quality will be in terms of diversity (spread) and convergence of its compounding solutions. In our experiments we use normalized fronts (*i.e.* the minimum and maximum value of every objective achieved by all algorithms) when reporting the performance scores. Consequently, all fronts are bounded in the range [0,1], so that the reference point is chosen to be [1,1].
- IGD+ (*Inverted Generational Distance Plus*): this second metric measures the average distance from the points in a reference set to the closest points in the Pareto front approximated by the algorithm under evaluation. Contrarily to HV, the lower IGD+ is, the closer the algorithm will be to the reference Pareto front, which is usually set to be the true Pareto front. In our case, the reference set is chosen to be the *super Pareto front* comprising the non-dominated solutions resulting from the aggregation of the Pareto front estimated by all algorithms. Similarly to HV, IGD+ accounts for both diversity and convergence.
- EPS (*additive Epsilon indicator*): this third indicator, which only regards the convergence of the algorithm being evaluated, reports how much the Pareto front estimated by the algorithm should be additively shifted in each objective to dominate a reference set, which is again set to be the super Pareto front defined above. Again, the lower EPS is, the better the Pareto front estimated by the algorithm is considered to be, as it requires a smaller shift to match the reference set.

Mathematical definitions of these metrics are widely available in the literature (see *e.g.* (Fonseca et al., 2005; Riquelme et al., 2015)). These indicators jointly evaluate convergence to the true Pareto front and diversity across the objective space. HV measures the volume dominated by the estimated front, IGD+ captures the average proximity to a reference set, and EPS quantifies the minimum additive shift required to dominate the reference. Their use ensures a robust and balanced comparison of algorithmic performance in the context of strategic decision-making for integrated transport systems. Once the best performing algorithm is selected based on the results of these quality indicators, further analysis are performed over the results provided by this overall best algorithm.

5. Results and discussion

In this section, we present the findings of our case study and provide a comprehensive analysis of the results. Section 5.1 reports the performance collected from the execution of the optimization algorithms, which allow us to select the MOEA to be employed for exploring the solution space in the remaining experiments. Next, Section 5.2 examines the Pareto front approximation produced by the best performing solver in the benchmark, providing insights on the available solutions within the problem constraints and boundaries. To finish, Section 5.3 discusses in depth on two different solutions contained in the Pareto front, representing them on a map and comparing the scope and implications of each IPFT deployment corresponding to such solutions. The implementation of these solutions are represented on a map, in Fig. 9, allowing to compare the scope and implications of each proposal.

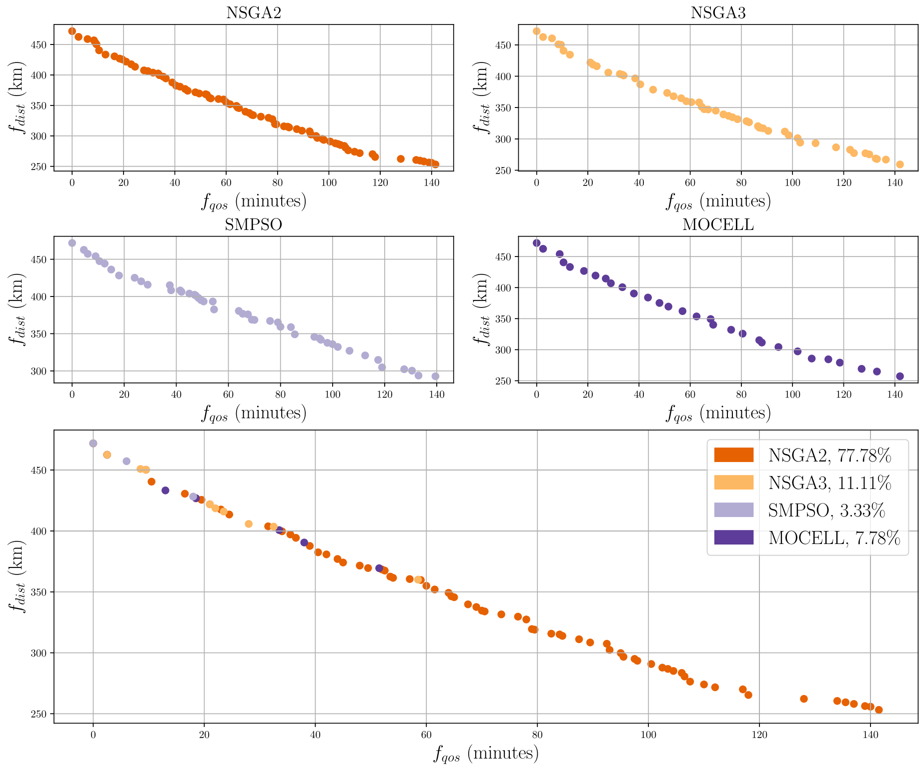

Fig. 7. Non-dominated Pareto front produced by every MOEA (four top subplots), and their contribution to the super Pareto front (bottom subplot), which is composed by all non-dominated solutions of the aggregation of the above non-dominated fronts.

5.1. Selecting the optimization algorithm

The evaluation of the optimization algorithms yields Fig. 7, which illustrates the non-dominated fronts generated by each algorithm, as well as the aggregated set of non-dominated solutions—referred to as the super Pareto front. As shown in the figure, over 75% of the solutions in the super Pareto front were discovered by NSGA2, slightly more than 10% by NSGA3, with the remainder contributed by MOCELL and SMSPSO. Notably, only in the region of the super Pareto front corresponding to low values of $f_{qos}(\cdot)$ (i.e., high $f_{dist}(\cdot)$) do non-dominated solutions emerge from algorithms other than NSGA2. This observation suggests that, in practice, employing multiple solvers may be beneficial when seeking double stop configurations that minimally affect passenger-perceived QoS. Conversely, for solutions with greater impact on both distance and QoS objectives, using NSGA2 alone appears sufficient to identify Pareto-dominant alternatives within this range.

A complementary analysis about the performance of the optimization algorithms is presented in Table 1, where we report the values of the multi-objective quality indicators of the non-dominated front obtained for each MOEA. The gray shade highlights that NSGA2 performs best for all three metrics, followed by NSGA3 and MOCELL. Clearly SMPSO achieves the lowest indicator values in the three indicators considered, showing a subpar performance in terms of both convergence of the objectives and spread of the solutions. This ranking among MOEAs as per the quantitative indicators reported in the table aligns with the composition of the super Pareto front plotted in Fig. 7, which evinces a dominance of solutions contributed by NSGA2 and an almost negligible presence of solutions produced by SMPSO. As a result, NSGA2, albeit not providing all the solutions contained in the super Pareto front, is selected for the rest of the experimental analysis.

5.2. Analysis of the Pareto front

The Pareto front discovered by the NSGA2 algorithm is illustrated in Fig. 8, providing also information about double stops that each solution

Table 1
Multi-objective quality indicators computed for the non-dominated front of solutions produced by every MOEA over the scenario considered in our experimental setup. The best values are shaded in gray.

	NSGA2	NSGA3	SMPSO	MOCELL
HV (↑)	0.587	0.551	0.454	0.558
IGD+ (↓)	0.001	0.021	0.088	0.017
EPS (↓)	0.008	0.068	0.181	0.063

includes. Additionally, 1000 random valid solutions are appended to the chart, aimed to help visualize the performance of the algorithm. The chart highlights that several of these random solutions are worse than the baseline: the quality of service is degraded (*i.e.* the introduced lag is a positive value) and yet the distance to be traveled is above 471 kilometers, which corresponds to the baseline solution. This is due to the travel cost associated to delivering the packages to the header depots $n^{l,\circledcirc}$ of the corresponding bus lines (*i.e.* those where a double stop will be implemented), which, added to the route of the delivery vehicle, produces a mileage sum greater than the baseline. The function $f_{dist}(\cdot)$ evaluates each solution by solving the TSP under the 10 sampled parcel demand distributions and returning the maximum travel distance observed. This design ensures robustness: if a random solution yields a configuration of double stops that performs poorly under at least one demand distribution, $f_{dist}(\cdot)$ will capture this weakness by assigning a high value. It is also remarkable that random solutions are mostly composed of a few double stops, which hardly reduce the emitted pollution. Since the randomly generated solutions needs to be valid, meaning following the problem boundaries defined at Section 4, valid solutions with few double stops to set are obtained more frequently. In summary, the random search is inefficient by several reasons: (1) solutions are distanced from the Pareto front; (2) the search space below 300 kilometers is barely explored; (3) given a similar value of one evaluation metric, the non-dominated solution

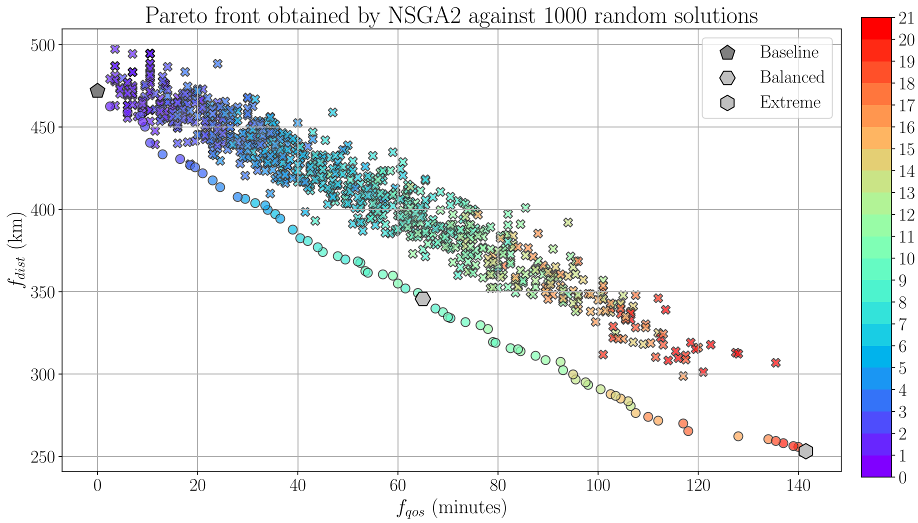

Fig. 8. Pareto front discovered by NSGA2 (circles) and 1000 randomly generated valid solutions (crosses). The color scale depicts the number of double stops to be implemented for each solution. Baseline solution and the later referred to as *balanced* and *extreme* solutions appear in gray color.

needs fewer double stops to be implemented. These facts justify tackling the problem by means of multi-objective optimization algorithms.

Centering the discussion on the Pareto front, 15000 evaluations are enough to find a dense set of non-dominated solutions, where a valid solution is available for a large combination of objective metrics. The number of double stops to be deployed increases as the travel cost reduces, but there are groups of feasible solutions that implement the same number of double stops and still produce different results in terms of travel cost and introduced delay. This behavior can be explained by observing Fig. 6. For instance, installing a double stop at the bus stop 23 implies covering the largest number of inhabitants among considered bus stops and would be the highest reduction in the number of packages to be delivered by a single vehicle. However, a high number of packages also implies exceeding the maximum capacity of the bus (*i.e.* more than 400 parcels would be expected for $Q^{\max} = 100$), which notably increases the overall delay to be experienced by the bus passengers. Moving to the opposite case, a few buildings are in the range of an isochrone centered on bus stop 81, which make the average demand of packages that would be covered in that area below the maximum capacity of the bus. The total population of Bilbao city is around 345000 inhabitants, so $D = 3450$ parcels to be delivered everyday is expected on this case study. The installation of a double stop at bus stop 81 appears to be a sub-optimal design decision, as it would only meet 2.6% of the daily demand. This is particularly concerning given that similar delays would affect other stops that could potentially meet a larger percentage of the parcel demand. However, the impact on the route a single vehicle would take to deliver the remaining parcels cannot be easily inferred. One possible solution is to implement a combination of double stops, including bus stop 81, which would significantly reduce the travel distance and, consequently, the pollution associated with the delivery system. In the following analysis, two non-dominated solutions are selected, examining the location of the double stops, the number of parcels, and the number of inhabitants served by the proposed freight-sharing system.

5.3. Analysis of specific solutions

Two non-dominated solutions are selected for further analysis: a *balanced* solution (located in the middle of the Pareto front) and an *extreme* solution that corresponds to the lowest number of kilometers to be traveled. Jointly with the baseline solution, the benefits and downsides of each proposal are discussed.

Fig. 9 represents the deployment of the double stops described at the balanced and extreme solution, respectively. Starting with the balanced solution, 9 double stops are suggested to be implemented, with a low overlap between their isochrone areas (excepting isochrone 11 and 15). The packages to be delivered to each double stop ranges between 35 and 260. The value of $Q^{\max}$ makes half of the routes to need two buses to carry all parcels and even two routes to allocate three buses. Ideally, the algorithm should search for those stops that do not need a high number of buses to cover their expected parcel demand, due to the time penalty λ associated to each additional bus. However, an overlap between isochrone areas can reduce the number of buses carrying goods, since the parcels demanded at those buildings located at the intersection are evenly distributed between the corresponding double stops. The overlap of the isochrone areas at bus stops 50 and 56 serves as an example to illustrate the above. They have an expected demand of 120 and 290 respectively (check Fig. 6 and multiply the population by $H = 0.01$)

When two isochrone areas overlap, the parcel demand associated to those buildings situated inside the overlapping area is evenly distributed between the corresponding double stops. Therefore, thanks to selecting these two double stops, the expected daily parcel demand at both areas decreases to 92 for the bus stop 50 and 260 for 56, so the system stakeholders would only organize 1 bus to the route that goes through bus stop 50 instead of 2 (so 120 parcels could be delivered). The double stops that require three buses, which are 17 and 56, are also the ones that contribute the most to the total delay associated with the balanced solution: 10.5 and 12.5 min. However, this metric is distributed among the buses on that line, so that the maximum delay a passenger would experience is 4.5 min (i.e. maximum delay associated to a bus transporting Q^{max}).

Moving to the extreme solution, it can be appreciated that most of the double stops from the balance solution also appear in this proposal. Some regions of the city has few bus stops as candidates to be treated as double stops (see Fig. 4). For instance, the double stop 77 is located in a neighborhood of Bilbao that is only connected to the rest of the city by few transportation lines, due to geographical features that hinder the urbanization of the intermediate zone. This makes installing a double stop valuable from the algorithm's perspective, since $f_{dist}(\cdot)$ will be reduced to a greater extent than when selecting other stops in the city. In that region, only four stops fulfill the requirements to be treated as double stop: 75, 76, 77 and 78. However, Fig. 6 illustrates that is precisely the isochrone area around the bus stop 77 the one that encapsulates most population, making it the preferable choice for most non-dominant solutions. Certain bus stops consistently appear as double-stop candidates in several Pareto front solutions, indicating

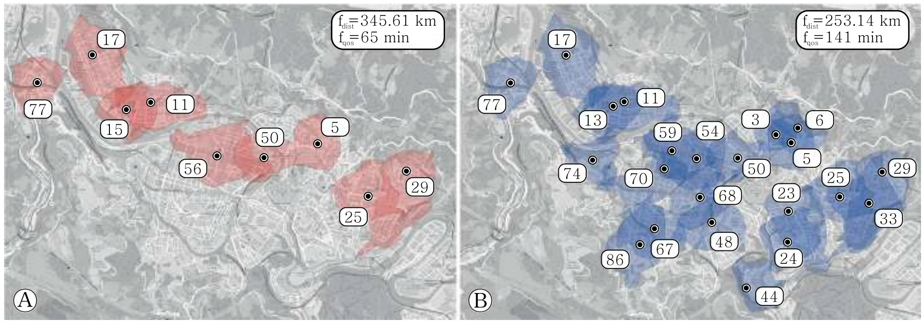

Fig. 9. Resulting isochrone areas for a balanced solution (A), and for a extreme solution that is aimed at minimizing f_{dist} metric (B).

that they contribute more significantly to reducing the cost functions (i.e. $f_{dist}(\cdot)$ and $f_{qos}(\cdot)$) than other candidates. For instance, the double stop 17 reduces the distance to be traveled by a delivery vehicle noticeably, due to the large covered area, in a region of Bilbao with scarce candidates to be converted into double stops.

Focusing on the objective metrics, the baseline solution involves a single vehicle to travel 471 km to deliver all packages, without altering the quality of service of any bus line. The balanced solution reduces the traveled distance to 346 km (*i.e.* 26% reduction) and produces an average of 7 min of delay per route, needing two buses, which makes the average delay a passenger will experience 3.5 min. Repeating these calculations for the extreme solution, it delivers a traveled distance of 253 km (i.e. 46% reduction) and produces an average of 6 min of delay per route. Again, on average two buses are needed, making the delay for passengers equal to 3 min. In summary, the balanced option focuses on covering the most populated areas of the city, by identifying the combination of bus stops that minimizes the distance traveled to deliver the remaining packages while causing only a minimal reduction in public transportation service quality. For the extreme option, however, the goal is to reduce $f_{qos}(\cdot)$ while maintaining a maximum coverage around the urban area. This translates into selecting those bus stops with an slight overlap, so that the delay can be reduced by sharing the demand between double stops but no additional kilometers are added to $f_{dist}(\cdot)$ due to the installation of additional depots at the line heads.

Both balanced and extreme solutions have been selected for the sake of a focused discussion on the output of the algorithms in the comparison. These results demonstrate the feasibility of the proposed methodology towards its final goal: to promote research on freight-sharing transportation systems in the form of realistic use cases and actionable algorithmic proposals. The values returned by the evaluation function $f_{dist}(\cdot)$ represent the worst-case scenario. For the same $f_{qos}(\cdot)$ value, a lower mileage is expected for the other nine parcel demand distributions considered during the optimization. Likewise, slight variations may occur during real-world operations.

While our model and the results discussed herein assume that all parcels are delivered to collection points, this reflects a plausible regulatory or pilot framework that cities may adopt to reduce freight traffic and emissions. The area under study (the city of Bilbao, Spain) is a good example of this approach, as it already enforces a low-emission zone that restricts access to the city center based on vehicle age and environmental classification. In practice, the relative share of home deliveries versus collection point pickups is a critical variable influencing the effectiveness of IPFT systems. A higher share of home deliveries would reduce the marginal benefit of using buses for freight, as delivery vehicles would already be traveling longer distances and closer to residential areas. Conversely, a greater reliance on collection points increases the potential for consolidation and efficiency gains through IPFT. Although our current model does not simulate mixed delivery modes, future work should explore how varying these shares affects system performance and environmental impact. We revisit this idea in the discussion of future research directions.

6. Conclusions and future work

Over recent decades, significant attention has been given to optimizing routing and scheduling problems, particularly with goals of integrating passenger and freight transport (Mourad et al., 2019; Masson et al., 2017). Often, the objectives of customer satisfaction and timely delivery conflict with policy aims, creating operational and managerial challenges (Fatnassi et al., 2015). Additionally, the high costs associated with these initiatives can deter research efforts and tools for the practical implementation of IPFT systems. As a result, the demand for efficient FLM logistics has surged, especially in developed countries, partly driven by global trends and the impacts of the Covid-19 pandemic (Cavallaro and Nocera, 2024). With limited vehicle availability and the necessity for fixed-time deliveries, enhancing routing and scheduling can simultaneously boost customer satisfaction and reduce operational costs (He et al., 2023). This integration of passenger and cargo flows is of great interest to scholars and policymakers at both European and national levels (Hatzenbühler et al., 2023).

In this study, we have developed a strategic model for implementing an IPFT system, particularly focusing on the operation and location of double stops. The goal is to widen freight delivery capacity, potentially reducing external costs if overall mileage decreases. The model aims to determine the conditions under which IPFT can effectively function within public transport, while maintaining service quality and keeping acceptable financial burdens on public authorities. While the present optimization framework focuses on minimizing passenger delays and reducing excess freight mileage, IPFT systems may offer broader benefits that extend beyond these operational objectives. By reducing the need for dedicated delivery vehicle trips, such systems can help lower overall urban vehicle miles traveled, alleviate congestion, and decrease greenhouse gas and pollutant emissions. They may also open new revenue opportunities for public transport authorities through freight service contracts, contributing to the financial sustainability of transit networks. However, the recognition of these wider impacts in decision-making can be hindered by the fact that transport policies and economic appraisal tools are not always aligned in how they account for road externalities, potentially undervaluing environmental and congestion-related gains (Cavallaro and Nocera, 2022). Although these wider impacts are not explicitly modeled here, acknowledging them provides a more comprehensive understanding of the potential value of IPFT in urban mobility strategies.

Algorithmically, we have shown that the formulated combinatorial optimization problem can be efficiently tackled by resorting to evolutionary multi-objective optimization, using a solution encoding strategy that numerically indicates which bus stop(s) are selected to become stops with a double purpose: to drop/pick up passengers and to deliver goods to collection points. Search operators allow exploring efficiently the discrete solution space underneath the formulated combinatorial problem, eventually yielding an approximation of the set of Pareto-optimal solutions that balance optimally between mileage and the impact of the IPFT service (delays) to the passenger transportation.

Validation through numerical experiments in Bilbao, Spain, has shown promising results. These experiments highlight the potential of our approach to address multiple, often conflicting objectives. The success of public transport agencies hinges on maintaining high passenger satisfaction, which ensures continued use of the system. The presented methodology can be effectively applied to real cases in which city managers and logistic operators can adjust the balance between objectives and obtain solutions that satisfy those specific needs. Conservative freight load values have been used aiming to preserve passenger comfort and travel time perceptions. Additionally, the Pareto front analysis allows us to prescribe a particular solver as algorithmic approach to solve the combinatorial problem.

6.1. Future research directions

We envision several research directions for follow-up studies:

- To begin with, all experiments have adhered to a deterministic schedule, though real-world factors like last-minute changes, roadworks, or accidents can cause further disruptions that may affect the optimality of the chosen double bus stops over time. Future research should consider these stochastic elements, as well as the integration of localized urban data into the optimization framework. This includes modeling pedestrian flows around candidate stops, assessing infrastructure readiness for parcel handling, and incorporating traffic congestion patterns into the delay and distance functions. On the side of the collection points, aspects like staff availability at different times of the day or by the size of the businesses (which could lead to a tiered business system) could have a significant impact on the efficiency of the framework. Moreover, Automatic Vehicle Location (AVL) or Automatic Passenger Counting (APC) data could also be used – wherever available – to identify fine-grained off-peak periods in bus occupancy. Such enhancements would allow for more context-aware decision-making and improve the operational realism of the proposed IPFT system.
- More along this line, the formulation of the problem stated in this manuscript assumes a static configuration of double stops, which reflects a strategic planning decision rather than an operational one. While this abstraction is suitable for long-term infrastructure and service design, it does not capture temporal variations in demand or transit conditions. Making the selection of double stops more dynamic (potentially adapting to varying bus capacity, evolving demands, or real-time traffic data) is a promising direction for future work. A time-expanded or stochastic formulation could better reflect the operational complexity of real-world IPFT systems and support more responsive decision-making.
- A sensitivity analysis becomes particularly relevant and a research direction of practical impact. While our current study fixes key parameters (such as parcel demand per inhabitant, walking time thresholds, and bus capacity) to reflect conservative and realistic estimates, future work should explore how variations in these parameters affect system performance. This is especially important in operational settings where demand fluctuates, service frequency varies, and infrastructure constraints evolve over time. Conducting sensitivity analysis would allow assessing the robustness of the proposed double bus stop choices and better understand the trade-offs involved in adapting the IPFT system to urban environments of different nature.
- Another important direction for future research is to incorporate mixed delivery modes into the modeling framework. The current study assumes exclusive delivery to collection points, which simplifies the analysis and aligns with emerging urban logistics trends. However, real-world scenarios often involve a mix of home and collection point deliveries.The experiments presented in this paper assume that all demand can be satisfied with the IPFT service, while some part of this demand could be reluctant to the service. Considering an hybrid demand approach that balances home delivery and IPFT-based delivery could help comparing efficiency trade-offs. Modeling this variability would require demand segmentation, behavioral assumptions, and dynamic routing strategies. Exploring how different delivery shares affect the trade-offs between passenger service quality and freight efficiency would enhance the applicability of IPFT systems in diverse urban contexts. This hybridization can also be accounted for in terms of alternative delivery methods, which could include a range of solutions from e-bikes to drones.
- An interesting path to follow involves the evaluation of the economic implications of passenger delays caused by parcel unloading operations. While our current model includes delay as an optimization objective, it does not monetize passenger time, which is an important factor when considering cumulative waiting across all passengers. Although the impact is minimized by restricting freight operations to valley hours (when passenger volumes are low), even short delays may carry non-trivial economic costs in certain urban contexts and peak hours. Incorporating passenger time valuation into the framework would enable a more comprehensive cost–benefit analysis and better inform decision-making with an optimized balance between impact and user satisfaction.
- An important operational consideration is the synchronization between the bus arrival and the collection point staff. In our scenario, it has been assumed that workers are notified in advance of the expected arrival time, allowing them to prepare for the unloading process. While this may require a brief interruption of customer service (especially in single-staffed establishments), this coordination is common in existing courier systems. Moreover, since the IPFT service operates during valley hours, the likelihood of disrupting ongoing customer interactions is reduced. Future work could explore more robust synchronization mechanisms and assess their impact on shop operations and user acceptance.
- Finally, our study has assumed shortest distance between delivery points (by means of TSP) as a way to compute the delivery vehicle mileage improvement, but other factors as delivery times or feasibility when a fleet size is considered could be even more relevant. This is the reason why the exploration of other means to compute this impact (for instance, by considering a dynamic resolution of the TSP based on real-time traffic information) is prioritized as a next follow-up for this research. Additionally, while mileage serves as a practical proxy for environmental impact, future work will aim to integrate explicit emissions modeling into the framework. This would allow the system to account for vehicle-specific emission factors, traffic conditions, and terrain characteristics, enabling more accurate assessments of pollutant outputs and supporting more informed, sustainability-oriented decision-making. In this regard, exploring various loading conditions and the impact of zero-emission fleets is important. Future studies could also focus on EV fleet characteristics to address charging coordination issues and the role of small electric vehicles in FLM duties on a well-to-wheel basis. Further research may address the possibility of realizing significant environmental gains in terms of externalities.

CRediT authorship contribution statement

Eric L. Manibardo: Writing – original draft, Validation, Software, Methodology, Investigation. **Ibai Laña:** Writing – review & editing, Validation, Supervision, Methodology, Funding acquisition, Conceptualization. **Ignacio (Iñaki) Olabarrieta:** Methodology. **Silvio Nocera:** Writing – review & editing, Validation, Funding acquisition, Conceptualization. **Javier Del Ser:** Writing – review & editing, Validation, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

We have used public data, properly cited and linked in the experimental part of the manuscript.

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