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Last-mile logistics: trends, models and innovative solutions

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Introduction

The rapid digital transformation and growing internet accessibility have profoundly reshaped global commerce, fueling the expansion of e-commerce across both established and emerging markets. Over the past two decades, this evolution has transformed traditional brick-and-mortar stores into virtual marketplaces, enabling customers to access goods and services anytime and anywhere. The shift has resulted in a sharp increase in parcel volumes, creating significant logistical challenges related to deliveries and returns. The COVID-19 pandemic further accelerated this trend, as lockdowns and social distancing drove reliance on online shopping, solidifying e-commerce as a cornerstone of the global retail landscape.

Against this backdrop, the concept of *city logistics* has gained increasing attention. In general terms, city logistics focuses on planning for efficient people and freight mobility systems while minimizing negative externalities (environmental and social impacts). To this end, numerous multi-stakeholder initiatives have been recently launched to promote more sustainable practices, with the overarching goal of improving *last-mile logistics* delivery operations. Among the investigated solutions, *self-collection* has emerged as an increasingly popular strategy, allowing customers to autonomously collect parcels at dedicated facilities (*pick-up points* and *parcel lockers*). This model offers multiple advantages: logistics providers benefit from streamlined operations, lower costs, and reduced failed deliveries, while customers experience higher flexibility in delivery options. Reduced urban traffic and pollution are other relevant side effects that also interest public policymakers.

Notwithstanding these positive aspects, self-collection also comes with some challenges. Its success, in fact, significantly hinges on *customers' acceptance*, i.e., on their actual willingness to adopt this delivery method. Beyond cultural and demographic factors, accessibility is a crucial determinant in this context, as customers usually prefer self-collection facilities conveniently located in their proximity. This evidence compels logistics providers to make strategic network design decisions, balancing the economic costs of activating and operating self-collection facilities with the need to ensure broad service coverage. Navigating these trade-offs, alongside the challenge of securing customer acceptance, underscores the critical importance of carefully selecting facility locations as a multifaceted strategic priority for decision-makers. Furthermore, the implementation of a self-collection network demands a radical rethinking of territorial logistics to enhance daily delivery operations. At the core of this transformation lies the definition of dedicated areas (or districts) to optimize route planning, which not only slashes operational costs but also enhances service reliability and customer satisfaction—key drivers of competitive advantage in the sector.

Building on an established collaboration with Poste Italiane, the leading Italian logistics provider and partner of this research, the present thesis delves into the following interrelated problems: (i) the *strategic design of self-collection networks* and (ii) the *tactical planning of parcel delivery districts*. Specifically, this research aims to devise decision-making models and methods highlighting the benefits of integrating self-collection solutions into last-mile logistics. In particular, we propose deterministic and probabilistic approaches for the optimal siting of pick-up points in urban areas. These methods rely upon accessibility measures and explicit customer choice models to maximize service levels while containing network expansion costs. Based on the produced scenarios, we also formalize a general districting procedure that, leveraging combined home delivery and self-collection strategies, designs robust parcel delivery areas under uncertainty on customers' demands and daily visits. Representative case studies provided by Poste Italiane are employed, offering a practical, real-world framework to apply the proposed developments and generate valuable managerial insights for a wide range of stakeholders.

The remainder of the thesis is organized into six chapters as follows.

In Chapter 1, we provide some context behind the problem we investigate, arguing on recent trends and challenges characterizing the last-mile logistics and parcel delivery sectors, as well as on reliable solutions, such as self-collection. The chapter also overviews the Italian case, discussing recent projects and initiatives promoting the *city logistics* paradigm and advancing sustainable urban mobility and freight logistics.

Chapter 2 reviews the literature on last-mile logistics, focusing on two key streams: (i) customer behavior and (ii) decision-making approaches. The former examines factors influencing customer adoption of innovative delivery strategies like self-collection. The latter encompasses some main methodological and modeling frameworks, spanning strategic facility location problems and tactical distribution districting. Our analysis also identifies some emerging gaps in these areas, shaping the contributions of the thesis.

Chapter 3 focuses on Poste Italiane, the partner and primary stakeholder of this work. The chapter describes Poste Italianes's transformation from a classical postal provider to a fully-fledged logistic operator. We also emphasize its ongoing effort to promote self-collection, presenting the evolution of its national delivery network and the selected case studies used as representative testbed instances for our research.

In Chapter 4, we address the strategic problem of locating pick-up points in urban areas. Starting from the status quo, i.e., the current network of Poste Italiane, we use spatial analysis to evaluate users' accessibility of pick-up points and propose three strategies for contracting, reorganizing, or expanding the network. These strategies, implemented by solving tailored facility location models, strike a balance between cost efficiency and customer accessibility, showcasing the economic impact of different network design decisions against given service levels offered to customers.

For the same problem, Chapter 5 proposes a probabilistic approach, that is, integrating explicit customer choice in the network design decisions. Using a Multinomial Logit (MNL) model to describe customers' preferences, we seek to maximize the expected degree of adoption of self-collection, demonstrating the value of comprehensively describing customer behaviors on strategic network design.

In Chapter 6, the focus is on the second problem of interest, i.e., the tactical design of urban delivery areas. In particular, we propose a novel districting approach to divide urban areas into districts to be assigned to operators for daily delivery activities. These districts are designed to ensure that, among various practical criteria, expected operators' workloads are within given limits. Notably, the approach considers uncertainty from parcel demand fluctuations and customer preferences, producing robust planning solutions that quantify the benefit of combining home delivery and self-collection strategies in last-mile delivery operations.

Finally, the thesis ends with a summary of the work done, its main conclusions, and potential avenues for future research.

CHAPTER 1

Recent trends in last-mile logistics

Summary

The rapid growth of e-commerce over the past decade has significantly transformed the global retail landscape. This change, driven by technological advancements and the increasing digitalization of businesses, has impacted customer behavior and reshaped logistics operations. Additionally, the global pandemic has further accelerated this trend, resulting in a notable rise in online shopping. As a result, the demand for efficient parcel delivery and collection services has increased, putting new pressure on logistics stakeholders, especially in the last-mile logistics phase, which is the most critical and expansive. This chapter examines the recent growth of e-commerce and its direct impact on the volumes of parcels delivered and collected worldwide. It analyzes solutions to make last-mile logistics more efficient, specifically focusing on self-collection strategy. Lastly, it examines the concept of city logistics in Italy, focusing on programs and initiatives proposed to promote sustainable freight logistics in urban areas.

1.1 The rise of e-commerce and its impact on parcel deliveries

E-Commerce has experienced exponential growth, particularly from the mid-2010s onward. Global sales reached around $1.50 trillion in 2014 and nearly tripled to $2.8 trillion in 2020, with projections suggesting a further increase to $6.5 trillion in 2029 (Statista, 2024). This surge can be attributed to several factors related to digital transformation that drastically change customers' purchasing habits. Among them is the widespread use of electronic devices such as smartphones, improved internet access, and the availability of user-friendly e-commerce platforms (Mihailă et al., 2021). Furthermore, the COVID-19 pandemic accelerated this trend as lockdown and social distancing measures forced customers to move to digital channels (Bhatti et al., 2020; Susmitha, 2021). In fact, *business-to-customer (B2C)* e-commerce experienced significant growth in developed economies right during the pandemic. Big countries such as the United States (US) and China witnessed a substantial increase in online retail activity. In the US, e-commerce sales grew by 44% in 2020, the highest annual growth rate in over two decades (U.S. Department of Commerce, 2022). Similarly, in China, online retail sales reached $2.8 trillion in 2020, marking a 14.8% year-over-year increase and solidifying the country's position as the largest e-commerce market globally (Xiong et al., 2024).

With online shopping becoming more prevalent, the number of parcels to be delivered has grown exponentially. In particular, global shipping volumes increased significantly in 2019-2021, from 103 to 159 million per year, with expected projections of 256 billion by 2027 (Figure 1.1, Statista, 2023). In the United States, the US Postal Service reported that it handled more than 7.6 billion packages in 2021, a sharp increase from 6.2 billion in 2019 (United States Postal Service, 2021). Private logistic providers, like UPS, also saw dramatic increases. The latter, for example, reports 14.8% more in the average daily volume in 2020 (UPS, 2021) compared to the previous year. Similarly, in Europe, the parcel delivery market has expanded. Between 2017 and 2021, domestic parcel increased by 14.6% annually, compared to an annual increase of 6.4% in the period of 2013-2017, with the biggest countries such as Germany, France, and Italy leading the charge (Copenaghen Economics, 2021).

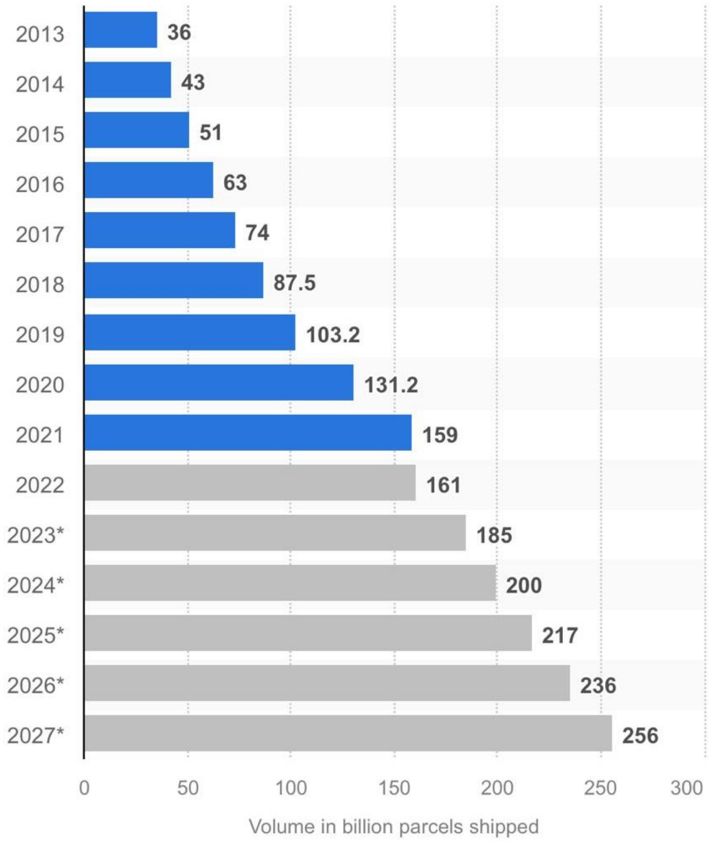


Figure 1.1: Global parcel shipping volumes between 2013 and 2027 (Statista, 2023)

Overall, the global shift towards e-commerce has also reshaped customer expectations regarding efficiency. *Online customers*, accustomed to the convenience of e-commerce, increasingly demand faster, more flexible, and more transparent delivery services. This includes options like same-day or next-day delivery, real-time tracking, customized delivery windows and eco-friendly options (Tzavlopoulos et al., 2019; Vakulenko et al., 2019). Additionally, the flexible and priceless e-commerce return policies also resulted in a substantial increase in the number of items being returned to retailers. In fact, more and more online customers are purchasing goods with the knowledge that they can easily return them if they don't meet their needs. Managing returns (known as *reverse logistics*) is a costly process that poses challenges due to the need for efficient collection, inspection, and redistribution (Yang et al., 2023)

The aspects above contribute to creating a complex landscape for stakeholders involved in direct and reverse logistics, such as providers, retailers, transport companies, and policymakers. Indeed, they must balance the need for efficiency with the growing pressure to reduce delivery times and offer innovative delivery options while managing operational costs. Consequently, there has been a surge in solutions aimed at optimizing the delivery supply chain to effectively manage these conflicting pressures, all while upholding profitability and ensuring customer satisfaction.

1.2 Last-mile delivery and city logistics

Logistics strategies have increasingly focused on innovations and optimizations, mainly focusing on the last phase of the delivery supply chain. *Last-mile logistics* refers to the final leg of the delivery process, beginning when a shipment reaches its starting point in (or next to) an urban area, following long-haul transportation, and ending when it is successfully delivered to the final customer's chosen destination. In the traditional last-mile paradigm, considering the so-called *"home delivery"*, this phase usually starts from a depot inside a city and ends with customers' households. While the last mile typically covers a relatively short distance compared to the entirety of the supply chain, it poses significant challenges and accounts for a disproportionate share of the total cost and complexity of delivery operations, accounting for over 50% of total delivery costs (Allen et al., 2018b). This portion of the process is especially critical in urban areas, where population density, traffic congestion, and customer expectations for fast and reliable service converge. Hence, as e-commerce has grown, the pressures on last-mile logistics have increased dramatically, leading to significant challenges for providers, municipalities, and other stakeholders involved in urban logistics (Paddeu et al., 2024).

When dealing with urban logistics operations, one must consider that cities have narrow streets, high traffic density, and limited parking, making it challenging for delivery vehicles to reach their destinations efficiently. Additionally, urban customers often reside in multi-story buildings with limited or no direct access, requiring drivers to invest extra time and effort to complete each delivery. Clearly, as the number of daily deliveries grows, these inefficiencies become more significant, posing a critical issue for providers (Pahwa and Jaller, 2022). As home delivery is the preferred solution for customers, failed deliveries are another significant problem in last-mile logistics. These occur when recipients are not available to receive their parcels, forcing delivery attempts to be repeated, with increasing costs. Studies have shown that failed deliveries can account for up to 15% at the first attempt and 20% at the second one (Seghezzi et al., 2022).

Along with the economic aspects, even environmental ones are critical. Delivery routes in urban areas are often fragmented, with vehicles making multiple stops for relatively small parcels, leading to increased fuel consumption and emissions per delivery. The frequent stops, idling engines, and low-speed travel through congested streets all contribute to higher levels of pollution compared to long-haul transportation (Ranieri et al., 2018). Furthermore, the rise of same-day and next-day delivery services intensifies these problems, as logistics companies often deploy more vehicles and make less consolidated trips to meet tight delivery windows

(Buldeo Rai et al., 2019). Finally, several attempts to reach recipients that are *"not at home"* during the first scheduled delivery further contribute to increasing such issues. Studies suggest that last-mile delivery vehicles can account for up to 30% of urban traffic emissions, worsening local air quality issues and contributing to global greenhouse gas emissions (Allen et al., 2018b). In several big cities where delivery traffic is predominant, trucks and vans are responsible for a disproportionate share of CO_2 emissions relative to their volume on the road (Clausen et al., 2016).

In this context, the concept of *"city logistics"* has emerged as a paradigm for optimizing urban delivery operations while minimizing negative externalities such as congestion and pollution (Savelsbergh and Van Woensel, 2016). City logistics focuses on the efficient movement of goods within urban areas, balancing the needs of businesses, customers, and municipal authorities. The core idea is to promote innovative, efficient and sustainable solutions for urban last-mile logistics following the objective of reducing costs and traffic and "giving the streets back to the people" (Bertolini, 2020). Achieving these goals encompasses a wide range of activities, including coordinating deliveries, finding new strategic and technological solutions, and promoting collaborations between various stakeholders such as logistics providers, municipal authorities, and businesses. Indeed, one of the key characteristics of city logistics is the emphasis on partnership between private and public actors, as such a complex environment requires integrated approaches that balance commercial needs with public policies on sustainability (Crainic et al., 2021; Plazier et al., 2024).

1.2.1 Private and public stakeholders

In city logistics, several key stakeholders can play a critical role in shaping the efficiency and sustainability of urban freight transport systems. These can be broadly categorized into *(i) public authorities, (ii) logistic providers, (iii) e-commerce retailers, (iv) researchers, (v) technology partners*, and *(vi) end customers.*

(i) Public authorities

Local governments and municipalities are key players. They are responsible for creating the regulatory frameworks that govern urban freight operations, such as traffic management, parking regulations, environmental zones, and emission restrictions or time windows for delivery. Furthermore, several studies emphasize the role of public authorities in fostering sustainable solutions by providing infrastructure like urban consolidation centres and promoting the use of green technologies (e.g., electric vehicles) for last-mile deliveries (Gatta and Marcucci, 2016; Lagorio et al., 2016).

(ii) Logistic providers

Logistics providers are directly responsible for the physical movement of goods within urban areas. They face the operational challenges of delivering to dense, congested city centres while adhering to regulatory schemes and customer demands for efficiency and sustainability (Govindan et al., 2019; Nila and Roy, 2023). They play a crucial role in developing and adopting innovative delivery solutions (e.g., parcel lockers, pick-up points, crowd-shipping) or new technologies enabling efficiency improvement in traditional solutions (e.g., electric vehicles, cargo bikes, drones).

(iii) E-commerce retailers

E-commerce retailers are increasingly involved in city logistics due to the growing demand for fast and flexible delivery options. As customers push for quicker deliveries, businesses need to adapt their strategies. Indeed, they are often, together with logistic providers, at the forefront of innovation, experimenting with alternative delivery models and economic incentives to customers to promote their adoption (Kawa and Zdrenka, 2024; Zhang et al., 2024).

(iv) Researchers

Researchers also play a crucial role in city logistics by providing the theoretical and empirical foundations needed to tackle the complex challenges of urban freight transport. Their involvement ranges from developing advanced models and cutting-edge techniques to enable more efficient and sustainable urban delivery systems and assessing their economic and environmental impact(Cattaruzza et al., 2017). Through pilot projects and living labs, in collaboration with other stakeholders, academics can evaluate the effectiveness of developed innovative technologies and delivery strategies in real-world environments, helping to scale successful solutions. They also play a key role in analyzing policy impacts, offering insights into how regulatory measures can balance efficiency and sustainability (Cherrett et al., 2012).

(v) Technology partners

Another important stakeholder group includes technology firms that provide the digital infrastructure for city logistics operations. These companies offer solutions like real-time tracking, dynamic routing, data analytics, and innovation in automation (e.g., robots and drones) to enhance the efficiency of freight movements. The integration of information technology in logistics is a key enabler for optimizing delivery routes, predicting traffic conditions, and minimizing emissions (Chu et al., 2024).

(vi) End customers

End customers indirectly but significantly influence city logistics, as the B2C market is strongly affected by their behaviour (Wang et al., 2020b). Customer expectations for faster delivery options have put pressure on logistics systems to provide increasingly sophisticated solutions. At the same time, increasing environmental awareness is prompting customers to choose more sustainable delivery options when provided. For these reasons, relevant importance is given to understanding customer behaviour and preferences for appropriately reorganizing systems in order to match their evolving willingness (Lim et al., 2018; Sharma and Ghosh Choudhury, 2014).

1.3 Efficient (and sustainable) solutions for last-mile delivery

The traditional paradigm of last-mile logistics revolves around home delivery, where goods are transported directly to the customer's doorstep. While home delivery provides some conveniences for customers, it is often inefficient for other stakeholders due to the aforementioned challenges (Kiba-Janiak et al., 2021). Hence, these inefficiencies have led to a demand for more innovative solutions in the field. Several surveys addressing alternative last-mile concepts have been proposed (Boysen et al., 2021; Mangiaracina et al., 2019). They define solutions according to different transport vehicles (e.g., vans, cargo bikes, drones or autonomous vehicles), storage facilities (e.g., a central depot and/or micro-consolidation centres), and/or handover options (e.g., attended home delivery or self-collection by customers) considered to complete the task of last-mile delivery.

As previously mentioned, the most common delivery method involves a human courier driving a van along a route to customers' households, where they personally receive their packages in an attended home delivery. While some providers offer decision support systems to couriers for route planning and vehicle loading, many existing software tools lack the flexibility to account for driver-specific knowledge, such as traffic conditions or ongoing roadworks (Allen et al., 2018a). Hence, the first technological innovation that stakeholders are looking for is *AI-Powered Route Optimization* tools that allow for optimizing delivery routes in real-time based on traffic, weather, and customer availability, improving delivery speed and reducing operational costs, regardless of the way the delivery is performed in terms of vehicles and handover options. In this regard, partnerships between providers, researchers, and leading companies in the field are key elements in achieving this goal.

From this starting point, we can broadly classify (i) *solutions improving traditional (home) delivery* and (ii) *manned/unmanned self-collection.*

1.3.1 Solutions improving traditional (home) delivery

The first category includes solutions that make transportation more efficient and sustainable within urban areas, regardless of the final handover option, which remains mainly home delivery. Among these solutions, the most relevant are *cargo bikes and electric vehicles (EVs), autonomous vehicles (AVs), drones*, and *crowd-shipping.*

Cargo bikes and electric vehicles (Figure 1.2) are playing an increasingly critical role in improving sustainability and efficiency in last-mile logistics. Cargo bikes, typically pedal-assisted or fully electric, offer a nimble solution for navigating congested city streets where larger vehicles would face delays. They reduce carbon emissions significantly compared to traditional vans and are ideal for short distances and lightweight deliveries, such as parcels and groceries. Studies show that cargo bikes can complete deliveries up to 60% faster than vans in busy urban areas, and they cut operational costs due to their lower fuel and maintenance needs (Gruber et al., 2014). On the other hand, electric vehicles can carry larger volumes than cargo bikes, making them suitable for bulkier goods while offering a sustainable alternative to combustion-engine vehicles. The shift to EVs in last-mile logistics has been shown to decrease greenhouse gas emissions between 17% and 54% per day, depending on the delivery distances (Chiara Siragusa and Perego, 2022). Additionally, EV adoption is encouraged by regulations in many cities that are implementing low-emission zones or congestion charges, pushing logistics companies towards greener fleets (van Duin et al., 2022).

Autonomous vehicles delivery (Figure 1.3) is emerging as a transformative solution for last-mile logistics, offering a significant reduction in costs, operational inefficiencies, and human resource dependence. These vehicles, ranging from small ground robots to full-sized autonomous delivery vans, can operate with minimal human intervention, improving delivery accuracy and speed. Notably, one of their key benefits is their ability to work 24/7. In urban environments, smaller autonomous robots are used for short-distance deliveries, navigating sidewalks

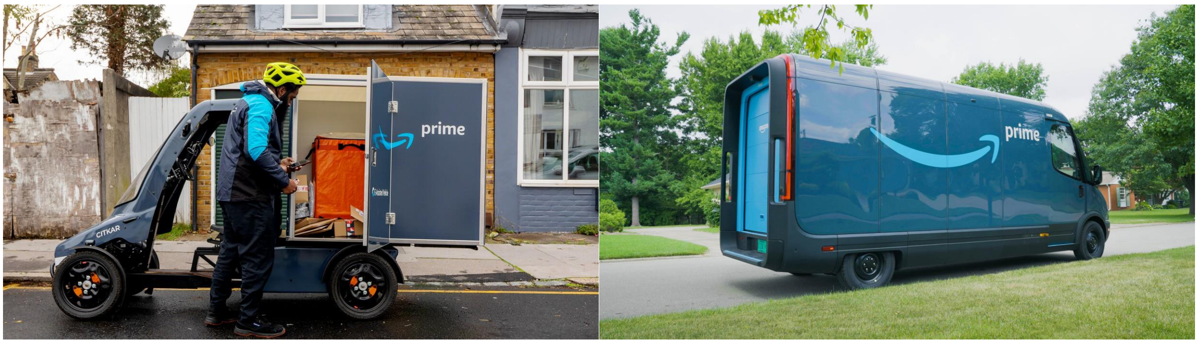


Figure 1.2: Cargo bike (left, Amazon, 2023), Electric Vehicle (right, Amazon, 2022)

and pedestrian zones, while larger autonomous trucks or vans handle bulkier deliveries, often in suburban areas. These AVs also contribute to environmental sustainability, as they are designed to be electric, lowering carbon emissions and aligning with urban policies on reducing traffic and pollution (Reed et al., 2022). Clearly, such a disruptive technology requires adequate regulatory frameworks, technology reliability, and public acceptance. However, most countries still lack appropriate legislation concerning the operation of fully autonomous vehicles on public roads, bike lanes, and pedestrian paths. This is partly due to concerns about whether these vehicles can handle unpredictable and uncommon scenarios safely (Fagnant and Kockelman, 2015).

Figure 1.3: Autonomous Vehicle (FedEx, 2022)

Unmanned Aerial Vehicles, commonly known as *drones* (Figure 1.4), are for sure the most futuristic solution to optimize last-mile delivery following sustainability paradigms. Similar to AVs, drones have the potential to significantly lower delivery costs by eliminating the need for drivers and trucks and reducing congestion-related expenses. Conversely, they may have a shorter delivery time compared to AVs, further enhancing efficiency (Behnke, 2019). However, there are several technological and regulatory limitations. From the technological point of view, drones face challenges with payload capacity, battery life, and weather conditions, which can limit their use for heavy or long-distance deliveries. Furthermore, synchronizing their launch and landing with other vehicles (e.g., trucks) is a non-trivial problem (Di Puglia Pugliese et al., 2021; Moshref-Javadi et al., 2020). From the regulatory side, the main issues concern the necessity of having a comprehensive law framework governing airspace usage, flight altitudes, and safety standards for operations, especially in urban areas. Furthermore, the need for reliable obstacle-avoidance systems adds further complexity to their large-scale deployment (Smith et al., 2022). For all these issues and challenges, such a strategy is gaining substantial attention from researchers and companies involved in developing advanced solutions to implement it in real contexts.

Figure 1.4: Drone (DHL, 2023)

With *crowd-shipping, or crowdsourced delivery*, the last-mile delivery is outsourced to "common" people using their personal travel routes Carbone et al. (2017). By tapping into existing commuter flows, crowd-shipping reduces both costs and environmental impact (Mohri et al., 2023; Simoni et al., 2020). It also provides flexibility for companies to meet spikes in demand without expanding their fleet, which can reduce delivery costs of 25%–29% depending on compensation fees (Pourrahmani and Jaller, 2021). From the customer perspective, crowd-shipping has seen encouraging acceptance, especially when coupled with real-time tracking and communication via mobile apps. Many customers appreciate the option of faster and more flexible delivery times. However, some concerns persist about package security and delivery reliability, which companies are addressing through measures like insurance coverage and verified drivers.

1.3.2 Manned/unmanned self-collection

The second category includes the most relevant solution that proposes an alternative handover option to home delivery: the *self-collection or self-service.* With the latter, customers can autonomously go and collect parcels from dedicated manned *pick-up points* and/or unmanned *parcel lockers* (Figure 1.5). Pick-up points are typically local shops, bars, or tobacconists providing a human-assisted collection service during business opening hours. Parcel lockers, instead, are automated and unassisted facilities mainly located at the entrance of supermarkets, shopping malls, or close to points of interest.

Self-collection has gained traction as the most adopted alternative to traditional home delivery, becoming an integral part of many last-mile logistics strategies within all social and geographical contexts. With self-collection, customers retrieve their parcels from pick-up points or parcel lockers, giving them more control over the timing and location of their retrieval. This model has seen increased adoption in city logistics as it aligns with e-commerce growth and changing customer behaviors, where flexibility and convenience are highly valued. Although its implementation is especially noticeable in urban areas and densely populated regions, where

Figure 1.5: Pick-up points (left, Poste Italiane, 2021), Parcel lockers (right, DHL, 2024)

access to these points is more feasible, it is increasingly expanding also in suburban and rural areas as well.

Below, we describe the characteristics, advantages, and disadvantages of this strategy and compare them to home delivery in depth. It is worth noticing that, in the following, when no distinction is needed, we refer to both pick-up points and parcel lockers as *self-collection facilities*.

1.3.3 Comparison between solutions

A comprehensive comparison of home delivery, manned and unmanned self-collection, has been proposed by Rohmer and Gendron (2020) and presented in Table 1.1).

Table 1.1
Comparison between home delivery and manned/unmanned self-collection (Rohmer and Gendron, 2020)

	Home delivery	**Manned Pick-up point**	**Unmanned Parcel locker**
Customer attendance	Yes	No	No
Delivery times	Tight time windows	During opening hours	At any time
Types of deliveries	All kinds of deliveries	Depending on equipment	Depending on the design
Capacity at delivery location	Unlimited	Limited (station)	Limited (station and locker)
Customer self collection	-	During opening hours	Any time
Collection time window	-	Short-Long	Short-Long
Use of vehicle capacity	Poor	High	High
Number of failed delivery	High	Close to none	Close to none

The table highlights that, from the provider's perspective, regardless of the facility type, self-collection can help consolidate deliveries and optimize vehicle capacity (Moslem and Pilla, 2023; Ranjbari et al., 2023). Additionally, it almost zeroes failed deliveries and the corresponding rescheduling costs (Praet and Martens, 2020). Undoubtedly, the most significant advantage for customers is the flexible time window for collection, especially for parcel lockers that can be visited 24/7. Clearly, these systems also pose some challenges, such as restrictions on the types of deliveries allowed and limited capacity at delivery locations. Additionally, the initial investment costs can be high, as alternative delivery facilities need to be established (i.e., the case of parcel lockers). Comparing the two self-collection delivery concepts, parcel lockers provide longer and more flexible operating hours but are often more restrictive in terms of capacity and require a higher initial investment. In summary, while self-collection can enhance operational efficiency and lower delivery costs, it is crucial for service providers to carefully evaluate the associated investments before implementing these solutions.

The choice of investing in a self-collection network strongly depends on the specific service needs and customer preferences, balancing long-term benefits with the necessary investments. Indeed, the propensity of customers to frequent self-collection facilities is significantly influenced by their proximity to these locations. When self-collection facilities are conveniently situated nearby, customers are more likely to choose them due to the ease of access and reduced travel time. This convenience factor plays a critical role in decision-making, as customers tend to prefer options that save them time and effort. Additionally, the presence of self-collection facilities in densely populated areas or in attractive places (i.e., inside or next to shopping centres) can increase the number of customers opting for this strategy. Conversely, if facilities are too far away or difficult to reach, customers may opt for standard delivery services, undermining the effectiveness of the strategy.

Clearly, in this framework, customer habits also play a crucial role. Factors such as time spent at home, work schedules, and daily routines significantly influence whether individuals choose to collect their items personally. For example, users who work long hours or have irregular schedules may prefer extended-hour self-collection facilities, allowing them to pick up their orders at their convenience. Conversely, individuals who frequently work at home may be more inclined to choose traditional home delivery.

Therefore, in promoting the strategy of self-collection, decision-makers must consider the issues of physical proximity and accessibility while also taking into account factors that influence customer habits. However, an excessive number of self-collection facilities can undermine the benefits of consolidation and, consequently, the cost savings achieved through the adoption of this strategy. The trade-off between economic costs and the desirable capillarity of the service, influencing customer acceptance, makes the decision about self-collection network design and service deployment a non-trivial problem for decision-makers (e.g., logistics providers).

1.4 Programs and initiatives

The involved stakeholders collaborate in several initiatives and funding programs launched in Europe to promote sustainable city logistics and enhance the efficiency of last-mile delivery systems. These are largely focused on reducing traffic congestion, minimizing carbon emissions, and adopting innovative technologies and solutions in urban freight management.

The *Recovery and Resilience Facility (RRF)*, a core element of the *EU's NextGenerationEU* initiative has allocated significant financial resources to promote sustainable urban logistics and improve last-mile delivery systems across Europe. With a total budget of €723.8 billion, the RRF aims to help EU member states recover from the economic impacts of the COVID-19 pandemic while supporting the transition towards a greener and more digital economy. A substantial part of this funding is directed towards green mobility initiatives, including freight logistics. In general, measures prioritize the implementation of smart logistics systems that integrate digital technologies with innovative delivery solutions (European Commission, 2021).

These initiatives align with the broader objectives of the European Green Deal, which adopted a set of proposals to make the EU's climate, energy, transport and taxation policies fit for reducing net greenhouse gas emissions by at least 55% by 2030, compared to 1990 levels (European Commission, 2020).

Deeply investigating the measures, one of the key priorities under the RRF is to decarbonize transport, including the adoption of electric and alternative fuel vehicles in urban delivery fleets. The RRF encourages local governments and other stakeholders to invest in electric vehicles (EVs) and develop infrastructure for charging stations, promoting the replacement of fossil fuel-based delivery trucks with zero-emission alternatives. These can also be included in the paradigm of *multimodal transport*, which links different transport modes, improving the sustainability and efficiency of freight transport in urban areas. Moreover, the RRF provides funding for the development of urban consolidation centres (UCCs) and micro-hubs (e.g., *self-collection facilities*), which streamline freight logistics by consolidating goods (also allowing customers to collect them autonomously) and reduce the number of vehicles entering congested urban centres. Finally, the RRF funds strongly support the implementation of digital technologies, such as *smart logistics platforms* that use data analytics, AI, and IoT to optimize delivery routes and timings, enhancing the overall efficiency of freight logistics.

To benefit from support under the RFF, EU member states have submitted national recovery and resilience plans with detailed proposals for how they will use these funds to support smarter urban logistics systems by adopting innovative solutions for sustainable last-mile logistics. In their plan, they have also outlined reforms and investments to be implemented by end-2026 and the commitment of all the stakeholders involved in each project, with clear milestones and targets.

1.4.1 The National Recovery and Resilience Plan in Italy

Italy has formally received the European Union's funds through its *National Recovery and Resilience Plan (NRRP)*, a wide-ranging initiative to drive economic recovery and sustainable growth following the impact of the COVID-19 pandemic (Camera dei Deputati, 2021).

The plan integrates a broad investment agenda and a robust reform package. It allocates €191.5 billion from the RRF, alongside an additional €30.6 billion from a national Complementary Fund, which was established by Decree-Law No. 59 on May 6, 2021, based on a multi-year budgetary increase approved by the Council of Ministers on April 15. Together, these resources amount to €222.1 billion. Furthermore, €26 billion has been earmarked for additional projects and for strengthening the Development and Cohesion Fund through 2032, bringing Italy's total funding pool to approximately €248 billion.

The NRRP focuses on three strategic priorities shared at the European level: digital transformation, ecological transition, and social inclusion. In addition to addressing the damage caused by the pandemic, the Plan aims to tackle structural weaknesses in Italy's economy and drive a transition toward environmental sustainability. The NRRP is also set to reduce economic and social inequalities, including regional, generational, and gender-based disparities.

For regional distribution, the NRRP has allocated around €82 billion specifically for Southern Italy, which represents 40% of the €206 billion that can be directed geographically. Additionally, the Plan places a significant focus on investments aimed at empowering young people and women, recognizing the importance of reducing historic inequalities affecting these groups.

The structure of Italy's NRRP is organized into six main "missions," each representing a strategic area of focus designed to drive the country's recovery and transformation (Figure 1.6).

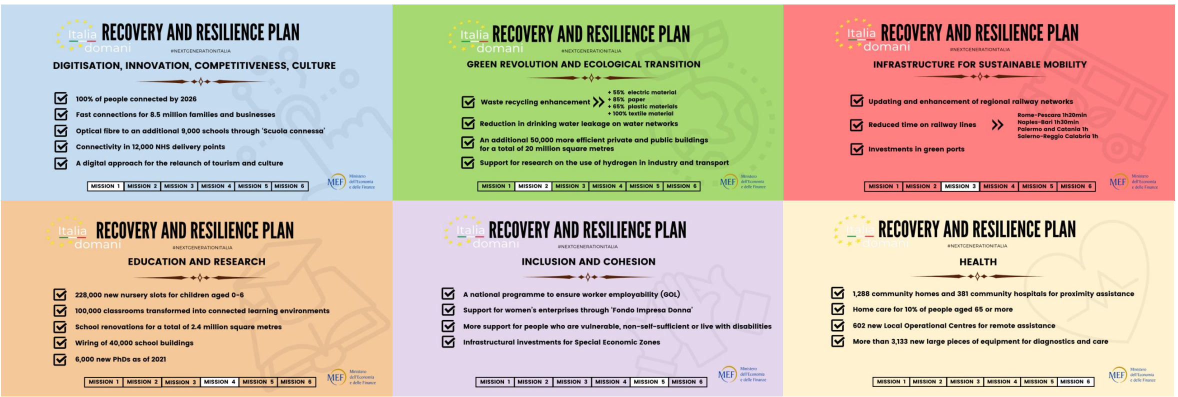


Figure 1.6: Missions of National Recovery and Resilience Plan (Ministero dell'Economia e delle Finanze, 2021)

Below is a brief overview of each mission.

- *Digitisation, Innovation, Competitiveness, Culture* aims to modernize Italy's digital infrastructure, improve public administration digitalization, and support innovation in businesses. It also includes projects to enhance cultural heritage and tourism;

- *Green Revolution and Ecological Transition* focuses on Italy's transition to a sustainable and green economy. It includes investments in renewable energy, sustainable mobility, circular economy practices, and measures to protect biodiversity. Key objectives are reducing carbon emissions and promoting a cleaner environment;

- *Infrastructure for Sustainable Mobility* prioritizes infrastructure upgrades to improve connectivity and reduce environmental impact, particularly in transportation and city logistics. Projects include expanding high-speed rail networks, enhancing local transport, and increasing the safety and efficiency of urban logistics systems;

- *Education and Research* aims at strengthening Italy's educational and research systems. This mission focuses on improving access to quality education at all levels, investing in research and development, and promoting skill-building to better align education with labor market needs;

- *Inclusion and Cohesion* supports initiatives to reduce inequalities and increase social inclusion, with a focus on employment, social services, and community development. It includes measures to promote gender equality and youth employment and address the needs of vulnerable populations.

1.4.2 The National Centre for Sustainable Mobility

One of the six missions outlined by the PNRR is *Infrastructure for Sustainable Mobility*, which led to the establishment of the *National Centre for Sustainable Mobility* (CNMS), *(MUR CN00000023)*. The center, whose grant is about 394 euros, has the critical goal of establishing skilled Italian leadership that is deeply connected with local communities and businesses capable of guiding future progress toward inclusive, sustainable, and carbon-neutral mobility (MOST, 2023). The center comprises 25 universities and research institutions with over 865,000 students, along with 24 private companies whose combined revenue exceeds 135 billion euros. Such a collaboration strengthens the research and development (R&D) chain in both research and the economy, accompanied by improved technology transfer mechanisms.

The project is organized as an *hub and spoke* model, designed to optimize and coordinate the activities. This is based on a central "hub", which coordinates different "spokes" representing R&D activities associated with different transportation themes.

The Hub is based in the University Politecnico of Milan and carries out strategic direction, management, and coordination activities. The fourteen Spokes, which are responsible for research activities coordinated by universities and involving partner companies, are distributed across the entire national territory (Figure 1.7).

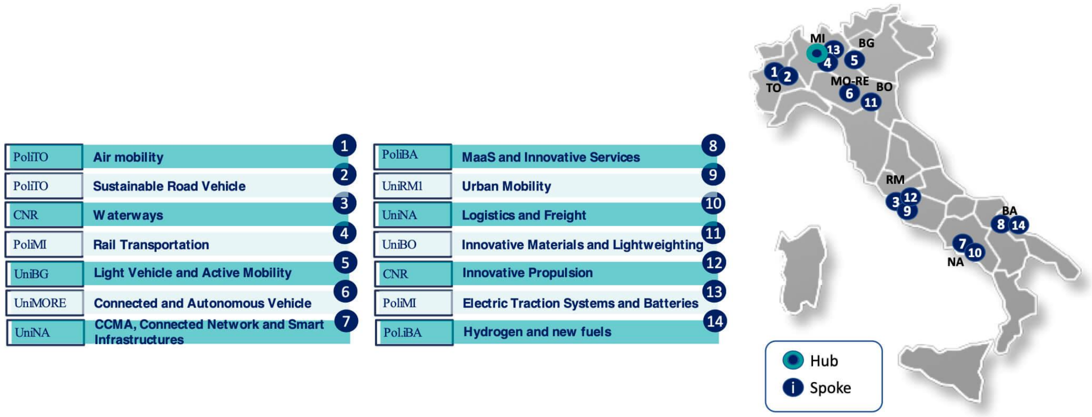


Figure 1.7: CNMS: hub and spoke model (Agenda Digitale, 2024)

A specific focus within the CNMS is on freight logistics. The spoke is coordinated by the University of Naples Federico II, and the objectives are to foster a comprehensive development of logistics and freight transport systems that leverage four core pillars. The first focuses on technological innovation, including digitalization and data analytics, to enhance efficiency and adaptability. The second pillar prioritizes sustainability in environmental, social, and economic terms, aiming to reduce ecological impact while meeting societal needs. The third pillar focuses on optimizing operations and establishing new business models to improve performance and resource allocation across supply chains. Lastly, the fourth pillar promotes effective and coordinated policymaking and governance to ensure alignment across sectors, fostering collaborative frameworks that support consistent standards and address global logistics challenges.

These pillars mainly focus on innovative last-mile and city logistics solutions. Specifically, the concept of city-logistics-as-a-service (CLaaS) is promoted in terms of a holistic system that matches supply and demand with an innovative approach leveraging real-time optimization, prediction of customers' behaviour, dynamic pricing of services, personalised level of service options, and different use of assets (vehicles, depots and/or self-collection points). To promote this concept, the collaboration between different involved stakeholders represents the crucial way to develop and simulate innovative solutions from a multi-objective perspective, adopting a rolling horizon for long-and medium-term strategic objectives while considering short-time tactical and operational constraints.

Among these solutions, self-collection is the most investigated by universities and research institutions involved in the project. Regarding the latter, at the strategic level, network design decisions are crucial and challenging. This decision involves creating a well-integrated network of collection points that balances density and distance, thereby reducing delivery times and operational costs by matching customers' preferences. Choosing locations for self-collection facilities involves considering customer proximity, accessibility, and the distance to points of interest to optimize territorial coverage. Besides, intrinsic customer' habits also play a crucial role in the success of the strategy, hence influencing this decision. Therefore, considering discrete choice model techniques that can predict behaviour introduces additional complexity to the problem. On the tactical and operational level, regularly replenishing self-collection points while minimizing operational and routing costs is a complex challenge. The new infrastructure configuration necessitates a redesign of the current territorial arrangement by reorganizing urban areas into smaller units for effective logistics operations. This must take into account the uncertainty related to the varying demand at each point, which may not be visited every day.

Achieving these goals requires a scientific effort to develop optimization models and algorithms that deliver both strategic and operational efficiency. By drawing on the collaborative approach of the project, researchers can leverage the informational resources and expertise of logistics operators to test, validate and apply the proposed solutions in real-world case studies with actual data. This approach facilitates the advancement of simulation techniques using digital twins, enabling greater scalability and the practical application of developed solutions in industry settings.

1.5 Conclusions

The rapid growth of e-commerce in the past decade has transformed the retail landscape, significantly influencing customer behaviors and logistics operations. This chapter examined the surge in online shopping and its impact on parcel delivery and collection volumes. It highlighted how the rapid increase in e-commerce not only transformed customer purchasing behaviors but also placed unprecedented demands on logistics systems worldwide.

In particular, the chapter delved into solutions that stakeholders are looking for to optimize the most critical phase: the last-mile logistics. Specifically, an in-depth analysis of self-collection has been performed, showcasing how this solution can promote efficiency and sustainability in an urban context. Indeed, by allowing customers to pick up their parcels at convenient locations autonomously, logistics providers are able to reduce delivery costs and pollution in crowded cities. Finally, the chapter focuses on the Italian case and examines the CNMS, the project developed within the NRRP to promote sustainable mobility and freight logistics.

CHAPTER 2

Self-collection in last-mile logistics: literature review, gaps, and contributions

Summary

This chapter provides an overview of the key research areas related to self-collection in last-mile logistics. The existing literature on this topic can generally be divided into two main categories: studies that focus on customer behavior and those that address logistical decision-making challenges associated with strategy implementation. The elements in this chapter provide the reference background for the models and applications of the following sections of the thesis. Through this analysis, we identify existing gaps and declare the contributions of the thesis.

2.1 Main research streams

The academic literature on self-collection can be broadly categorized into two main research streams: studies that explore *customer behavior and participation* and those that focus on *logistics strategic and tactical decision-making* required for implementing the delivery solution (Ma et al., 2022).

On one side, customer behavior research examines factors that drive customer engagement with self-collection options, such as perceived convenience, accessibility, and service reliability (Wang et al., 2018). This branch of literature often emphasizes psychological, social, and economic factors that influence how and why customers choose self-collection over traditional delivery options, ultimately impacting the system's usage rates and customer satisfaction levels. Understanding these dimensions is crucial because the success of self-collection solutions depends not only on the quality of operational planning but also on the willingness of customers to actively participate (Ma et al., 2022). The other stream concerning decision-making frameworks is primarily interested in the logistical optimization needed to ensure the efficiency and scalability of self-collection systems. This area can be subdivided further into strategic and tactical decision problems.

Strategic decisions involve the self-collection *network design*, i.e., the problem of determining the optimal size and the configuration of the self-collection network. This type of decisions roots into *location analysis*, and, specifically, *Facility Location Problems (FLPs)*, a well-established field of operation research that aims to identify the best location for one or several facilities in a given space to serve a given demand (actual or potential) from a set of customers (Laporte et al., 2019). In the context of self-collection, these models help determine the most suitable geographic locations for collection points, ensuring their placement in areas where they are either convenient for customers or operationally feasible.

On the other hand, tactical decisions involve the problem of designing appropriate *delivery areas* for daily operations. This relates strictly to operational routing problems that aim to identify the daily visiting tour to minimize costs and externalities. Indeed, defining appropriate fixed delivery zones, each with specific characteristics helps to optimize routing, reduce operational costs, and improve service efficiency. This decision involves literature related to *Districting Problems (DPs)*, concerning grouping small geographic areas, called basic units, into larger geographic clusters, called districts, such that they are balanced, contiguous, and compact (Kalcsics and Ríos-Mercado, 2019).

The literature highlights the importance of integrating insights from customer behavior studies with operational strategies, balancing customer needs with logistical feasibility. Together, these streams of research provide a comprehensive framework for developing self-collection solutions that are both customer-close and operationally sustainable (Figure 2.1). Therefore, although the models and applications presented in this thesis relate to logistics decision-making problems, they also incorporate elements of customer behaviour to address the complexities of such strategic and tactical issues.

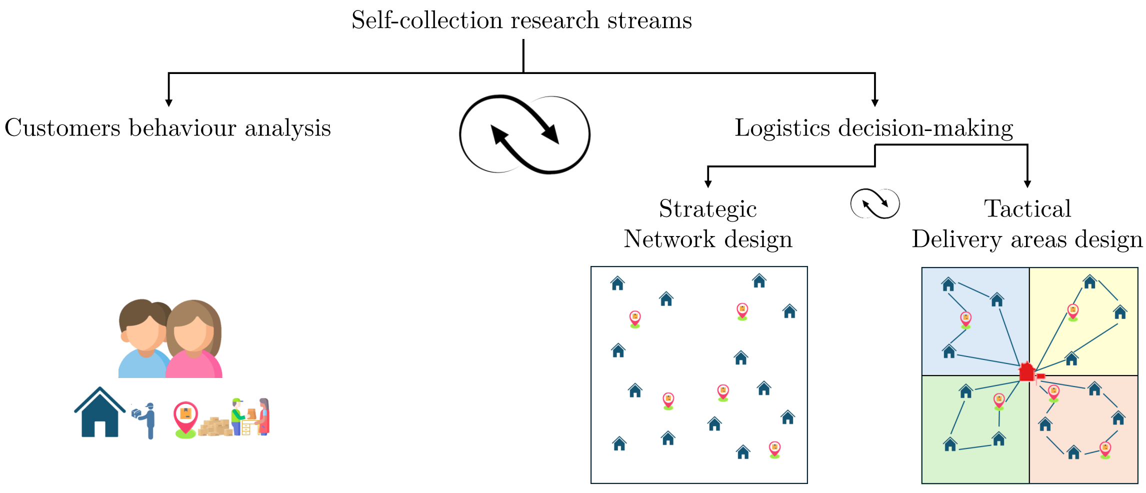


Figure 2.1: Research streams framework

In the remainder of the chapter, leading works related to customers' behavioral stream are presented in Section 2.2. Then, in Section 2.3, self-collection facility location problems are investigated. Finally, in Section 2.4, distribution districting problems for last-mile logistics are described.

2.2 Customer behavior

Customer behavior analysis is a multidisciplinary field that examines how individuals, groups, or organizations make decisions regarding the purchase, use, and disposal of goods and services. It explores how emotional, cognitive, and social factors shape customer preferences and behaviors. Emerging in the mid-20th century, the field draws on psychology, sociology, anthropology, and behavioral economics to understand consumption patterns and their underlying drivers in different sectors. Indeed, studies on the topic have been distributed across different fields, reflecting its relevance in understanding decision-making in various contexts.

In retail and marketing, research explores how pricing, promotions, and branding influence purchasing choices. For example, studies demonstrate that emotional appeals and brand loyalty play a significant role in shaping customer preferences in competitive markets (Kotler and Keller, 2016). Similarly, the rise of e-commerce has highlighted the importance of website design and online reviews in influencing purchasing behavior (Gefen et al., 2003).

Customers' behavior has also gained prominence in technology adoption, where frameworks such as the Technology Acceptance Model (TAM) help explain customer decisions to embrace innovations like smartphones or wearable devices (Davis, 1989). Factors like perceived usefulness, ease of use, and social influence often drive these choices.

In sustainability and environmental conservation, customer behavior research examines the adoption of eco-friendly products and practices. Studies suggest that values like environmental concern and social responsibility significantly affect decisions to purchase green products (Peattie, 2010).

In the transportation and logistics sector, customer behavior insights are utilized to analyze mode choices and preferences for sustainable mobility options, such as public transport or electric vehicles. Here, models like the MultiNomial Logit (MNL) are commonly used to evaluate the trade-offs customers make between cost, convenience, and environmental impact (McFadden, 1972; Train, 2009). The MNL is a widespread quantitative methodology that has been further enabled by advances in data availability. The model evaluates the probabilities of selecting mutually exclusive alternatives based on their attributes and customer-specific characteristics. By capturing how features and attributes influence preferences, the MNL model has become a powerful tool for understanding and predicting customer acceptance toward products and services within different business contexts and, specifically, in transportation and freight logistics.

2.2.1 Self-collection acceptance

Customers' acceptance and satisfaction are crucial to the success of self-collection services, and recent research has increasingly examined customer perceptions and motivations related to this strategy. The first studies on the topic focused on identifying key factors influencing customers' acceptance, often adopting well-established behavioural theory. Yuen et al. (2018) applied the so-called Innovation Diffusion Theory (usually investigating how innovations or technologies become accepted and spread through societies) to assess the compatibility between customers' lifestyles and their use of self-collection. By means of a survey from a sample of customers in Singapore, the authors prove that characteristics of innovation, relative advantage compared to home delivery, compatibility with past experiences, and trialability positively influence the intention to use self-collection services. In their subsequent work, considering customers from China, they also include perceived value and transaction costs in factors affecting adoptions (Yuen et al., 2019). Similarly, Wang et al. (2018) and Tsai and Tiwasing (2021) considered customer data from Singapore and Thailand, respectively, highlighting the impact of attitudes and readiness toward self-service, the advantage compared to home delivery, and the perceived security increase in customers' adoption of parcel lockers.

Other works investigate the problem by considering factors generating value for customers who adopt the service. In particular, Vakulenko et al. (2018) identified four key value categories in the self-collection experience: functional, emotional, social, and financial. Each of these values plays a distinct role in shaping customers' preferences and ongoing engagement with self-collection.

Functional value is derived from practical or utilitarian service attributes, such as convenience, security, and reliability. Numerous studies indicate that customers perceive self-collection as beneficial when it offers seamless and dependable service. For instance, flexible pickup times, privacy in the collection, and reduced risk of missed deliveries (for customers working outside all day) are widely seen as a positive aspect (Vyt et al., 2022; Wang et al., 2023; Zhou et al., 2020). Additionally, facilitating conditions such as clear usage instructions, prompt assistance, and efficient problem resolution significantly enhance the likelihood of adopting self-collection (Tang et al., 2021). However, high technological aspects can also be perceived as barriers for some customers' categories. For example, when considering parcel lockers, touch-screen interfaces or complex retrieval procedures can discourage use for customers unable or unwilling to adopt digital tools. Indeed, Chen et al. (2020) found that a low perceived ability to use parcel lockers, often due to technical or design limitations, diminishes the convenience value, reducing users' willingness to engage with self-collection services.

Emotional value in self-collection is tied to how well the service aligns with customers' identities, personalities, aspirations and habits. Research shows that self-collection depends not only on rational factors but also on irrational ones like habits and attitudes (Cai et al., 2021; Wang et al., 2021b). In particular, (Wang et al., 2020a) found that self-enhancement value is a stronger intrinsic motivator. Indeed, even without external rewards, most self-enhancers actively use the self-collection service to manage their e-commerce deliveries. The COVID-19 pandemic further heightened the importance of emotional value, as health concerns increased the appeal of self-service options that reduce interpersonal contact, allowing for safe parcel collection (Wang et al., 2021a, 2022).

Social value is another crucial aspect, defined by the influence of recommendations and endorsements from trusted sources. The perceived value of self-collection can be enhanced when it is recommended by individuals or groups, such as family, friends, or media, particularly in communities where social influence plays a strong role in customers decision-making (Cai et al., 2021).

Financial value in self-collection lies in the monetary benefits or savings, primarily through reduced delivery fees. Many retailers offer discounts or waive fees for customers who choose self-collection over home delivery, making this option attractive to cost-conscious customers. These perceived savings add clear, tangible value that encourages adoption (de Oliveira et al., 2017). Indeed, Milioti et al. (2020) and Merkert et al. (2022) used Logit Models to prove that, when all the other attributes are fixed, customers tend to prefer home delivery, indicating that self-collection services need additional financial advantages to compete effectively.

Environmental awareness also plays a crucial role. For example, customers who prioritize eco-friendly practices are more likely to prefer self-collection service, as it can help reduce the carbon footprint associated with last-mile delivery (Belvedere et al., 2024; Kokkinou et al., 2024; Wang et al., 2021b).

A fundamental stream of literature deals with physical accessibility aspects. Several studies show that walking distance to self-collection points is a significant factor, with longer distances reducing the likelihood of adoption. Indeed, customers' willingness to choose self-collection depends on the number of dedicated facilities within a short travel distance (Luo et al., 2022a; Kim and Wang, 2022). Hence, locational convenience is essential, and strategic decisions about the placement of collection points are essential for boosting customer acceptance and incentivizing regular use of self-collection services. Well-positioned collection points not only enhance accessibility but also play a vital role in making self-collection a preferred, convenient alternative to home delivery.

This comprehensive body of research highlights the complexity of customer perceptions and preferences regarding self-collection, underscoring that successful service adoption hinges on addressing various customer needs and expectations. It emphasizes the importance of service designs that optimize multiple dimensions of value, such as cost savings, convenience, accessibility, and delivery speed to create a compelling and competitive alternative to home delivery. By integrating these factors thoughtfully, service providers can not only attract initial users but also support long-term, sustainable adoption, ensuring that self-collection becomes a widely accepted, preferred choice in such a delivery landscape.

2.3 Network design

This section discusses existing studies related to strategic decisions regarding self-collection network design. Specifically, after describing general concepts about Facility Location Problems (Section 2.3.1), two different streams of literature dealing with their application to self-collection are investigated. Indeed, extant contributions in the field can be effectively classified depending on the assumed spatial interaction between customers and facilities, that is, how users' propensity and patronization mechanisms are represented. Specifically, it is possible to distinguish *deterministic* (Section 2.3.2) and *probabilistic* (Section 2.3.3) approaches.

2.3.1 Generalities on Facility Location Problems

In general, determining where to locate facilities is a critical decision for any public or private organization from both strategic and operational perspectives. Such choices can significantly impact the entire supply chain, influencing connections between plants and warehouses with suppliers as well as the relationship between facilities and the customers, who may access products and services (for example, through self-collection delivery).

Given the importance of these decisions, a wide body of research—encompassing theory, modeling, and practical solutions—has emerged since the 1960s, thanks to contributions from academics and industry experts. This has led to the establishment of the research field known as *location analysis*.

Seminal works in the modern study of location analysis include Cooper (1963) and Hakimi (1964, 1965), though the earliest known studies trace back to the 17th century, with the first documented location problem attributed to Weber (1929). Since that time, location analysis has grown into a dynamic area of research, covering a broad spectrum of issues and drawing insights from fields such as economics, geography, and logistics. Recent comprehensive collections on the topic are presented in Eiselt and Marianov (2009) and Laporte et al. (2019).

At the core of location analysis lies the study of *Facility Location Problems* (FLPs). The aim of these problems is to identify optimal locations for one or more facilities within a defined area to meet specific demands (either actual or potential) from a set of customers. The concept of "optimal" is shaped by the nature of the problem, the objectives in question, and the constraints applied (Laporte et al., 2019).

As noted by Eiselt and Laporte (1995) and ReVelle and Eiselt (2005), the primary elements of an FLP include:

- *Location space* representing the area within which facilities are placed to meet demand. This space can be *continuous*, on a *network*, or *discrete*. In a continuous space, facilities can be located anywhere, though forbidden zones may exist due to geographical or technical restrictions. In network spaces, facilities are positioned on nodes or edges within a network, while in discrete spaces, placement is limited to specified candidate sites;

- *Facilities* to be positioned, which provide goods and/or services to meet demand. These facilities are typically characterized by attributes such as cost, capacity, attractiveness, and the number and types of services offered. Specifically, the number of facilities may be predetermined or treated as a decision variable. Facility costs may include both activation and operational expenses. Facilities can also vary by the number of goods or services offered, as in *single-commodity* vs. *multi-commodity* facilities (Pirkul and Jayaraman, 1998). Additionally, facilities may differ in terms of the products or services provided and may have specific structural relationships, such as *hierarchical* (Farahani et al., 2014) or *multi-level* (Ortiz-Astorquiza et al., 2017). Capacity refers to the maximum demand a facility can serve; facilities with unlimited capacity are known as *uncapacitated*, while those with limited capacity are referred to as *capacitated problems*;

- *Customers* who require products and services from located or prospective facilities. Customers may either be dispersed continuously across the space or concentrated at specific points, known as *demand nodes*. Each demand point typically has a designated demand value for particular services;

- *Objectives* to achieve. Different criteria define the objectives for optimizing location decisions. In most cases, objectives are either cost-based (or, conversely, profit-based) or coverage-oriented. For cost-based objectives, attention is given to location costs (i.e., fixed establishment costs) and/or allocation costs (i.e., variable costs for providing goods or services) (Fernández and Landete, 2019). Coverage-oriented objectives aim to meet as much demand as possible within a specific distance from a facility (García and Marín, 2019), thus, in some way, maximizing accessibility conditions. Other goals may depend on the nature of the facilities and the services offered and can be included in multi-objective models (Farahani et al., 2010);

- *Constraints* to meet, which can vary greatly depending on the specific problem. Common constraints include economic or budget limitations, capacity restrictions, topological requirements (such as minimum or maximum distances between facilities or zoning laws), and technical or technological limitations;

- *Interactions* between customers and facilities, as well as among facilities themselves. Customers can be assigned to or served by facilities to meet their demands, with the allocation being either mandatory or based on preferences and utility functions. This distinction leads to *location-allocation* versus *location-choice models* (Drezner and Eiselt, 2002). Coverage typically involves the existence of at least one facility within a certain distance of a customer (Berman et al., 2010). Interactions among facilities can relate to competition for market share (Aboolian et al., 2007) or collaboration to ensure a minimum service level for customers (Berman et al., 2011). Interactions are strongly affected by customers' behavior and their attitudes toward the service offered by facilities.

Depending on the combinations of these key elements, a wide variety of mathematical models can be created. Classification schemes for these models are proposed by Revelle et al. (2008) and Farahani et al. (2012).

2.3.2 Deterministic approaches

Deterministic approaches to the facility location problem for self-collection assume that users with access to a nearby self-collection facility are willing to utilize it. These models typically rely on coverage and closest-assignment paradigms as sufficient conditions to ensure that customers will use self-collection services. Building on this assumption, a variety of models and solution methods have been proposed to determine optimal facility locations, with objectives ranging from maximizing logistics providers' profits to optimizing customer convenience and minimizing operational costs.

Table 2.1 summarizes the main contributions in the field by indicating the reference, the objective(s), and the considered facility.

Deutsch and Golany (2018) introduced one of the first mathematical models focused on locating parcel lockers to maximize total profit for logistics providers. This model considers various costs, including potential discounts for users based on their travel distance to a parcel locker and losses incurred from potential customers who are unwilling to travel beyond a specified maximum radius. This maximum radius represents the threshold distance beyond which customers are unlikely to use the service, thus defining the facility's effective catchment area.

In a similar vein, Schwerdfeger and Boysen (2020) addressed the location of mobile parcel lockers, which have the unique feature of being able to change locations throughout the day. This model includes a solution approach that assigns users prescriptively within a maximum walking range, thus providing flexibility in meeting fluctuating demands in different areas at different times. The objective here is to balance the cost of relocating lockers with the goal of maintaining optimal coverage within user-defined proximity constraints.

Xu et al. (2021) further advanced the field by proposing two multi-period location models for both attended (e.g., pick-up points) and unattended facilities (e.g., parcel lockers). In their approach, facility location is treated as a time-dependent decision, allowing for parcel lockers to be relocated across different periods in order to adapt to changing demand patterns over time, with objective functions focusing on minimizing service provider costs while ensuring users are within a maximum coverage distance from a locker.

A multi-objective approach to parcel locker location was investigated by Che et al. (2022), who aimed to (i) maximize demand coverage, (ii) minimize overlap among lockers (i.e., the number of customers served by multiple lockers), and (iii) reduce idle locker capacity. This approach acknowledges the complexity of managing high-density areas, where overlapping coverage can lead to under-utilization of lockers in some locations and excessive demand in others. By minimizing overlap, the model aims to distribute demand more evenly across lockers, improving overall service efficiency.

Similarly, Kahr (2022) developed a model under demand uncertainty, with the goal of maximizing expected profits for the service provider, in which potential fluctuations in customer demand, using probabilistic measures, are included.

Some studies have focused on optimizing travel distances or other accessibility metrics. For instance, Yang et al. (2020) proposed a bi-level model for locating parcel lockers, aiming to minimize provider costs at the upper level and customer travel distances at the lower level. This hierarchical structure prioritizes service cost-effectiveness for providers while also accounting for customer convenience. Another related approach was proposed by Luo et al. (2022a), who defined a bi-objective model to minimize setup and shipping costs for the service provider while maximizing accessibility for customers. Accessibility is quantified by an exponential decay function, which decreases as travel distance increases.

Some models also address the location problem under multi-period planning and demand uncertainty. Rabe et al. (2020) introduced a simulation-optimization model to address the long-term planning of parcel locker locations, factoring in fluctuating customer demand over a planning horizon. The objective function here seeks to optimize installation costs while minimizing the distance between customers and assigned lockers. This approach enables more efficient long-term infrastructure planning that remains responsive to anticipated demand changes.

Finally, Avgerinos et al. (2022) developed a model for locating pick-up points within managed printing services motivated by a click-and-collect application. Their model is based on a heuristic approach that balances installation costs and customer assignment distances, providing an efficient solution for cases where multiple types of collection points serve different client needs.

In summary, these studies collectively emphasize the importance of location optimization in self-collection services, using various deterministic and multi-objective models to address diverse aspects such as cost minimization, demand coverage, and adaptability to demand fluctuations.

2.3.3 Probabilistic approaches

Probabilistic approaches address the need to model realistic customer behaviors by moving beyond deterministic assumptions where proximity is the primary driver of facility use. These models, as highlighted by Lin et al. (2020), recognize that "customers take the initiative in

Table 2.1
Self-Collection Facility Location Problems: deterministic approach

References	Objective(s)	Facility
Deutsch and Golany (2018)	max. profit	parcel lockers
Schwerdfeger and Boysen (2020)	max. accessibility	parcel lockers
Xu et al. (2021)	min. costs	pick-up points, parcel lockers
Che et al. (2022)	max. coverage, min. overlap, min. idle capacity	parcel lockers
Kahr (2022)	max. profit	parcel lockers
Yang et al. (2020)	min. costs, max. accessibility	parcel lockers
Rabe et al. (2020)	min. costs, max. accessibility	parcel lockers
Avgerinos et al. (2022)	min. costs, max. accessibility	pick-up points

e-commerce" and thus may choose whether to use self-collection, as well as which specific facility to patronize. Customers' preferences are often unpredictable, and proximity is not always the most decisive factor, necessitating probabilistic models to capture a more nuanced, individualized decision-making process.

Table 2.2 summarizes the main contributions in the field by indicating the reference, the objective(s), and the considered facility.

One commonly used model in this context is the MultiNomial Logit (MNL) model, which calculates the probability of customers choosing a specific facility based on various attributes, such as accessibility. Lin et al. (2020) represent the first known application of MNL to the self-collection facility location problem. In their model, customer demand for pick-up points is predetermined, and the likelihood of each customer's choice is determined by an accessibility function that decreases with distance from the facility. Using this model, they propose a mathematical optimization that identifies new facilities to open and existing, underused facilities to close, aiming to maximize the overall accessibility for customers and thereby improve service efficiency.

In a follow-up study, Lin et al. (2022) expanded on this approach by refining the customer choice mechanism through the introduction of the Threshold Luce Model (TLM). This model reduces the choice set for each customer by excluding "dominated alternatives," or facilities with accessibility levels significantly lower (beyond a given threshold) than more preferred options. This refined model thus accounts for customers' tendency to disregard facilities deemed inconvenient, thereby providing a realistic basis for a parcel locker location model focused on maximizing logistics providers' profits.

Further extending the probabilistic framework, Peppel and Spinler (2022) and Zhang et al. (2023) incorporate the home delivery option directly into the MNL-based customer choice model. In their approach, customers weigh the utility of self-collection versus home delivery, where utilities are influenced by factors such as travel distance, delivery fees, and home presence. By capturing the trade-off between these options, the models aim to position parcel lockers optimally within urban environments to maximize providers' profitability or cost-efficiency.

A different yet related objective is explored by Lyu and Teo (2022), who use a probabilistic framework to design a network that minimizes the proportion of parcels undelivered to lockers.

This approach underscores the importance of location optimization not only for profitability but also for reliability in meeting delivery targets.

Lastly, the recent work of Peppel et al. (2024) advances probabilistic modeling by incorporating mobile parcel lockers, aiming to locate eligible deposits and stop points with minimal operating costs. This model takes into account dynamic, location-based decision-making for mobile units, where accessibility is optimized while accounting for fluctuating demand and operating expenses.

Overall, probabilistic models provide a richer representation of customer behaviour by integrating choice-based decision mechanisms like MNL and TLM, which may consider various factors beyond distances. These models allow decision-makers to better align facility location decisions with customer preferences, ultimately fostering more efficient, profitable, and customer-centric self-collection networks.

Table 2.2
Self-Collection Facility Location Problems: probabilistic approach

References	**Objective(s)**	**Facility**
Lin et al. (2020)	max. accessibility	parcel lockers
Lin et al. (2022)	max. profit	parcel lockers
Peppel and Spinler (2022)	min. costs	parcel lockers
Lyu and Teo (2022)	max. on-time deliveries	parcel lockers
Zhang et al. (2023)	min. costs	parcel lockers
Peppel et al. (2024)	min. costs	parcel lockers

2.4 Design of delivery areas: base concepts

This section discusses existing studies related to tactical and operational decisions regarding the design of delivery districts in last-mile logistics. Specifically, after describing general concepts about *Districting Problems* (DPs) and introducing some applications, the literature dealing with distribution districts for last-mile logistics with self-collection is investigated (Section 2.4.1).

Districting Problems (DPs) aim to partition small geographic areas, typically referred to as Territorial Units (TUs), into a predefined number p of larger geographic areas, called districts (or clusters), in a way that meets specific planning criteria (Kalcsics and Ríos-Mercado, 2019). Among the most common criteria are the following.

- *Compactness*: although there is no universally accepted definition of compactness, this criterion generally refers to a district's adherence to certain topological properties, suggesting that the district should ideally be "rounded" in shape and "undistorted".

- *Contiguity*: according to this criterion, it should be possible to move between any two territorial units within the same district without crossing another district. As a consequence, the resulting district plan will be free of enclaves (or, conversely, exclaves) or any isolated parts.

- *Balance*: assuming each territorial unit is associated with a certain intensity of activity (e.g., service demand, population, area), this criterion mandates that districts should be balanced in terms of the same activity measure. This means that they should serve the same demand or have comparable sizes, whether in terms of demographics or geographic scale.

Other criteria can also be considered depending on the specific field of application. For instance, in the reorganization of existing districts (a problem often referred to as *redistricting*), it is frequently required to maintain some degree of conformity (or similarity) with existing administrative boundaries or to account for natural and geographical obstacles, such as mountains and lakes, that may affect the contiguity of the districts to be established (Bozkaya et al., 2003; Kalcsics et al., 2005; Ríos-Mercado, 2020). Figure 2.2 shows an example of a districting plan with four districts.

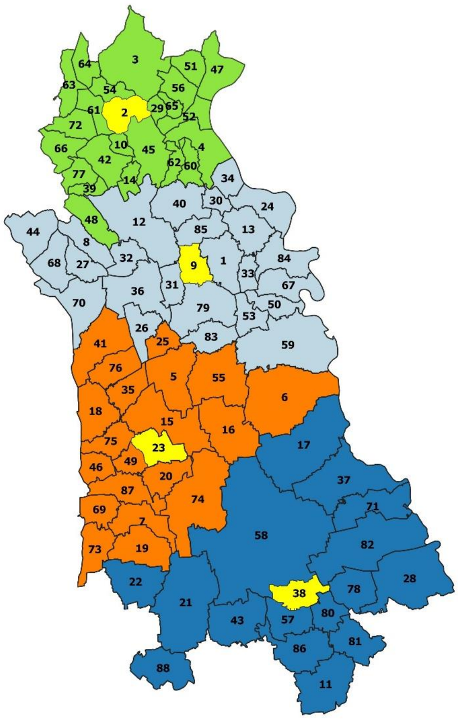


Figure 2.2: An example of a districting plan

Together with Distribution (or Delivery) Districting, whose background is detailed next as the focus of the thesis, other main classical application areas are (i) Political Districting (Bozkaya et al., 2003; Hess et al., 1965; Ricca and Simeone, 2008; Ricca et al., 2013), (ii) Sales Territory Design (Ríos-Mercado and Fernández, 2009; Salazar-Aguilar et al., 2011; Zoltners and Sinha, 2005), and (iii) Service Districting (Yanık et al., 2019; Yanık and Bozkaya, 2020; D'Amico et al., 2002; Ferland and Guénette, 1990).

2.4.1 Applications in distribution logistics

The organization of service areas for pick-up and delivery operations in distribution logistics involves complex districting problems that address the division and assignment of Territorial

Units (TUs) to distribution points or drivers. The distribution districting problem for last-mile aims to divide urban areas into delivery areas (i.e., districts) comprising basic territorial units, each with a certain number of delivery points (self-collection points, households), and assign these areas to one or more delivery workforce units (Sandoval et al., 2022). As highlighted by Kalcsics and Ríos-Mercado (2019), the creation of delivery districts represents a core application of districting problems. Traditionally, postal and logistic service providers partition a municipality or urban area into districts, each assigned to one or more delivery personnel who handle the distribution of mail and parcels to homes, businesses, and different delivery points within their designated zones. Research in this area is heavily motivated by the need to solve Vehicle Routing Problems (VRPs) under conditions of significant demand uncertainty and variability. VRPs are logistical optimization problems that deal with designing efficient routes for vehicles to fulfill service demands within a specified time frame, and in scenarios of unpredictable demand, they become even more challenging to manage. Besides, given that last-mile routes often vary daily, the approach is to establish fixed territories for certain delivery personnel or groups and estimate the length of their routes within these territories (Haugland et al., 2007; Lei et al., 2012). Therefore, the operational issue of identifying delivery routes is approached in a strategical/tactical manner (Arevalo-Ascanio et al., 2024).

One significant advantage of delivery districts is that drivers become increasingly familiar with their designated areas over time, leading to performance improvements. Familiarity allows drivers to optimize their own routes within their districts, respond to on-the-ground conditions, and establish stronger relationships with some regular visit points (e.g., self-collection) (Zhong et al., 2007).

Defining stable, cohesive service areas helps in reducing the overall complexity of delivery and collection operations. The objective of these problems is to ensure that each delivery district maintains cohesion, compactness, and workload balance, the latter comprising routing and stop times for delivery. Compact districts, in particular, help minimize the total travel distance required for each route, which can also result in significant fuel savings, reduce emissions, and align with green logistics objectives. Instead, balanced workloads contribute to sustainable operations by ensuring that each driver covers a manageable number of deliveries, which helps prevent overburdening employees while simultaneously optimizing resources (Jarrah and Bard, 2012; Zhou et al., 2002) By distributing workload equitably across districts or establishing upper limits on workload per district (Gliesch et al., 2020; Ríos-Mercado and Salazar-Acosta, 2011), organizations favour a high percentage of on-time deliveries and promote more harmonious and efficient working conditions. Employees who perceive their workload as fair tend to show higher job satisfaction and morale, which is beneficial to both employee retention and performance.

In this section, the main contributions dealing with the distribution districting problems for last-mile delivery are investigated. These reflect the complexity and multi-dimensional nature of distribution districting problems. In particular, the focus is on studies addressing last-mile applications and tackling the operational delivery problem from a tactical perspective by including routing aspects. The topic is still emerging, which indicates that the existing literature on the subject is somewhat limited and continuously developing.

One of the first contributions was provided by Bender et al. (2020), which proposed a two-stage solution approach for the assignment of drivers and vehicles to customers. They balanced districts based on vehicle routing solutions for historical sample days. For the tactical planning stage (first stage), they proposed a solution approach that simultaneously determines the design and number of districts while also assigning heterogeneous vehicles and drivers. In the operational planning stage (second stage), they proposed a model that reallocates basic areas based on the actual demand of a given day, aiming to maintain consistency with the driver and vehicle assignments established in the previous stage. A similar approach is proposed by Lespay and Suchan (2022) and tested on a real-world application at a food company in Chile.

Álvarez-Miranda and Pereira (2021) and Sandoval et al. (2022) also studied a real-world last-mile logistics design problem faced by a delivery company in Chile. The company's operational structure divides urban areas into districts and outsources each district's parcel delivery operations to an external last-mile contractor. However, due to growing parcel volumes and declining service performance—particularly with express deliveries—the company was compelled to redesign its existing territorial structure. The need for such a restructuring highlights how traditional districting models can be adapted to address new service expectations and logistics demands. In their works, the customers distribution is deterministic, while service time is estimated by considering different routing measures. Sandoval et al. (2022) computed the TSP for each district with the nearest neighbour algorithm, while Álvarez-Miranda and Pereira (2021) applied the tsp tour length estimation proposed by Cavdar and Sokol (2015).

The latter was also used by Moreno et al. (2020), who aimed to partition clients into the smallest number of districts while ensuring that the daily delivery workload (including routing estimation time) does not exceed the total hours in a working day.

Zhou et al. (2021) proposed a genetic algorithm to optimize the operations of a company distributing highly perishable products across multiple clients in a multi-period planning horizon. The study underscores the importance of aligning districting decisions with real-world business constraints, such as product shelf-life and customer demand patterns. In a follow-up study, Zhen et al. (2023) further developed this model by introducing an additional complexity: integrating customer demand frequency. This addition considers the specific days on which each customer requires service within the planning horizon, presenting an added layer of complexity to districting and routing solutions.

Torres et al. (2024) proposed a DSS aiming to design delivery zones for each driver of a logistics company that match demand while achieving key objectives: (i) ensuring a balanced workload among drivers, (ii) maximizing the percentage of daily deliveries completed, (iii) creating compact sectors to minimize route distances, and (iv) maintaining high day-to-day consistency in sector boundaries, which enhances both driver safety and the effective use of their local knowledge.

Research interest in last-mile delivery specifically focuses on urban contexts where congestion and environmental concerns add new layers of complexity. Ouyang et al. (2022, 2023a,b) explore these challenges by developing a strategy known as *Community Logistics*. This approach involves dynamically generating service regions, or "communities," and corresponding vehicle departure schedules in response to real-time data. The objective is to balance service regions, manage order delay times, and maximize vehicle utilization rates, adapting dynamically based on incoming orders and vehicle availability. The strategy involves consolidating deliveries to optimize route efficiency and reduce unnecessary trips, which is particularly beneficial for minimizing operational costs and reducing environmental impact in dense urban settings.

Finally, motivated by a problem of the leading Chilean postal provider, Álvarez-Miranda et al. (2025) proposed a multi-criteria approach to divide a geographical area into non-overlapping districts, each managed independently by a logistics agent. The division must meet criteria to ensure feasibility, with a focus on equitable workload distribution among delivery workers. The procedure is applied to minimize disparities in both street length and workload across districts while also maintaining necessary conditions for assignment, contiguity, and compactness.

Overall, the field of distribution districting for last-mile is rapidly evolving, with contemporary research increasingly focused on meeting the demands of a highly dynamic logistics landscape. Balancing workload (or satisfying upper bound constraints) and optimizing customer satisfaction (maximizing on-time deliveries) to advancing last-mile delivery efficiency in urban areas are gaining increasing attention from researchers dealing with the topic.

2.5 Emerging gaps

From the literature analysis performed on strategical and tactical logistics decision-making, various emerging gaps can be identified.

A fundamental aspect is represented, as also argued by Ma et al. (2022), by a lack of integrated studies synergizing the customers' behavior stream with the network design. We notably observe that extant papers are scarcely interested in investigating how the combination of different customer behaviours may influence decisions on self-collection network design. Furthermore, much attention should be paid to the interplay between self-collection and home delivery and the decisions that can be leveraged to increase customers' propensity towards self-collection.

In addition, most of the papers focus on optimization modeling and algorithmic frameworks from an academic point of view. As such, there is room for studies providing informed recommendations on network design in realistic cases built upon fine-grained geographical data.

Following again the managerial path, it is worth noticing that the majority of studies focus on parcel lockers. Specifically, to the best of our knowledge, there are not many studies dealing with pick-up point location, even if this problem makes sense for a number of managerial cues. Typically, local shops acting as pick-up points are not affected by significant space limitations, nor do they require specific installations or raise layout definition and delivery sequencing problems, which allows customers greater flexibility (e.g., longer in-shop storage times for collection). Moreover, they are widely distributed throughout urban areas. On the one hand, this gives service providers leeway for optimized decision-making; on the other, it means multiple access options for users within relatively limited distances. It is worth recalling that pick-up points are assisted facilities. Often, this is a significant incentive for customers who prefer human interaction. Additionally, it represents an economic opportunity for shop owners since users visiting them for a parcel may also purchase other items they need. Hence, due to the characteristics above, studying problems concerning network design for pick-up points has a significant managerial impact.

Regarding delivery zone design, the current literature shows that most of the studies focused on operational solutions, with minimal integration of districting and routing to support long-term planning and adaptability. Districting problems combined with routing aspects have been scarcely explored, and few approaches have considered dynamic factors affecting last-mile logistics. Furthermore, there is a lack of contributions dealing with self-collection that incorporate the probability of visiting facilities to develop a robust tactical districting plan with balanced workloads. This gap is particularly relevant given that, with the rise of self-collection, the likelihood of visiting different types of locations can vary significantly. Such variability can greatly impact the workload distribution across delivery districts, underscoring the need for approaches that account for these fluctuations to maintain efficiency and balance.

2.6 Contribution of the thesis

The contribution of this thesis originates from the case study of Poste Italiane, the leading logistics provider in Italy and a partner of this research, presented in Section 3. Specifically, the thesis is structured as a pathway for addressing logistics problems and issues associated with the self-collection network, starting from the strategic network design and progressing to the tactical problem of defining delivery districts. To this aim, we develop tailored models and algorithms, incorporating factors and elements derived from customer behavior studies, and apply them to real-world cases provided by Poste Italiane.

Specifically, regarding the network design, we propose two studies that aim to give a twofold contribution to the extant literature on self-collection location. First, we want to bring insights to practitioners and the literature by providing informed recommendations on pick-up points network design strategies built upon fine-grained geographical data in real instances. Second, we aim to synergize the behavioral literature with the strategic decision-making one by proposing location models that explicitly include factors affecting customers' choices. This way, we can assess how the combination of different behaviours impacts the decision about pick-up points network design. To do this, in Chapter 4, we propose a deterministic approach that uses accessibility measures to design an effective network of pick-up points, aiming to balance costs and service levels. In Chapter 5, we take the discussion further by employing a probabilistic approach that incorporates customers' choices into the location decision. This study focuses on determining the optimal locations for a predefined number of pick-up points, with the goal of maximizing the percentage of customers choosing self-collection, calculated using a Multinomial Logit model.

Instead, regarding the design of delivery areas, in Chapter 6, we propose a new districting approach for the last mile aimed at forming delivery areas to be assigned to operators. These are designed to ensure that the expected workload (comprising routing aspects) of each district remains within specific limits. Notably, the workload is subject to uncertainty, driven by factors such as (i) fluctuations in parcel demand and (ii) customer preferences, which influence the likelihood of visiting individual households and pick-up points.

2.7 Conclusions

This chapter presented the background of literature on last-mile logistics. In particular, it classifies studies into two streams: customers' behavioural and logistic decision-making. Customers' behavioural studies investigate factors and habits affecting customers' choices toward innovative delivery strategies like self-collection. Conversely, the stream of decision-making frameworks for the strategy implementation focuses on the logistical optimization required to ensure the efficiency and scalability of self-collection systems. This area can be further divided into strategic and tactical decision-making issues. In the strategic area, literature about Facility Location Problems to address the problem of self-collection network design has been investigated. In the tactical one, distribution districting problems with routing aspects for delivery have been analyzed.

From this analysis, some gaps have been identified, and consequently, the contribution of the thesis has been highlighted.

CHAPTER 3

The case of Poste Italiane

Summary

This chapter presents the case of Poste Italiane, the leading Italian postal provider. As a result of more than tripled delivery volumes and revenues in the last years, the company has embarked on a decision process to design an effective pick-up points network, pushing customers to adopt this innovative solution. As a consequence, it is looking for efficient delivery solutions that consider this new network configuration. To these aims, the company has engaged in a range of collaborations with various stakeholders, including partnerships with universities, within which the research presented in this thesis is framed.

In the following, we introduce the company and detail its transformation from a basic postal provider to a comprehensive logistics operator. We focus on its self-collection network and present some case studies that constitute the foundation for the subsequent applications.

3.1 Creation of value and operating results

Poste Italiane is one of Italy's oldest and most significant companies, founded in 1862 shortly after national unification to ensure postal services across the country. Initially focused exclusively on delivering mail and telegrams, the company gradually expanded its scope and today stands as a leader not only in postal services but also in financial, insurance and logistics services. In the 1990s, Poste Italiane underwent a major transformation, transitioning from a public entity to a joint-stock company, with Italy's Ministry of Economy and Finance as the primary shareholder.

Currently, the company has been listed on the Mercato Telematico Azionario (MTA) since 2015. As of December 31, 2023, 29.26% of its shares are held by the Ministry of Economy and Finance (MEF), and 35% by Cassa Depositi e Prestiti (CDP), also controlled by the MEF, while the remaining shares are owned by institutional and retail investors (Figure 3.1).

Historically, the core business centred around traditional mail services, an essential function for both individuals and businesses. However, due to the gradual decline in traditional mail services, which significantly reduced the volume of physical correspondence, the company recognized the need to adapt, identifying areas of growth that aligned with its strengths. Hence,

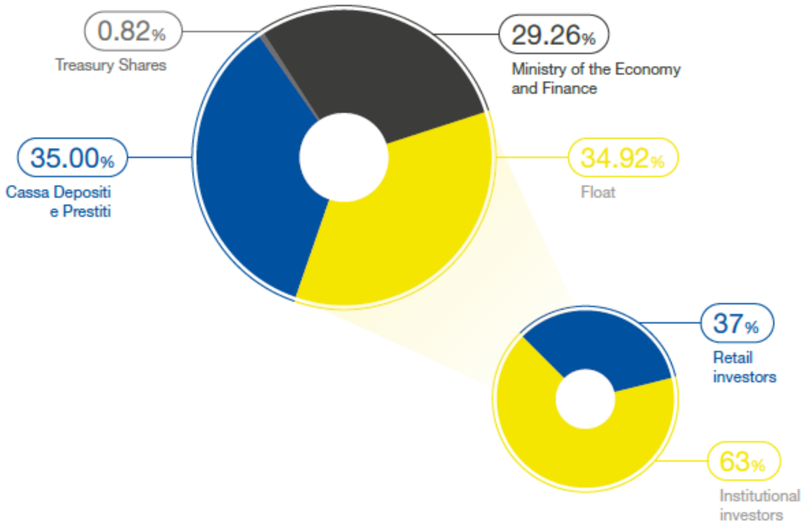


Figure 3.1: Poste Italiane's ownership (Poste Italiane, 2024a)

the company embraced innovation, modernized its operations, and invested in technology to create a more efficient and scalable business model.

The transformation also reflects a broader strategic vision, focusing on innovation, sustainability, and digitalization. Poste Italiane embraced emerging technologies to enhance its operational efficiency and customer experience. At the same time, it committed to aligning its business practices with environmental, social, and governance (ESG) principles, ensuring long-term sustainability and fostering stronger relationships with stakeholders. This shift has resulted in continuous value creation. In particular, the company's share increased by 11.30% in 2023, with revenues passing from €9.232 billion at the beginning of the year to €10.275 billion at the end of December (Poste Italiane, 2024a).

In this context, today, Poste Italiane's operations are organized into four Strategic Business Units (SBUs), also called operating segments: (i) Mail, Parcels and Distribution, (ii) Financial Services, (iii) Insurance Services, and (iv) Payments and Mobile.

- *Mail, Parcels and Distribution* manages national mail and parcel delivery services, with a growing focus on advanced logistics and distribution network optimization due to the rise of e-commerce. Poste Italiane leverages a broad infrastructure to improve efficiency and offer value-added services for both private and business customers;

- *Financial Services* includes a wide range of financial services, such as current accounts, postal savings, loans, and investment products. With its extensive network of post offices and digital solutions, Poste Italiane provides an alternative to traditional banking, offering financial access even in underserved areas;

- *Insurance Services* mainly focuses on life insurance, savings, and pension plans. This segment benefits from customer trust, positioning Poste Italiane as a reliable partner for managing personal and financial risks. It uses a diversified network to sell policies tailored to various security and future planning needs;

- *Payments and Mobile* encompasses digital payment and mobile services, including PostePay, one of Italy's leading payment solutions. Poste Italiane has expanded its digital offerings to include prepaid cards, e-wallet services, and mobile banking solutions, meeting the growing demand for Italy's secure transaction services. It also includes mobile and fixed-line telephony, electricity and gas services.

The digital transformation undertaken by Poste Italiane in recent years has profoundly impacted not only the range of services it offers but also its overall distribution model. Through an omnichannel strategy, the company has developed the ability to adapt to the evolving needs of its customers, integrating physical, digital, and remote channels to create a cohesive and versatile service ecosystem. This transformation is not limited to specific areas of the business but extends across all of Poste Italiane's Strategic Business Units, serving as a unifying framework that enhances service delivery in every segment.

Digital channels, supported by remote contact points, complement Poste Italiane's historical physical network, which remains a core asset for customer engagement. The omnichannel model has allowed Poste Italiane to sustain its role as a trusted provider of services while simultaneously evolving to meet the demands of a digital-first world. For example, the single app infrastructure launched in 2023 is designed to bring all Poste Italiane services into one platform, streamlining access for customers and reinforcing the integration between different channels. The Covid-19 pandemic further accelerated this transition, showcasing Poste Italiane's ability to respond rapidly to changing market conditions. By leveraging its digital platforms, the company introduced innovative, personalized products and new communication channels to maintain and strengthen customer relationships during a period of disruption. This adaptability demonstrates how the omnichannel approach supports all areas of Poste Italiane's business, ensuring consistency and continuity in the services provided.

3.1.1 Mail, parcels and distribution

The strategic objective of the Mail, Parcels and Distribution segment is to accelerate its transformation from a traditional mail operator into a comprehensive logistics provider while ensuring both economic and environmental sustainability in its operations. This strategy focuses on optimizing distribution networks, consolidating leadership in the Business-to-customer (B2C) market, and expanding into the segment by introducing targeted offerings and initiatives aimed at enhancing the customer experience. The successful transformation, investments, and innovation initiatives undertaken in recent years enabled the company to process approximately 2.3 billion mail units, deliver 256 million parcels, and manage over one million parcels daily in 2023. During the same year, the sector achieved break-even ahead of schedule, generating revenues of €3.7 billion, a 2.6% year-on-year increase.

In particular, parcel revenues totalled €1.4 billion, remaining stable compared to the previous year. This performance was supported by an increase in volumes, particularly in the B2C segment, which saw 203 million units delivered in 2023, reflecting a 12.4% year-on-year growth. The fourth quarter was especially strong, with B2C volume growth reaching 17.1% compared to the same quarter of the previous year (Poste Italiane, 2024a). This trend was confirmed in the first quarter of 2024, when parcel revenues exhibited robust growth, increasing by 10.0%. This performance was underpinned by a significant rise in B2C parcel volumes, which totalled

69.1 million units, marking a 22.2% increase compared to the same period in 2023.

3.2 Parcel logistics network

The Company's mail and parcel services are provided through two synergistic logistics networks: the postal logistics network, which manages mail and, sometimes, has evolved to also handle small parcels, and the parcel logistics network.

Starting in 2020, there has been an increase in the interchange of small parcel volumes ("carriable" parcels, i.e., those weighing less than 5 kg), with cost-effectiveness serving as a key differentiator. Delivery of these products within Italy can be dynamically managed by the postal and parcel logistics network, as well as the courier logistics network, adopting a flexible approach aimed at maximizing efficiency across different areas.

As part of the transformation plan for the Mail and Parcels segment and with the goal of establishing the Poste Italiane Company as an integrated logistics operator, a significant initiative was launched in 2023 to develop the Integrated Logistics market segment. This segment involves the third-party management of customers' warehouse goods and related delivery activities.

Since this thesis focuses on the logistics of postal parcel delivery, the emphasis of this section is on the dedicated logistical network that supports and enables this critical service. This involves examining the infrastructure, processes, and technological innovations specifically designed to handle the unique demands of parcel logistics, from collection and sorting to transportation and final delivery. In Figure 3.2, the company's parcel logistic network is shown. A description of each phase follows.

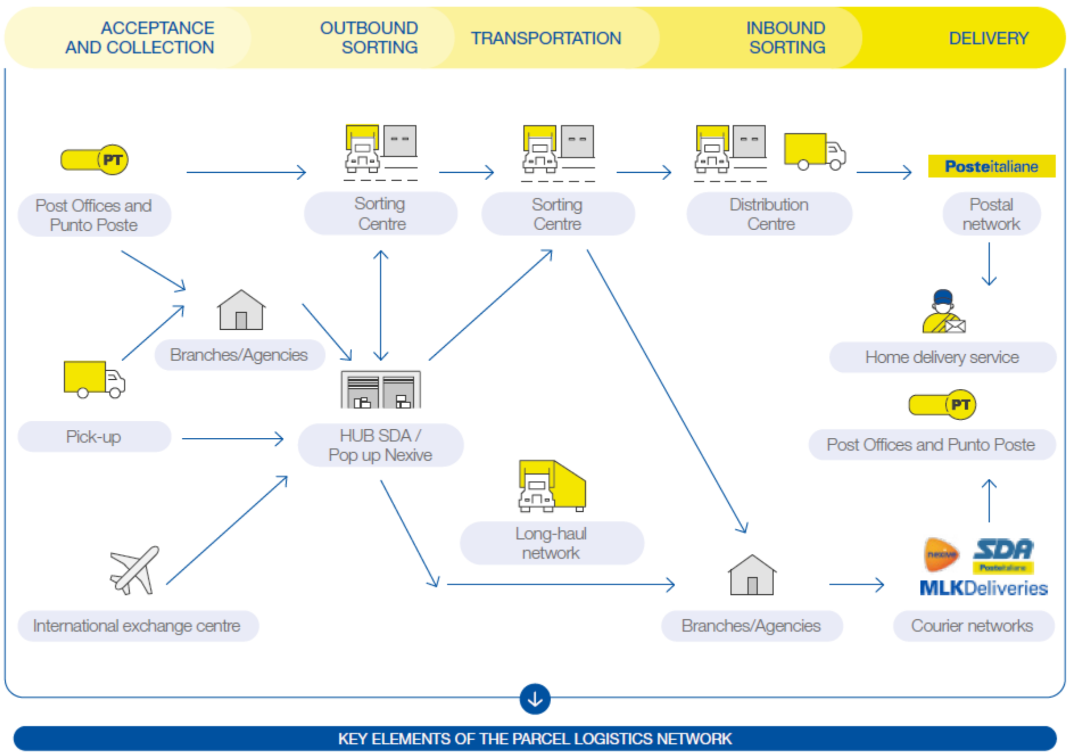


Figure 3.2: Parcel logistic network (Poste Italiane, 2024a)

- *Acceptance and Collection*

  During the acceptance phase, customers can use the postal network's facilities to send parcels. The acceptance channels include company-owned Post Offices and Punto Poste, which are self-service facilities established through service agreements for parcel collection. These facilities enable customers to send parcels and manage potential returns. Alternatively, customers can choose home pick-up services to send their parcels. In summary, the acceptance phase involves Customer-to-Business-to-Business (C2B2B) interactions.

  In the collection phase, operators visit the access points of the postal network to retrieve items and transfer them to Sorting Centers, where the outbound sorting process takes place. The collection activity can be managed directly by Poste Italiane, using its own personnel and vehicles, or outsourced to external entities tasked with carrying out these operations.

- *Outbound Sorting*

  Parcels collected through acceptance channels are routed to their respective Sorting Centers to undergo the outbound sorting phase. During this stage, parcels are grouped into homogeneous clusters based on product type, size, and destination. They are then prepared for long-distance transportation, ultimately being routed to the Sorting Centers within the destination logistics hubs.

- *Transportation*

  In this phase, transportation serves the purpose of connecting the various Sorting Centers to facilitate outbound and inbound sorting activities. Long-distance transportation is carried out through the National Transport Network, which consists of: A "fast" network, dedicated to transporting products with a J+1 service level, delivered via the so-called SAN (Nighttime Airport Service) network. A road transport network dedicated to products with a service level longer than J+1.

- *Inbound Sorting*

  Once parcels are delivered to the Sorting Centers within the destination logistics hub, the inbound sorting phase begins. During this phase, the goods are distributed to the designated delivery offices, namely Distribution Centers (CD). It is worth noting that this is the same mechanism applied during the collection phase, where acceptance channels are connected to the Sorting Centers via the delivery offices.

- *Delivery*

  The delivery phase represents the final stage of Poste Italiane's logistics chain, known as last-mile logistics. This phase involves delivering goods to the locations specified by customers, which include Post Offices, Punto Poste, or direct home delivery. As with the collection phase, delivery activities may be carried out by company-owned operators or by external carriers, such as SDA and MLK deliveries, with whom the company has partnered. It is important to note that while this is traditionally considered last-mile logistics, the collection phase can also be viewed as a related last-mile activity.

The description above highlights that Poste Italiane's last-mile network infrastructure consists of two primary components: company-owned facilities, which include Post Offices, and external facilities known as the Punto Poste network. The Punto Poste network features pick-up points, such as local shops that have partnered with the company to facilitate self-collection.

3.2.1 Post offices

The extensive network of post offices operated by Poste Italiane serves as a cornerstone of its operations, playing a crucial role in both logistics and community services. With thousands of locations distributed across Italy, post offices ensure accessibility and convenience, even in remote or underserved areas. As previously highlighted, in the context of parcel logistics, post offices are useful for the collection and final delivery of parcels. These facilities form a component of the last-mile logistics chain, allowing customers to drop off parcels for shipment, retrieve deliveries, or process returns. They function as collection points within Poste Italiane's Click & Collect network, offering flexible options for customers to pick up their parcels at their preferred time and place. In addition to serving individual customers, post offices act as logistical hubs that connect local communities to the broader postal network, ensuring the smooth movement of goods across regions.

Beyond their role in logistics, post offices perform a wide array of functions that reflect their status as multifunctional centres catering to diverse customer needs. Clearly, traditional postal services remain a significant aspect of their operations, offering letter mailing, registered mail, and telegram services. They also provide access to telecommunication services, which deliver mobile and broadband solutions to customers. Furthermore, post offices increasingly act as intermediaries for e-government services, such as issuing certificates, handling pension payments, and processing applications for government programs. Many locations also serve a retail function, selling stationery, small electronics, and other useful items, reinforcing their role as one-stop destinations for local communities. Finally, post offices play a crucial role in financial services, including bank accounts, savings plans, loans, insurance products, and payment solutions, allowing customers to manage their finances directly at their local post office.

The capillarity and versatility of Poste Italiane's post offices make them indispensable to the social and economic fabric of Italy. Table 3.1 indicates the number of post offices per Italian region.

The table presents the number of post offices across different regions in Italy. Lombardy stands out with the highest number of post offices (1,871), followed by Piemonte (1,385) and Campania (938), reflecting the larger urban populations and higher demand for postal services in these areas. Regions like Valle d'Aosta and Molise have significantly fewer post offices, with only 71 and 167, respectively, indicating lower population density and possibly less demand for extensive postal networks in these areas. Overall, Italy has a total of 12,755 post offices, which highlights the extensive reach of Poste Italiane's network.

3.2.2 Pick-up points

In 2020, in line with international trends, the company launched a self-collection project called *Punto Poste*. This service allows customers to pick up their parcels at locations other than traditional post offices, making the collection process more convenient and accessible.

Table 3.1
Number of Post Offices per region

Region	No. of Post Offices
Abruzzo	473
Basilicata	180
Calabria	617
Campania	938
Emilia-Romagna	891
Friuli-Venezia Giulia	331
Lazio	788
Liguria	426
Lombardia	1,871
Marche	406
Molise	167
Piemonte	1,385
Puglia	471
Sardegna	441
Sicilia	769
Toscana	900
Trentino-Alto Adige	323
Umbria	262
Valle d'Aosta	71
Veneto	1,032
Italy	**12,755**

The initiative has significantly expanded and now includes over 13,000 self-collection facilities. These consist of pick-up points (primarily tobacconists) that provide daily continuous service, operating up to 7 days a week.

Customers can select the preferred pick-up point when making an online purchase. Once the parcel arrives at the chosen pick-up point, the recipient receives a notification and can go to the tobacconist to collect the parcel by presenting an ID and the collection code. For pick-up points shops, joining the service is equally straightforward. After signing an agreement with Poste Italiane, shops receive specific training to manage the service and are provided with the necessary tools to handle parcels, such as barcode scanners and management software.

One of the main advantages of Punto Poste is its convenience, allowing customers to pick up parcels at nearby shops instead of waiting in long queues at post offices. These shops often have extended hours, including late evenings and weekends, offering more flexibility for customers to collect parcels at convenient times. Punto Poste also reduces waiting times and missed deliveries, as parcels are not left in storage and customers can pick them up immediately upon receiving a notification. Additionally, collecting parcels at Punto Poste shops ensures high security and reliability, as parcels are carefully stored in controlled environments, minimizing the risk of loss or theft.

Also, for shops, offering the Punto Poste service is an opportunity to attract new customers. People who visit a shop to collect a parcel may be drawn to the products on display and decide to make additional purchases. Providing a useful service can also help build customer loyalty. Regular users of the pick-up service at a shop are more likely to return for other purchases or services, fostering trust and continuity in their relationship with the shop itself.

Therefore, thanks to an extensive network, Poste Italiane already achieved notable environmental savings in 2023, avoiding approximately 11 million parcel delivery trips and reducing fleet mileage by about 2 million kilometres. This resulted in the prevention of the release of 244 tons of CO_2 equivalent and 866 kilograms of atmospheric pollutants. On average, only 15.5 grams of CO_2 equivalent were emitted per parcel delivered (Poste Italiane, 2024b). These results underscore Poste Italiane's commitment to sustainability and its efforts to minimize the environmental impact of its logistics operations.

However, Poste Italiane's self-collection service is still further expanding. Today, the Punto Poste network comprises 13,262 current pick-up points. Together with these, the company accounts for 21,413 potential pick-up points spread over the national territory. These are local stores with existing commercial agreements with the company. Hence, self-collection services can be easily activated at these points by leveraging past partnerships.

Table 3.2 illustrates the number of current and potential pick-up points across regions in Italy. Lombardy has the highest number of current points (1,673) and potential for growth (2,514), indicating a significant opportunity for expansion. Lazio, Campania, and Sicilia also show substantial gaps between current and potential points, suggesting room for further development in these areas. Conversely, Molise and Valle d'Aosta show smaller differences, with Molise having many current points (957) but low potential (185), and Valle d'Aosta with just 39 potential points. Regions like Basilicata and Friuli-Venezia Giulia show moderate room for growth, with potential increases from 176 to 303 and 204 to 417, respectively.

Table 3.2
Number of Current and Potential pick-up points per region

Region	No. of Current pick-up points	No. of Potential pick-up points
Abruzzo	343	750
Basilicata	176	303
Calabria	518	955
Campania	1,331	1,986
Emilia-Romagna	1,036	1,542
Friuli-Venezia Giulia	204	417
Lazio	1,159	2,121
Liguria	439	552
Lombardia	1,673	2,514
Marche	381	864
Molise	957	185
Piemonte	897	1,428
Puglia	1,120	1,161
Sardegna	368	575
Sicilia	1,096	1,905
Toscana	929	1,620
Trentino-Alto Adige	171	365
Umbria	195	552
Valle d'Aosta	311	39
Veneto	1,100	1,579
Italy	**13,262**	**21,413**

3.3 Sustainable mobility policies

Poste Italiane is one of the key partners of the National Centre for Sustainable Mobility. The company's involvement in the project reflects its commitment to supporting the transition to a more sustainable transportation system in Italy. Indeed, the Centre aligns seamlessly with the strategic objectives outlined in Poste Italiane's vision, particularly focusing on Sustainability and Innovation. Poste Italiane has established a robust R&D structure, driven by a team of industry leaders within its Engineering and Logistics division (PCL). This team is responsible for identifying and coordinating innovation opportunities across Poste's operational models, processes, and technologies, specifically in the mail and parcel logistics sector.

There are several areas of focus where the Centre can support Poste's R&D efforts. Below are seven key examples of ongoing R&D initiatives at Poste Italiane.

- *Freight Logistics and Urban Mobility for Last-Mile Delivery*

  Developing new urban logistics solutions for Smart Cities, including the identification of optimized and innovative delivery solutions, rules, and service standards for urban areas. Modeling logistics nodes and networks using models and algorithms and digital-twin technology to predict and optimize planning and operations.

- *Connected and Autonomous Vehicles (CAV)*

  Designing and developing an autonomous delivery service model for both urban and extra-urban environments.

- *Advanced Air Mobility (AAM)*

  Creating a cargo drone service model capable of carrying payloads over 150 kg and ranges of over 100 km, integrated with hospital logistics needs.

- *Hydrogen and New Fuels*

  Exploring sustainable propulsion systems for long-haul logistics, including green hydrogen and sustainable biofuels, to enhance the performance of heavy vehicles.

- *Electric Traction Systems and Batteries (ETSB)*

  Identifying new charging infrastructure networks for both manned and unmanned vehicles, improving and accelerating charging operations using innovative technologies, and enabling a Vehicle-to-Grid management model.

- *Light Vehicle*

  Test new "light delivery vehicles" characterized by high safety and loading efficiency. These are equipped with sensors (es.: Advanced Driver Assistance Systems) to ensure connection with other vehicles.

Among the various themes being explored within Poste Italiane's commitment to the project, particular emphasis is placed on last-mile logistics and innovative delivery solutions, such as self-collection. In this context, the activities outlined in this thesis have been developed through the collaboration between the company and the University of Naples Federico II, specifically within the Department of Industrial Engineering. The objective of the study has been to propose solutions to design and enhance an efficient self-collection network.

3.4 Self-collection network design: research opportunities

During the collaboration that formed the basis of this thesis, the objectives have been to develop and apply models and algorithms to real-world cases for Poste Italiane's self-collection operations. The focus was on designing an efficient self-collection network and solving the operational challenge of daily visit delivery.

The success of the self-collection strategy relies heavily on the location of facilities. It is essential to find a balance between accessibility for end-users, cost efficiency for the company, and operational feasibility. To achieve this, optimization models needed to be developed and tested to identify the best locations for collection points. Given the potential of the Punto Poste network, which includes both current and potential facilities, the company aimed to evaluate the impact of different solutions in terms of costs and benefits. Specifically, the company's goal was to determine the optimal size of the network and identify the best locations for collection points, taking into account factors such as urban population density and customer attitudes.

Equally important to the design of the network is its daily operation, which relies on a robust delivery strategy. Ensuring that all self-collection points are stocked with parcels in a timely and cost-effective manner presents a significant logistical challenge. The company objective, in this sense, was to test optimization algorithms aimed at solving this problem, focusing on solutions that minimize transportation costs while respecting constraints such as delivery time windows and fluctuating daily demand. These algorithms must account for the goal of improving the responsiveness and reliability of the self-collection network, which are essential factors for maintaining customer trust and satisfaction.

As highlighted, the collaboration was grounded in the use of real-world data provided by Poste Italiane, enabling the proposed models and algorithms to be tailored to the specific characteristics of the company's operations. Case studies were conducted to replicate real-life scenarios, allowing to validate the solutions in real environments. These included urban areas with high population density and delivery volumes.

3.4.1 Some representative case studies

Seven Italian cities were chosen among the most representative in terms of population and number of pick-up points. In particular, their official subdivision in census tracts (ISTAT, 2021), where information about the resident population is available.

Table 3.3 reports the main characteristics of the selected cities: the total population, the number of census tracts, and the number of current and potential pick-up points. It is worth noting that, within the current facilities, the number of post offices is indicated. For all the cities, the number of potential pick-up points is high, almost comparable to the current one. This leaves a wide margin for redefinition strategies, as it allows leveraging a large set of potential points, whose activation may eventually make the network configuration more efficient.

In particular, a specific focus for the application of models and algorithms proposed in the following part of the thesis is on the cities of Bologna and Napoli. The first was already chosen for other developed studies in collaboration with the company (Bruno et al., 2021a,b). The

Table 3.3
Characteristics of the selected sample

	Demand characteristics		Self-collection characteristics		Post Offices
City	**Population**	**No. of census tracts**	**No. of current pick-up points**	**No. of potential pick-up points**	**No.**
Roma	2,617,175	11,949	579	655	214
Milano	1,242,123	5,724	210	295	100
Napoli	962,003	3,860	222	260	71
Torino	872,367	3,852	157	207	71
Bologna	371,337	2,073	118	99	36
Firenze	358,017	2,188	110	117	42
Bari	315,841	1,577	93	75	37
Total	**6,423,022**	**29,646**	**1,489**	**1,633**	**571**

second is the third biggest Italian city in terms of population.

Bologna holds particular strategic importance for Poste Italiane as it stands out among Italian cities for the significant volume of logistics data collected related to parcel delivery. Its central location within Italy and its role as a major hub for transportation and logistics make Bologna a focal point for the company's operations. Furthermore, in the city, there is an extensive dataset of collected data associated with the logistics network that serves as a foundation for testing and implementing innovative solutions. For instance, data collected during 2023 indicates that, on average, the company delivers 3011 parcels per day in the city. Hence, by leveraging Bologna's data, Poste Italiane aims to refine its operational models and establish best practices that can be extended to other cities in the country.

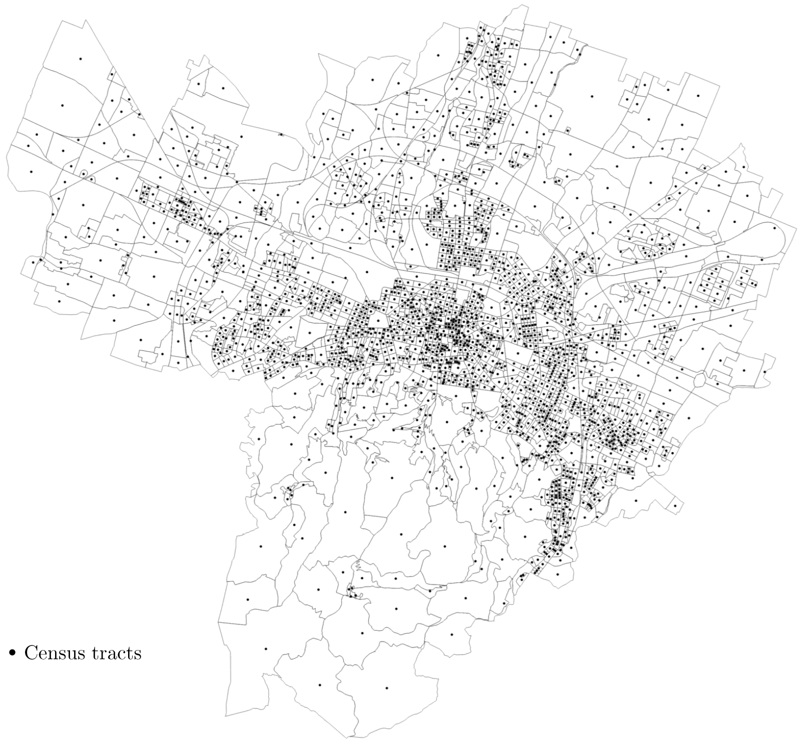
To apply the models and the algorithms, we discretized the location space into 2,073 and 3,860 territorial units (for Bologna and Napoli, respectively) corresponding to the city census tracts, and we assumed that all customers located in a census tract are concentrated in its centroid. The census tracts with centroids and the indication of the nodes where customers are actually located are shown, respectively, in Figures 3.3a and 3.3b for the city of Bologna. We need to emphasize that we assume that the number of potential customers is equal to the corresponding population. This assumption allows us to evaluate network design decisions w.r.t. to the largest possible set of potential customers.

As for the current and potential pick-up points, 118 [222] and 99 [260] facilities in Bologna [Napoli] were provided by the company, respectively. Their locations are displayed as blue and orange dots in Figures 3.4a and 3.4b for Bologna and Napoli, respectively. In particular, for Bologna, it is possible to notice that the points are mostly concentrated in the more central and densely populated areas of the city.

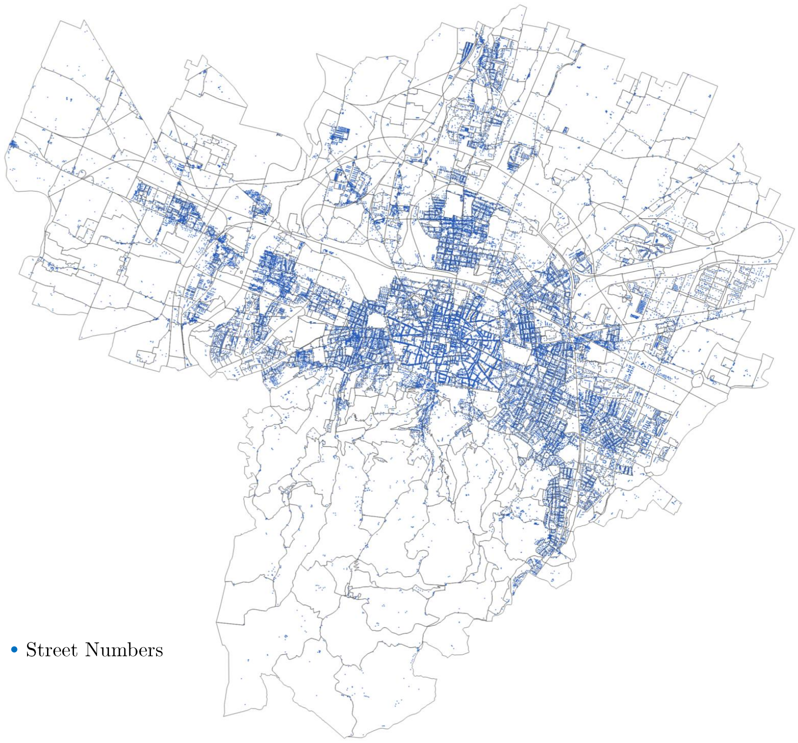
Finally, it is noted that for delivery operations, the company uses a single depot located almost in the city centre in Bologna, while three are in Napoli (in red, Figures 3.4a and 3.4b).

3.5 Conclusions

This chapter provided a comprehensive overview of Poste Italiane, detailing its organizational structure and the diverse business units that define its operations. Particular attention was given to its role as a leading logistics operator in the parcel delivery sector, emphasizing the importance of its extensive and integrated logistics network. A specific focus was placed on the company's self-collection network, highlighting its strategic role in meeting evolving customer



(a) Census tracts and centroids

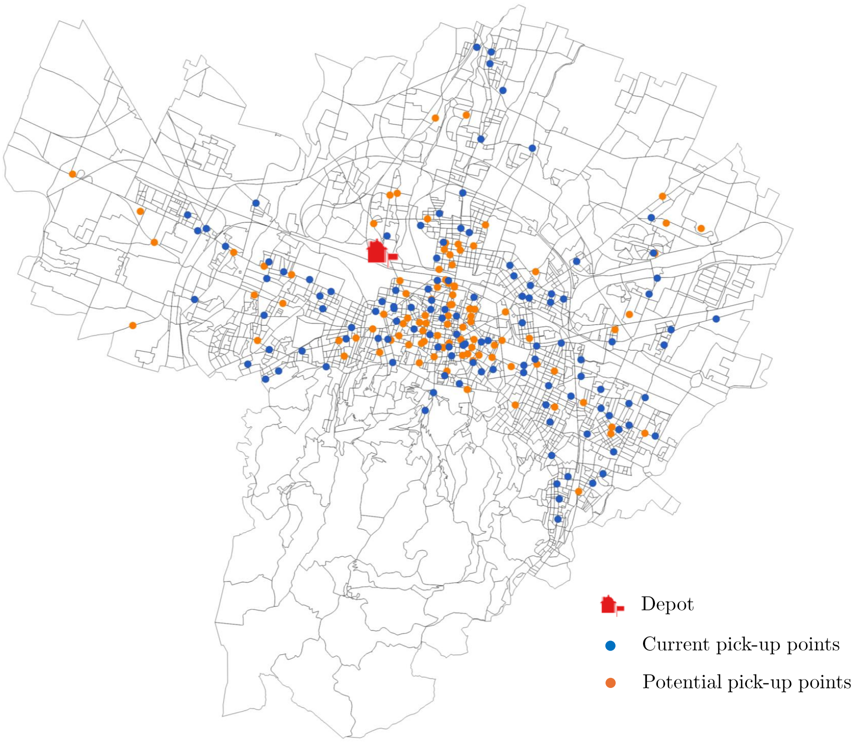


(b) Customer Nodes

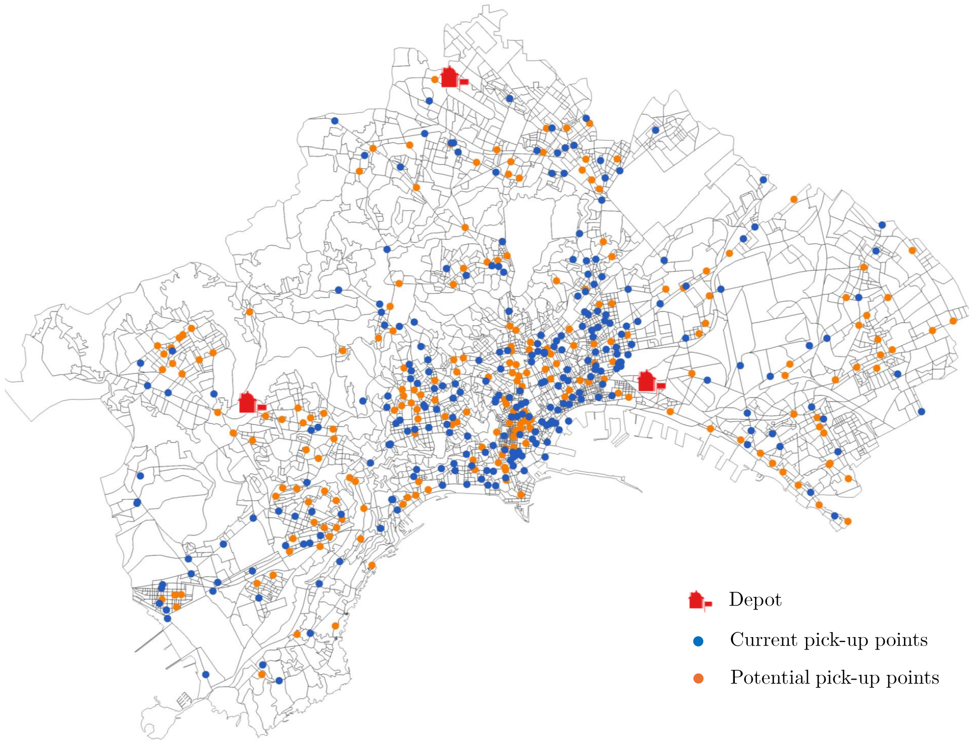
Figure 3.3: Maps of Bologna

demands and enhancing operational efficiency.

Moreover, the chapter outlined the research activities undertaken to address the challenges associated with network design and delivery strategy within the self-collection framework. These



(a) Bologna



(b) Napoli

Figure 3.4: Pick-up points and depots

efforts were contextualized through real-world case studies, leveraging Poste Italiane's data and logistical infrastructure. These case studies serve as the foundation for the models and optimization algorithms proposed in the subsequent chapters.

CHAPTER 4

Pick-up points network design strategies: a deterministic approach

Summary

This chapter addresses the problem of designing an effective pick-up points network. To this aim, it proposes location strategies that explicitly and simultaneously account for economic costs and users' accessibility. From a real case of Poste Italiane, the study uses spatial analysis to evaluate users' accessibility to the current self-collection network and proposes three strategies for contracting, reorganizing, or expanding it. To this end, tailored facility location models are used to identify the optimal network configuration to ensure certain accessibility levels to potential users. Empirical findings from a sample of Italian cities demonstrate the importance of exploring possible solutions to improve self-collection networks and make them more efficient. Hence, relying upon a real dataset, the chapter shows the value of informed decision-making by assessing, in an inherent multi-objective fashion, the economic and social dimensions involved in last-mile logistics problems.

4.1 Introduction and contribution

This chapter investigates the problem faced by Poste Italiane, which is looking for efficient solutions to promote the self-collection strategy. In particular, it has embarked on a decision process to design an effective pick-up points network, pushing customers to adopt this innovative delivery solution.

As highlighted in Section 3, the company already has a current network of pick-up points but can leverage numerous potential facilities where to activate the service. These are local stores with existing commercial agreements with the company. Thus, self-collection services can be easily activated at these points, allowing for a potential expansion or reorganization of the network. Therefore, the company is interested in appropriate methodological approaches to enhance decision-making by evaluating current choices and exploring possible improvement solutions.

Interestingly, the problem at hand trades off two conflicting needs: (i) identifying the optimal number and the location of pick-up points to contain operating costs for service provision and (ii) providing an adequate number of pick-up points within reach of customers. In the study, we consider the distance to be the factor affecting a customer's choice to patronize a facility and apply the coverage and closest assignment paradigms when approaching the problem. Hence, we place within the stream of literature focusing on the deterministic approach (Section 2.3.2).

To address the described problem, the chapter moves in two mutually supportive directions. First, it performs an extensive analysis of the customers' accessibility to the current self-collection network, thus outlining the baseline scenario (AS-IS). Second, taking this baseline as input, the chapter proposes three strategies to redefine it (TO-BE). The strategies are modeled through a facilities location problem placed within the stream of literature dealing with the deterministic approach (Section 2.3.2). Indeed, in the study, we consider the distance to be the factor affecting a customer's choice to patronize a facility and apply the coverage and closest assignment paradigms.

The strategies are applied to the sample of Italian cities in Table 3.3. These allow to assess the effect of different types of decisions concerning contracting, reorganizing or expanding the network. Specifically, assuming the number of pick-up points as a proxy of the provider's costs and the customers' accessibility as representative of their propensity for self-collection, the strategies have the goal of showcasing the economic impact of network design decisions against given or even improved service levels offered to customers. With this objective in mind, the chapter aims to bring insights to practitioners and the literature by showing the value of decision-aiding in self-collection for last-mile delivery based on empirical evidence from a major Italian player in the field.

The remainder of the chapter is organized as follows. In Section 4.2, the spatial accessibility analysis is presented, and findings from its application are discussed. Section 4.3 gives a formal description of the strategies, while results from their application are outlined in Section 4.4. Section 4.5 provides additional insights on operating costs associated with the strategies. Section 4.6 wraps up the chapter with the main conclusions and an outlook on related future research.

4.2 Spatial accessibility analysis

Spatial accessibility quantifies the relative ease of reaching a facility from a specific customer location. In line with the discussed literature, we use the *distance to the closest facility* as an accessibility measure (Bruno et al., 2021b).

To formally define it, we introduce some notation. With reference to a generic study area, let I be the set of discrete nodes where customers are located. This set is represented by the centroids of the census tracts. For simplicity, the number of customers c_i in each centroid was assumed to be equal to the corresponding population.

Then, let J^{cpu}_{PU} be the set of current pick-up points, and J^{po}_{PU} be the set of post offices that are considered, in this study, fixed pick-up points. Hence, the current network is represented by the set of points $J^{c}_{PU} = J^{cpu}_{PU} \cup J^{po}_{PU}$. The customers-to-pick-up points distances d_{ij} for each pair (i,j), $i \in I$, $j \in J^{c}_{PU}$ are computed as the shortest path on the road network.

Accordingly, we calculate the accessibility of customers in node $i \in I$ to the current network, say $d^c_i = \min_{j \in J^c_{PU}} d_{ij}$. Similarly, let J^p_{PU} the set of potential pick-up points and J_{PU} the whole set of pick-up points ($J_{PU} = J^c_{PU} \cup J^p_{PU}$), we can calculate the accessibility customer $i \in I$ to the whole potential network as $d_i^p = \min_{j \in J_{PU}} d_{ij}$.

This way, depending on the network, we obtain a discrete distribution of the accessibility distances in the study area. In order to synthetically interpret it, we calculate two main indicators:

- the *average accessibility distance*, d_{avg}, expressing the average distance customers should travel to reach the closest self-collection facility ($d_{avg} = \frac{1}{\sum_{i \in I} c_i} \sum_{i \in I} c_i d_i$)
- the *maximum accessibility distance*, d_{max}, indicating the accessibility conditions of the least-served customers ($d_{max} = \max_{i \in I} d_i$).

In addition, we consider a so-called accessibility function, expressing the fraction γ of customers having at least one self-collection facility within distance $\bar{d}$($\gamma(\bar{d}) = \frac{1}{\sum_{i \in I} c_i} \sum_{i \in I : d_i \leq \bar{d}} c_i$). Equivalently, we also say that $\gamma(\bar{d})$ is the fraction of customers covered within distance $\bar{d}$. Note that the pair $(\bar{d}, \gamma(\bar{d}))$ indicates, in practice, a service level associated with the network.

This section reports on the accessibility analysis performed on the selected cities. As an example, Figure 4.1 reports the case of Bologna. In that picture, we depict two lines: the *AS-IS accessibility*, calculated w.r.t. the *current network* (J_{PU}^c); the *potential accessibility*, obtained considering the whole network ($J_{PU} = J_{PU}^c \cup J_{PU}^p$). Extensive results are in Table 4.1, which reports, for each considered city, the percentages γ of covered customers for a sample of distances $\bar{d}$ (from 0.10 km to 1.00 km with a pace equal to 0.10 km), the average (d_{avg}) and the maximum (d_{max}) accessibility distances under both networks (AS-IS and Potential). In our analysis, we focus on distances below 1.00 km. Indeed, extant literature argues that customers are not willing to patronize self-collection points located farther than that distance (Kim and Wang, 2022). Hence, in our study, we also keep this value as a maximum threshold distance beyond which customers would not choose to self-collect their parcels.

Let us start by focusing on the AS-IS accessibility (solid blue line in Figure 4.1). About 70% of customers have the closest self-collection facility within 0.50 km, and almost 95% must travel no more than 1.00 km. As a result of the capillarity of the current network, we also observe that a significant share of customers (more than 35%) is covered within a minimal distance (0.30 km) and that, overall, the average accessibility (d_{avg}) equals 0.47 km. However, accessibility is not as good for all customers. Although limited, a fraction of them must travel longer distances to reach the closest self-collection facility, equal to 8.37 km in the worst case (d_{max}).

We now consider the potential accessibility (dashed blue line). As expected, the activation of all the pick-up points would improve customers' accessibility. However, such improvements are often not very significant when looking at the values involved. To this end, a comparative assessment is presented in Table 4.1, where the rows labelled with "Δ" display the difference between the obtained fractions γ for each distance (in percentage points), as well as the difference between the average and maximum accessibility distances. Specifically, adding all the potential pick-up points (99 in Bologna) would increase the fraction of covered customers within 0.30 km by 10.6 percentage points (from 36.0 to 46.6) and by about 8 percentage points for 0.20 and 0.40 km. These differences tend to smooth by $\bar{d}$. This means, in practice, that there would not be substantial benefit for customers in the worst AS-IS accessibility conditions. Observe, in fact, that the fraction of customers having an accessibility distance at most equal to 1.00 km

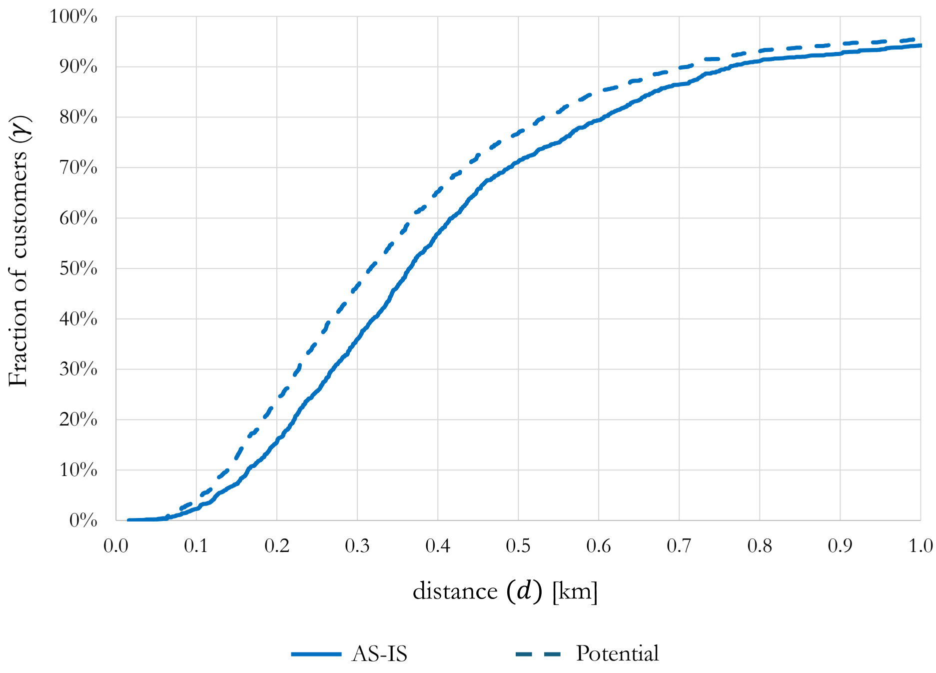


Figure 4.1: AS-IS vs. Potential accessibility in Bologna

would only increase by about one percentage point. This is reflected by the poor reduction in the average accessibility (about 60 meters) and the lack of impact on the maximum distance.

Although to different extents, similar considerations can be drawn for the other test cases. From Table 4.1, we notice that the average accessibility distance is equal to 0.63 km in the worst case (Roma), but it is below 0.50 km in four cases (Napoli, Torino, Bologna, Firenze).

Clearly, the activation of new pick-up points can yield some improvements in accessibility, but we observe that these gains are relatively limited compared to the high number of required activations (shown in Table 3.3). Triggered by the evidence from the performed accessibility analysis, the following questions arise:

- Is the current network design efficient? Is it possible to reduce the number of pick-up points while ensuring good accessibility conditions for customers?
- Is it possible to improve accessibility conditions for customers while limiting the investments resulting from network expansion?

To address the issues above, different strategies are proposed to redefine the network by explicitly accounting for customers' accessibility.

4.3 Strategies to redefine the self-collection network

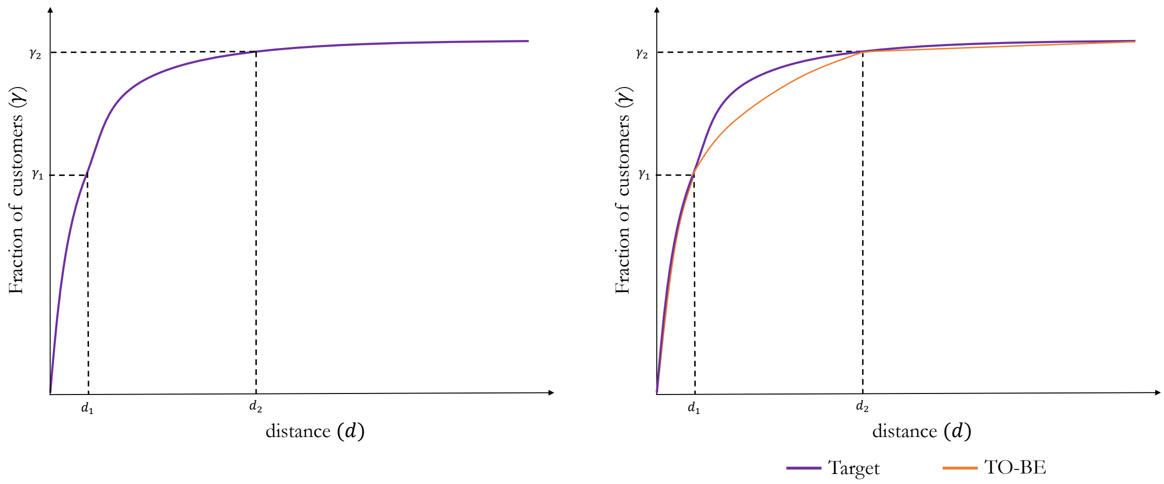
In this section, we propose three strategies to identify the optimal number and location of pick-up points. The goal is to reduce the provider's economic costs while keeping the network's capillarity on the territory and, hence, ensuring good accessibility conditions for customers. It is worth remembering that the location decisions do not involve post offices (J_{PU}^{po}).

In general, we assume that the service provider is interested in identifying the minimum number of pick-up points able to reproduce certain levels of target spatial accessibility.

Table 4.1
Fractions of covered customers (γ, in %) by distance $\bar{d}$, average (d_{avg}), and maximum (d_{max}) accessibility distances in the AS-IS and Potential networks for all the sampled cities

City	**Network**	$\bar{d}$ **[km]**										d_{avg} [km]	$d_{\max}$ [km]
		0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00		
Roma	AS-IS	3.1	15.1	32.8	47.6	59.3	67.2	73.7	78.2	82.0	84.9	0.63	14.62
	Potential	5.3	24.3	44.1	57.8	67.5	75.0	81.0	85.2	88.4	90.6	0.50	12.66
	Δ	2.2	9.2	11.2	10.2	8.1	7.8	7.3	6.9	5.5	5.7	-0.13	-1.96
Milano	AS-IS	2.0	10.8	24.6	39.6	54.4	66.1	75.7	82.3	86.9	90.5	0.56	4.95
	Potential	4.1	20.7	40.1	55.3	68.1	76.4	82.7	87.1	89.8	92.5	0.47	4.95
	Δ	2.1	9.9	15.5	15.7	13.7	10.4	7.0	4.8	2.9	0.0	-0.09	0.00
Napoli	AS-IS	4.0	20.7	40.4	57.2	69.5	77.2	83.0	87.7	90.3	92.1	0.46	3.58
	Potential	7.7	33.6	54.8	68.9	78.2	85.0	89.7	92.3	94.1	95.5	0.36	3.33
	Δ	3.7	12.9	14.4	11.7	8.8	7.6	7.8	6.7	4.6	3.4	-0.10	-0.12
Torino	AS-IS	2.3	16.6	37.8	59.3	72.9	83.9	90.2	93.7	95.5	96.5	0.42	5.06
	Potential	4.8	29.2	55.1	73.6	83.3	90.0	93.5	97.0	97.5	97.5	0.34	4.24
	Δ	2.5	12.7	17.3	14.4	10.4	6.1	3.3	1.9	1.3	1.0	-0.08	-0.82
Bologna	AS-IS	2.3	15.6	36.0	56.9	71.1	79.4	86.5	91.1	92.6	94.2	0.47	8.37
	Potential	3.9	23.7	46.1	65.2	76.8	84.3	89.3	94.5	95.6	96.7	0.41	6.58
	Δ	1.6	8.1	10.6	8.3	5.4	3.3	4.2	3.6	2.0	1.0	-0.06	0.00
Firenze	AS-IS	2.8	16.6	33.1	52.6	66.0	76.7	82.7	86.6	89.9	92.9	0.48	4.58
	Potential	5.1	25.8	46.6	64.4	74.5	83.1	87.8	91.7	92.7	94.9	0.47	4.58
	Δ	2.3	9.3	12.5	11.8	8.4	6.1	5.1	5.1	2.8	2.0	0.00	0.00
Bari	AS-IS	4.3	18.1	38.4	51.8	61.8	68.9	75.0	80.3	84.9	86.4	0.55	4.90
	Potential	5.6	28.0	48.5	60.8	68.5	75.3	80.7	84.9	88.1	90.2	0.46	3.39
	Δ	1.3	10.0	10.1	9.0	6.9	6.4	5.7	4.9	4.3	3.8	-0.09	-1.51

The general idea is to try reproducing some accessibility conditions in the final solution by "fixing" some service levels. To explain it, let us consider accessibility conditions depicted in Figure 4.2a with the generic target curve that depends on the given strategy. Besides, let d_1 and d_2 be two example distances, and γ_1 and γ_2 are the corresponding percentages of covered customers. To replicate the target conditions, we impose that service levels (d_1,γ_1) and (d_2,γ_2) are also met in the new network. At this aim, it suffices to ensure that the TO-BE curve, representative of the accessibility conditions in the final solution of the strategy, crosses points (d_1,γ_1) and (d_2,γ_2), as displayed in Figure 4.2b (see the solid orange line).



(a) Target and service levels

(b) Target vs. TO BE

Figure 4.2: Replicating the target accessibility

As we see from Figure 4.2, the target and TO-BE lines do not perfectly overlap. In particular, due to the fewer pick-up points located by the strategy, the target curve "dominates" the other. Of course, the similarity of the curves depends on the number of service levels (more service levels would yield higher similarity) and the chosen distances.

To account for these features we adopt a mathematical model whose formal description is provided below.

The devised strategies are implemented by means of a facility location problem, whose formulation is provided in this section.

In particular, we consider the presence of an exogenous (i.e., decision-maker-defined) set K of service levels to guarantee each associated with a given pair $(d_k,\ \gamma_k)$, $k \in K$. Without loss of generality, we assume d_k and γ_k to be non-decreasing with k. We consider the generic set J of pick-up points. Also, we introduce two families of decision variables:

- $y_j, \quad j \in J$, binary decision variables equal to 1 if the pick-up point j is located, 0 otherwise;

- $x_{ik}, \quad i \in I,\ k \in K$, binary variables equal to 1 if customers in i are covered within service level k, 0 otherwise.

Based on the above hypotheses and notation, and irrespective of the considered strategy, the generic mathematical model, say (S), can be formulated as follows:

$$
\begin{aligned}
\text{minimize} \quad & \sum_{j \in J} y_j && && (4.1)\\
\text{subject to} \quad & \sum_{j \in J : d_{ij} < d_k} y_j \geq x_{ik} && i \in I, k \in K && (4.2)\\
& \sum_{i \in I} c_i x_{ik} \geq \gamma_k \sum_{i \in I} c_i && k \in K && (4.3)\\
& y_j = 1 && j \in J^{po}_{PU} && (4.4)\\
& x_{ik}, y_j \in \{0, 1\} && i \in I, j \in J, k \in K && (4.5)
\end{aligned}
$$

Objective function (4.1) minimizes the number of located pick-up points. Constraints (4.2) ensure that customers in i are covered for service level k if they have at least one self-collection facility within distance d_k. Constraints (4.3) guarantee that the produced solution meets the predefined service levels. Indeed, they state that at least γ_k percentage of customers must be covered within distance d_k. Constraints (4.4) ensure that post offices are kept open. Note that, although location decisions do not involve post offices, these contribute to accessibility (being $J^{po}_{PU} \subset J^{c}_{PU} \subset J$). Finally, Constraints (4.5) define the nature of the decision variables.

It is worth noticing that the model does not account for capacity constraints at self-collection facilities. We remark, in fact, that our focus is on pick-up points, mainly corresponding to local shops (bars, tobacconists, etc.). As such, and differently from parcel lockers, we reasonably assume capacity is not a particular issue in the investigated problem. The general formulation of the model (S) can be tailored to account for each strategy. Details are given below.

Strategy 1 – Network contraction

In this first strategy, we assume the service provider is interested in identifying the minimum number of pick-up points within the current network (J^{c}_{PU}) to preserve AS-IS accessibility conditions as much as possible. Indeed, the corresponding mathematical model S_2 can be obtained from S assuming $J = J^{c}_{PU}$ and considering the AS-IS conditions as the target to reproduce.

Strategy 2 – Network reorganization

In the second strategy, we assume that the service provider is interested in identifying the minimum number of pick-up points among the whole potential network ($J_{PU} = J^{c}_{PU} \cup J^{p}_{PU}$) to preserve AS-IS accessibility conditions as much as possible. In practice, the strategy allows for the simultaneous activation of new pick-up points and the closure of existing ones, thus conceiving a reorganization of the self-collection network. The corresponding mathematical model S_2 can be obtained from S, assuming $J = J_{PU} = J^{c}_{PU} \cup J^{p}_{PU}$ and considering the AS-IS conditions as the target to reproduce.

Strategy 3 – Network expansion

The third strategy aims to attain potential accessibility conditions by expanding the network with the minimum required number of pick-up points. The corresponding mathematical model

S_3 can be obtained from S imposing $J = J_{PU} = J^c_{PU} \cup J^p_{PU}$ and considering the potential conditions as the target to reproduce.

Table 4.2 summarizes the required settings for each strategy.

Table 4.2
Pick-up points and accessibility conditions by strategies

Strategy	Pick-up points to activate (J)	Accessibility conditions to reproduce
1 – Network contraction	J^c_{PU}	AS-IS
2 – Network reorganization	$J_{PU} = J^c_{PU} \cup J^p_{PU}$	AS-IS
3 – Network expansion	$J_{PU} = J^c_{PU} \cup J^p_{PU}$	Potential

4.4 Application and results

Strategies are applied to two cases: Bologna and Napoli. Bologna is the representative instance for Poste Italiane pilot studies (see Section 3.4.1). Napoli accounts for a larger-sized case study characterized by a more homogenous distribution of self-collection facilities on the territory and three depots (Figure 3.4b).

To run the models, we need to specify the values for the set of service levels K and, thus, the pairs (d_k,γ_k), $k \in K$. The latter, we recall, are the distances and the corresponding fractions of covered customers used for replicating AS-IS and potential accessibility curves. The chosen settings are displayed in Table 4.3 for Bologna. As the table shows, we consider two settings for the number of service levels: (i) one service level (i.e., $|K| = 1$) and (ii) two service levels (i.e., $|K| = 2$). For each setting, we consider three different (d,γ)-pairs. This choice allows to assess the impact of the number of imposed service levels on the capability of faithfully reproducing the target accessibility conditions. It is worth remembering that when considering one service level, we impose that the TO-BE curve crosses the target by just one point. Therefore, we produce a less constrained location scenario that, reasonably, may not faithfully replicate the entire target curve. Conversely, when considering two service levels, we impose the TO-BE curve across two points. This produces a better replication of the target curve with a more constrained location scenario.

Table 4.3
Parameters' settings for the experiments

No. of service levels ($\|K\|$)	Distances (d)	Instances encode		
		Contraction	Reorganization	Expansion
1	$d_1 = 0.20$ km	S_1_0.20	S_2_0.20	S_3_0.20
	$d_1 = 0.30$ km	S_1_0.30	S_2_0.30	S_3_0.30
	$d_1 = 0.40$ km	S_1_0.40	S_2_0.40	S_3_0.40
2	$d_1 = 0.20$ km, $d_2 = 0.40$ km	S_1_0.20_0.40	S_2_0.20_0.40	S_3_0.20_0.40
	$d_1 = 0.30$ km, $d_2 = 0.50$ km	S_1_0.30_0.50	S_2_0.30_0.50	S_3_0.30_0.50
	$d_1 = 0.40$ km, $d_2 = 0.60$ km	S_1_0.40_0.60	S_2_0.40_0.60	S_3_0.40_0.60

The results of the strategies are presented in Sections 4.4.1–4.4.3. Section 4.4.4 delivers an overall comparison of the obtained solutions. For brevity, we only provide the detailed results for Bologna. In fact, similar considerations also apply to Napoli, whose extended results are in the Appendix B, Tables B1–B5.

4.4.1 Strategy 1—Network contraction

The results of the experiments obtained with one and two service levels are shown in Table 4.4, which reports, w.r.t. the AS-IS conditions: the variation in the fraction of covered customers for a sample of distance $\bar{d}$, expressed in percentage points (Δ_γ); the average variation in the fraction of covered customers ($\Delta_{\gamma_{avg}}$); the variation in the average accessibility distance ($\Delta_{d_{avg}}$); the variation in the number of located pick-up points (Δ_{PU}). To ease the comparison, the Table also reports the characteristics of the AS-IS scenario according to the same indicators. In the table, blue cells refer to the considered service levels. Therefore, the corresponding values are not reported as they are all equal to zero. Instead, Figure 4.3 displays and compares, by way of example, the accessibility functions of solutions S_1_0.20 and S_1_0.20_0.40 above with the AS-IS one.

We start our analysis by focusing on single service level cases and, in particular, on instance S_1_0.20 (dotted red line in Figure 5), that is produced for $(d_1,\gamma_1) = (0.20$ km, $15.6\%)$. We notice that the replication is faithful for distances lower than 0.20 km, and then it became poorer with a decrease of almost four percentage points in the fraction of covered customers at 0.50 km. Clearly, this is a consequence of a significant reduction in the number of located pick-up points (-22).

As regards other instances with a single service level, the increase in distance d_k leads to better replications of the AS-IS accessibility and reduced pick-up points' deactivations. The reason is that a single service level keeps the AS-IS accessibility at the imposed distance, but before and after the constrained point, conditions worsen due to the minimization objective. Therefore, by imposing distances that are closer to the centre of the considered range (up to 1.00 km), the entire curve is better reproduced.

Introducing a second service level allows for much better curve reproduction but limits the network's contractions. Indeed, when considering the solution S_1_0.20_0.40 (dashed red line in Figure 4.3), i.e., those obtained imposing $(d_1,\gamma_1) = (0.20$ km, $15.6\%)$ and $(d_2,\gamma_2) = (0.40$ km, $56.9\%)$, we notice that the replication is almost perfect. This result would come with five deactivations.

However, although (in general) two service levels help to reproduce the AS-IS conditions faithfully, it is interesting to analyze the solution S_1_0.40_0.60. In fact, the latter produces the same effects as its counterpart with one service level (S_1_0.40), both in terms of accessibility and deactivations. This proves that replication depends not only on the number of service levels but also on the chosen distances. Indeed, in this case, the first distance equal to 0.40 km makes the second service level almost useless.

4.4.2 Strategy 2—Network reorganization

Following the previous section, Table 4.5 summarizes the overall experimental results (as in Table 4.4). Additionally, Table 4.6 reports the number of deactivated and newly activated pick-up points in the produced solutions. Finally, Figure 4.4 presents the accessibility functions for two detailed cases.

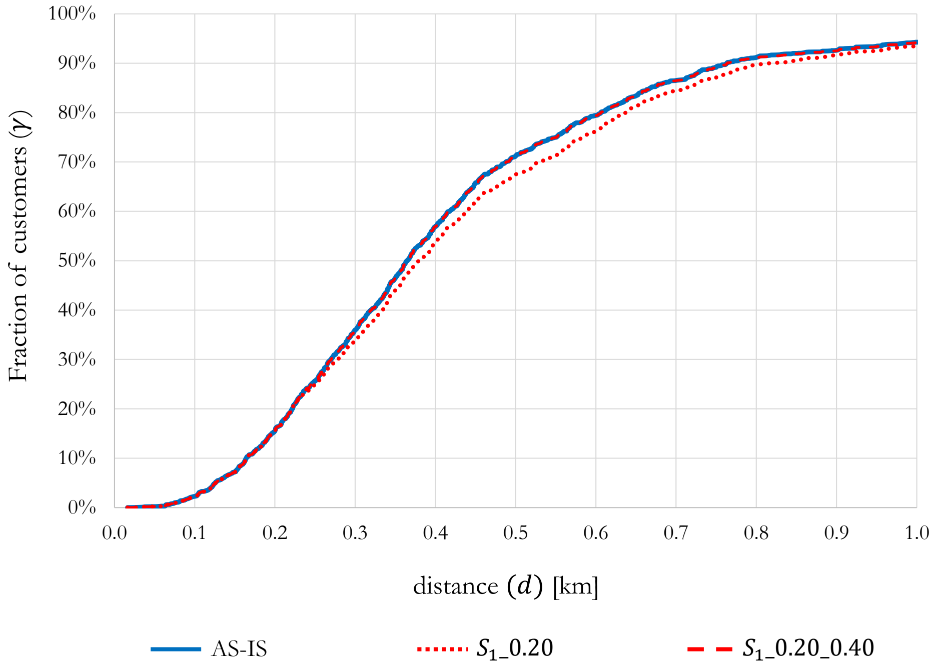


Figure 4.3: Strategy 1: solutions for instances $S_1\_0.20$ and $S_1\_0.20\_0.40$ (Bologna)

Focusing on the single-service-level solution $S_2\_0.20$ (dotted green line in Figure 4.4), we notice that, while the AS-IS conditions are maintained up to 0.20 km, considerable differences are observed for greater distances. Specifically, the fraction of customers covered decreases significantly, dropping by nearly 20 percentage points for 0.50 km and yielding an increase in the average accessibility distance of 0.17 km. However, it is worth noting that this would follow a substantial shrinkage of the current network, with 66 fewer pick-up points. Interestingly, as shown in Table 4.6, the latter results from the deactivation of 88 existing pick-up points and 22 new activations. Similar results are also produced by other one-service-level solutions.

Instead, adding another service level (solution $S_2\_0.20\_0.40$, dashed green line in Figure 4.4), decreases the fraction of covered customers by, at most, three percentage points (for 0.80 km), while the average accessibility remains practically the same. Interestingly, the reduction in located pick-up points is also consistent (-43).

Our analysis proves that the number of service levels significantly impacts accessibility in this strategy. In fact, with more options for location decisions (the whole network J_{PU} is considered), the reproduction of the curve is poorer with a single service level than in the previous strategy since more pick-up points can be deactivated. Conversely, in Strategy 1, the decision is more constrained (due to the smaller set of pick-up points to locate), and the differences between one and two service levels are lower. This is immediately evident by comparing results in Figure 4.3 and Figure 4.4.

Overall, the experiments indicate that a more efficient design of the current network is possible without compromising AS-IS accessibility. Besides, this reorganization strategy provides a lower bound on the number of located pick-up points, as it foresees about 35-55% (42 up to 118 and 66 up to 118, respectively) fewer in the network.

Table 4.4
Strategy 1 solutions vs. AS-IS in Bologna

AS-IS		$\bar{d}$ [km]												
		0.10	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**		d_{avg} [km]	$\lvert J^c_{PU}\rvert$
	γ	2.3	15.6	36.0	56.9	71.1	79.4	86.5	91.1	92.6	94.2		0.47	118
Strategy 1 – Contraction		$\bar{d}$ [km]												
		0.10	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**	$\Delta_{\gamma_{\text{avg}}}$	$\Delta_{d_{\text{avg}}}$ [km]	Δ_{PU}
S_1_0.20		-0.1	–	-2.1	-3.3	-3.8	-3.3	-2.1	-1.5	-1.0	-0.8	-1.8	+0.02	-22
S_1_0.30	Δ_γ	-0.1	-0.6	–	-0.9	-1.0	-0.9	-0.6	-0.6	-0.3	-0.2	-0.5	+0.00	-14
S_1_0.40		-0.2	-0.7	-0.7	–	-0.2	-0.0	-0.0	-0.1	-0.1	-0.1	-0.2	+0.00	-15
S_1_0.20_0.40		-0.1	–	-0.0	–	-0.1	-0.0	-0.0	-0.1	-0.1	-0.1	-0.1	+0.00	-5
S_1_0.30_0.50	Δ_γ	-0.1	-0.2	–	-0.1	–	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0	+0.00	-7
S_1_0.40_0.60		-0.2	-0.7	-0.7	–	-0.1	–	-0.0	-0.0	-0.0	-0.0	-0.2	+0.00	-14

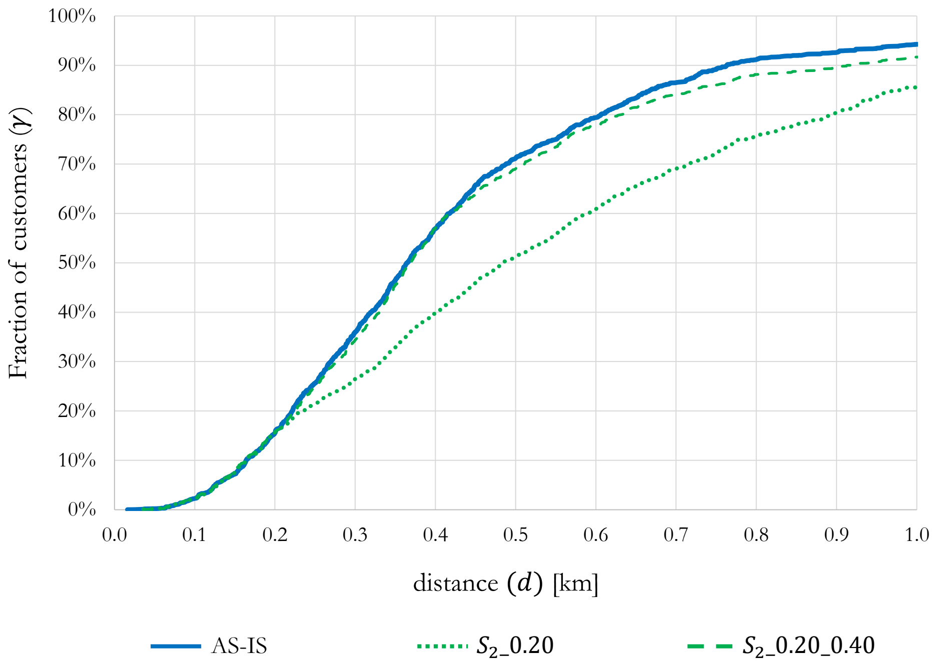


Figure 4.4: Strategy 2: solutions for instances S_1_0.20 and S_1_0.20_0.40 (Bologna)

4.4.3 Strategy 3—Network expansion

This strategy aims to improve customers' accessibility to the best possible conditions (i.e., those attainable with the potential network) at the minimum number of located pick-up points. Again, extensive results are reported in Table 4.7, whose last line indicates the variations between the Potential and AS-IS accessibility. Table 4.8 gives the total number of located, deactivated, and newly activated pick-up points in the produced solutions. Finally, the accessibility functions for two detailed solutions are depicted in Figure 4.5, where a comparison is made against the AS-IS and Potential conditions.

It clearly emerges that all the solutions bring improvements to the AS-IS conditions. How-

Table 4.5
Strategy 2 solutions vs. AS-IS in Bologna

AS-IS		$\bar{d}$ [km]												
		0.10	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**		d_{avg} [km]	$\lvert J^c_{PU}\rvert$
	γ	2.3	15.6	36.0	56.9	71.1	79.4	86.5	91.1	92.6	94.2		0.47	118
Strategy 2 – Reorganization		$\bar{d}$ [km]												
		0.10	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**	$\Delta_{\gamma_{\text{avg}}}$	$\Delta_{d_{\text{avg}}}$ [km]	Δ_{PU}
S_2_0.20		-0.0	–	-9.5	-17.2	-19.9	-18.6	-17.5	-15.4	-12.3	-8.7	-11.9	+0.17	-66
S_2_0.30	Δ_γ	-0.2	-1.4	–	-6.9	-9.4	-9.1	-9.9	-9.1	-7.3	-5.0	-5.8	+0.08	-50
S_2_0.40		-0.4	-2.8	-3.4	–	-2.3	-2.1	-2.7	-3.7	-2.9	-2.3	-2.3	+0.04	-47
S_2_0.20_0.40		-0.0	–	-1.7	–	-2.2	-1.6	-2.5	-3.0	-3.1	-2.6	-1.7	+0.03	-43
S_2_0.30_0.50	Δ_γ	-0.0	-1.7	–	-1.3	–	-0.0	-1.3	-2.2	-1.9	-1.8	-1.0	+0.02	-42
S_2_0.40_0.60		-0.2	-3.3	-3.6	–	-0.5	–	-0.6	-1.6	-1.3	-1.2	-1.2	+0.02	-46

Table 4.6
Strategy 2 solutions: deactivated and new activated pick-up points (Bologna)

Instance	Δ_{PU}	Deactivated pick-up points	New activated pick-up points
S_2_0.20	-66	-88	22
S_2_0.30	-50	-69	22
S_2_0.40	-47	-67	25
S_2_0.20_0.40	-43	-78	28
S_2_0.30_0.50	-42	-63	20
S_2_0.40_0.60	-46	-66	20

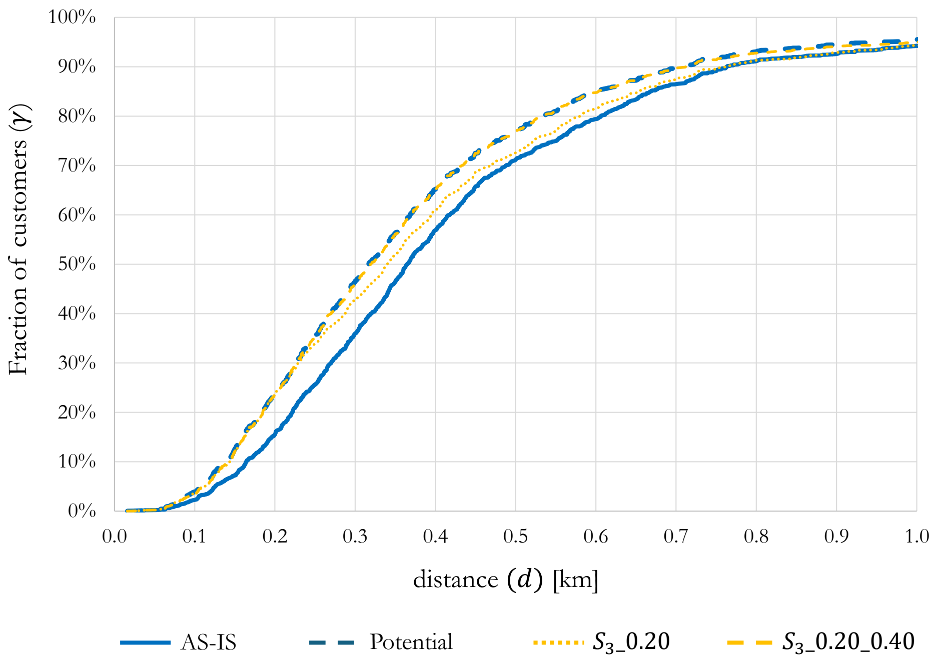


Figure 4.5: Strategy 3: solutions for instances S_1_0.20 and S_1_0.20_0.40 (Bologna)

Table 4.7
Strategy 3 solutions vs. AS-IS in Bologna

AS-IS		$\bar{d}$ [km]												
		0.10	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**		d_{avg} [km]	$\lvert J^c_{PU}\rvert$
	γ	2.3	15.6	36.0	56.9	71.1	79.4	86.5	91.1	92.6	94.2		0.47	118
Strategy 3 – Expansion		$\bar{d}$ [km]												
		0.10	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**	$\Delta_{\gamma_{\text{avg}}}$	$\Delta_{d_{\text{avg}}}$ [km]	Δ_{PU}
S_2_0.20	Δ_γ	1.3	8.1	6.8	4.0	1.5	2.1	1.1	0.2	0.3	0.1	2.6	-0.03	37
S_2_0.30		0.7	5.0	10.6	7.2	4.7	4.3	2.3	1.1	0.9	0.7	3.8	-0.04	33
S_2_0.40		0.5	2.9	7.2	8.3	5.0	5.1	3.1	1.6	1.4	0.8	3.6	-0.04	22
S_2_0.20_0.40	Δ_γ	1.2	8.1	10.1	8.3	5.7	5.4	3.3	1.6	1.5	0.8	4.6	-0.05	63
S_2_0.30_0.50		0.9	5.1	10.6	7.7	5.7	5.3	3.3	1.7	1.6	0.9	4.3	-0.05	43
S_2_0.40_0.60		0.5	2.9	7.2	8.3	5.3	5.4	3.3	1.9	1.9	1.3	3.8	-0.05	26
Potential	Δ_γ	1.6	8.1	10.6	8.3	5.7	5.4	3.3	1.9	1.9	1.3	4.8	-0.06	99

Table 4.8
Strategy 3 solutions: deactivated and new activated pick-up points (Bologna)

Instance	Δ_{PU}	Deactivated pick-up points	New activated pick-up points
S_2_0.20	37	-30	67
S_2_0.30	33	-22	55
S_2_0.40	22	-28	50
S_2_0.20_0.40	63	-15	78
S_2_0.30_0.50	43	-20	63
S_2_0.40_0.60	26	-27	53

ever, a non-negligible number of activations is required.

As for the other strategies, we start our analysis on single-service-level solutions and, in particular, on S_3_0.20 (dotted yellow line in Figure 4.5). The latter allows almost the same coverage as the potential within 0.20 km but diverges considerably for higher distances (e.g., 3.3 percentage points for 0.60 km). Obviously, this results from a marked increase in the number of located pick-up points (37 more compared to the current network). As discussed for the other strategies, using higher threshold distances appears beneficial. Indeed, it not only yields generalized improvements in customers' accessibility but also reduces the number of new activations. For example, solution S_3_0.40 yields a better replication of the potential curve (compared to other one-service-level solutions) with fewer pick-up points (+22 instead of +37).

However, results clearly highlight that solutions with two service levels achieve more significant improvements w.r.t. the AS-IS conditions. This result occurs with more pick-up points. Indeed, S_3_0.20_0.40 (dashed yellow line in Figure 4.5) perfectly reproduce potential conditions but with 63 more pick-up points.

Using higher distances improves replication and reduces the number of located pick-up points for two service-level solutions. In this respect, solution S_3_0.40_0.60 ensures almost perfect replication of potential accessibility from 0.40 km onwards, with 26 more pick-up points than the current network and only four more than its single-level variant (S_3_0.40, with 22 more than the current network).

In general, for all the solutions, we observe that the number of existing pick-up points being deactivated and newly activated ones are also considerable, again underlining the current network's inefficient design (see columns 4 to 7 in Figure 4.8).

4.4.4 Comparison and implications

The proposed strategies offer the possibility of analyzing various alternative scenarios regarding the number of located pick-up points and accessibility for customers, providing the company with an informative basis for contracting, reorganizing, or expanding its last-mile self-collection network.

To ease their comparison, Figure 4.6 displays the solutions obtained for Bologna, the AS-IS, and Potential scenarios as points with the number of located pick-up facilities and the corresponding average variation in the number of covered customers ($\Delta_{\gamma_{avg}}$) within 1.0 km as coordinates. Thus, the picture informs of the social and economic dimensions underlying our problem, showing the (proxied) costs associated with the produced network configurations against their capability to approximate the reference scenarios' accessibility.

In particular, solutions that yield higher savings in pick-up point locations lie in the lower part of the picture, characterized by worse average variation in the fraction of covered customers (and vice versa). In practice, from left to right, we move from "cheaper" to "more costly" solutions but also from "worse" to "better" accessibility conditions.

In this context, different configurations may emerge as relevant depending on the specific *decision-maker's strategic orientation*. In particular, three clusters of solutions associated with the strategies may be identified. In each of these, we notice that solutions with two service levels dominate those with one, proving the higher capabilities in reproducing customers' accessibility conditions (even with more pick-up points).

Looking into the figure, a more cost-attentive decision-maker may be interested in considering *Network reorganization strategy* (green diamonds). Indeed, by leveraging the high capillarity of the self-collection network on the territory, it allows the most considerable reductions of located pick-up points. However, this strategy can induce deterioration in the customers' accessibility (lower-left area). Therefore, among these solutions, the decision-maker may be interested in opting for those that guarantee similar accessibility levels to the current scenario (AS-IS). To this end, solutions obtained with two service levels represent interesting TO-BE configurations, reducing $\Delta_{\gamma_{avg}}$ of 1.7, 1.0 and 1.5 percentage points (for S_2_0.20_0.40, S_2_0.30_0.50 and S_2_0.40_0.60, respectively). Conversely, albeit producing higher points reduction, those with a single radius considerably worsen accessibility.

Nonetheless, these configurations would require deep restructurings, given the numerous deactivations/activations involved. Hence, their implementation calls for high flexibility and rapid network adaptability. Accordingly, if these conditions do not occur, *Network contraction* (red triangles) emerges as a viable option. In fact, these solutions allow reductions in the currently active pick-up points, with negligible impacts on accessibility, except for S_1_0.20 that reduces $\Delta_{\gamma_{avg}}$ of 1.8 percentage points.

The presented results clearly answer our first question. Although effective, the current

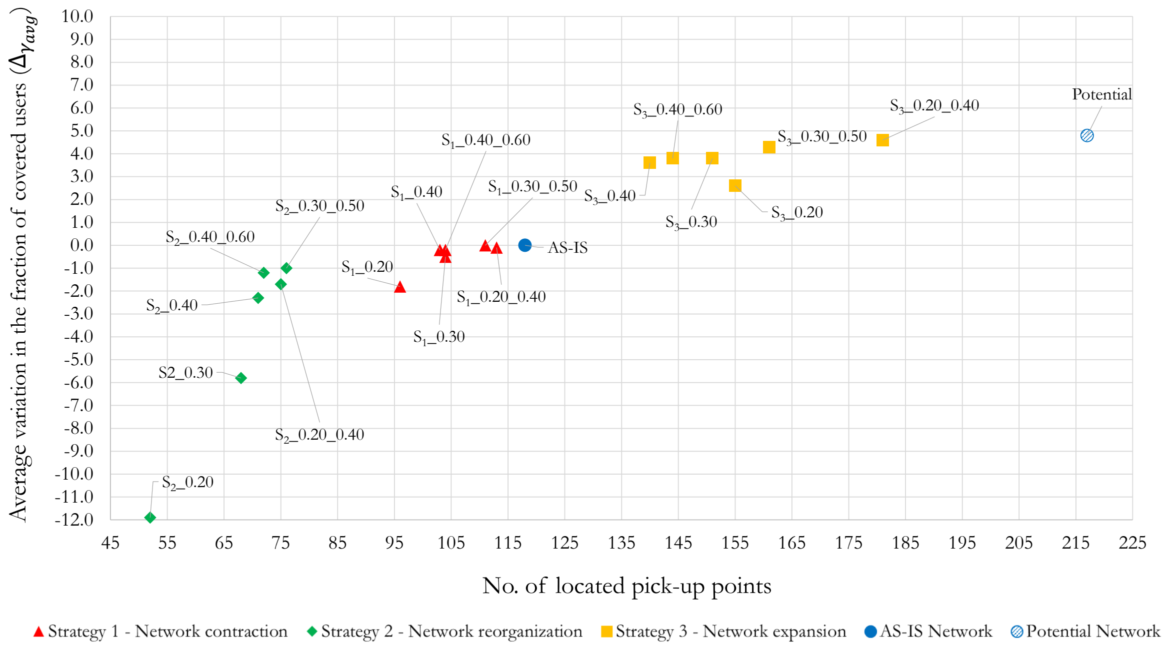


Figure 4.6: Comparison of the proposed strategies' solutions (Bologna)

self-collection network is not efficiently designed, and contraction or reorganization strategies, producing savings for the company, are implementable at an acceptable worsening of the customers' accessibility.

Furthermore, a customer-oriented decision-maker may be interested in analyzing the Network expansion strategies (yellow squares). The corresponding solutions provide improvements in the AS-IS accessibility with more pick-up points. From a practical point of view, it should be desirable to avoid the proliferation of pick-up points bringing minor marginal contributions to customers' accessibility. Hence, finding an appropriate trade-off between activation costs and improvement in accessibility conditions is necessary when expanding the network. With this aim in mind, solutions S_3_0.40 and S_3_0.40_0.60 are likely the most promising ones, given the minimized number of located pick-up points (140 and 144, respectively) and $\Delta_{\gamma_{avg}}$ values similar to the potential one.

The results of this strategy strongly depend on the set of potential pick-up points where to select locations. Indeed, as the preliminary spatial analysis also showed, the whole potential network would not largely improve accessibility. In this respect, we notice that 140 pick-up points (S_3_0.40) would be sufficient to practically achieve the best accessibility conditions, obtained with 218 points constituting the potential network. Given this consideration, replanning the set of potential candidates where to select new activation may emerge as a viable option to expand the network with a much better marginal contribution in terms of accessibility conditions.

Based on the results, we can positively answer our second question. In fact, if adequately informed by an analysis of marginal contributions that new activations produce, network expansion decisions can determine access improvements at relatively reduced investments.

All these considerations may be applied to the other considered test case (Napoli), whose results are shown in Figure 4.7. In particular, we notice that almost all the solutions of the contraction strategy would guarantee the same AS-IS accessibility with fewer points (see, for example, solution $S_1\_0.30\_0.5$ with 256 points compared to the current 293). For a more significant cost saving, the two service-level solutions of the reorganization strategy close the AS-IS conditions with much fewer points (spanning from 152 to 172). On the contrary, concerning the expansion strategy, only 13 more pick-up points (out of 300+ constituting the potential network) would make potential accessibility conditions attainable (solution $S_3\_0.40$).

The high generalizability of the obtained results is of significant importance for the decision-maker as it provides a pool of scenarios and solutions that seems not to depend on the specific considered urban context.

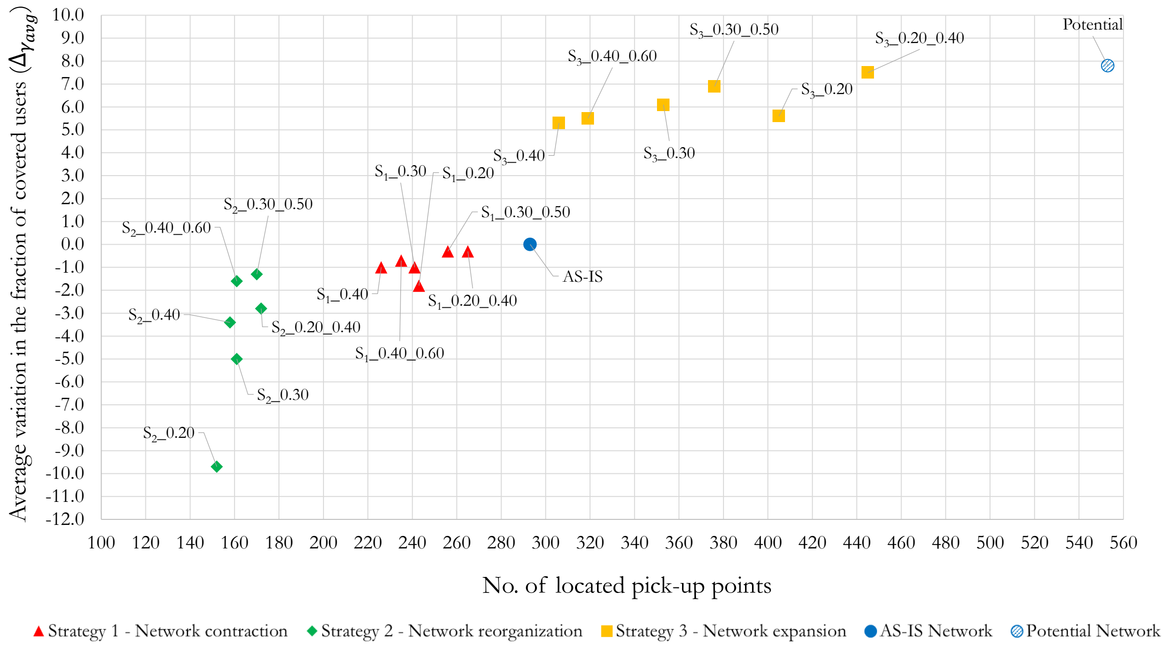


Figure 4.7: Comparison of the proposed strategies' solutions (Napoli)

4.5 Additional insights

So far, we have focused on the *number of located pick-up points*, as a proxy of the economic cost/investments borne by the service provider. Of course, this is consistent with the strategic nature of the problem. However, as discussed, last-mile logistics raises severe concerns due to its intensive shipment tours and related negative externalities (emissions, traffic congestion, etc.).

Therefore, in this section, we delve more into the produced solutions and assess the impact of self-collection network design decisions on *operating costs*. In our context, the latter mainly concerns travelled distances for visiting self-collection facilities, which can also provide a reasonable proxy for emissions. As such, our analysis offers additional informative basis to evaluate the proposed solutions from another economic perspective and, to some extent, also in sustainability terms.

To provide a routing cost evaluation, we used the open-source solver VRP Spreadsheet Solver version 3.8 (Erdoğan, 2017). In particular, for both the tested cities, we identified the depots that the company uses for the delivery and computed the routing under some operating conditions. Specifically, we supposed that all deliveries must be made in four hours and that the service time required for delivery orders at each point is equal to three minutes. We also supposed an average vehicle speed in urban areas of 15 km/h (Allen et al., 2018b; Seghezzi et al., 2022). By means of the solver, we identified the number of vehicles/operators p (from each depot) necessary to complete the delivery tour. In particular, starting from $p = 1$, we increased the number until reaching one satisfying the delivery time window constraints. Such an empirical approach allows for identifying the minimum number of necessary vehicles.

In Bologna, one depot is used to perform delivery tours, while, in Napoli, given its extension, three depots are considered. The position of depots for the cities is shown in Figures 3.4a and 3.4b, respectively. Hence, for each city and each produced scenario, the minimum number of vehicles and the total routing cost to visit all the located pick-up points have been identified.

The main results are in Table 4.9, where we report:

- For the AS-IS network: the number of vehicles/operators (p); the routing cost (R); the number of located pick-up points ($|J^c_{PU}|$).
- For each solution (and w.r.t. the AS-IS scenario): the variation in the number of vehicle/-operators (p); the percentage variation in the routing costs (Δ_R); the percentage variation in the number of located pick-up points (Δ_{PU}).

This way, the table summarizes the comparison between the economic dimensions involved: location and operating costs. We notice that in Bologna, the number of vehicles is the same for all the solutions of a given strategy. In particular, the same number of vehicles of the AS-IS scenario is required in the contraction strategy while just one more [less] in the reorganization strategy [expansion strategy]. Conversely, the differences are more marked in Napoli, when the reorganization strategy allows for a saving of two vehicles, while the expansion produces an increase of three units in the worst case (S_3_0.20_0.40).

Concerning the routing costs, we see similar results for both cities. As expected, we observe that pick-up points reduction [increase] yields the same effect on routing costs compared to the AS-IS scenario. In particular, in both cities, the correlation between these indicators is very high (98% for Bologna and 99% for Napoli), as also highlighted by Figures 4.8 and 4.9, graphically showing the correlation between these indicators for Bologna and Napoli, respectively. This result is particularly important since it proves that the number of points can be considered an effective proxy for delivery costs.

Focusing on each strategy, we observe that the first one induces cuts that range from 1% to 14% for Bologna and from 3% to 11% for Napoli. Clearly, Strategy 2 produces higher reductions that span from 17% to 32% in Bologna and from 20% to 28% in Napoli. Instead, we see more remarkable differences when comparing the results from Strategy 3. Indeed, while adding new pick-up points in Bologna leads to relatively limited, but non-negligible, routing increases (on average, from 13%), in Napoli, the average value is higher (23%). Interestingly, we observe the routing cost upsurging by almost 14% even when the lowest expansion effort is required, namely, 4% more pick-up points (solution S_3_0.40). The territorial distribution of pick-up points in the cities reasonably justifies this outcome. A more scattered distribution, as in Napoli (see Figure 3.4b), makes potential accessibility levels attainable with fewer but more dispersed pick-up points, leading to more significant routing increases.

Overall, the above evidence strengthens our previous conclusions, indicating that while contraction and reorganization strategies reduce operating costs, expansion strategy requires high operating costs, inducing decision-making to select solutions that get the best trade-off between costs and accessibility benefits.

Table 4.9
AS-IS vs Strategies: variation in the number of vehicles (Δ_p), routing costs (Δ_R), and located pick-up points (Δ_{PU})

		Bologna			Napoli		
AS-IS		p	R [km]	$\lvert J^c_{PU}\rvert$	p	R [km]	$\lvert J^c_{PU}\rvert$
		4	159.5	118	8	255.5	293
		Δ_p	Δ_R	Δ_{PU}	Δ_p	Δ_R	Δ_{PU}
Strategy 1 - Contraction	S_1_0.20	–	-14%	-19%	-1	-9%	-17%
	S_1_0.30	–	-9%	-12%	-1	-6%	-18%
	S_1_0.40	–	-9%	-13%	-1	-11%	-23%
	S_1_0.20_0.40	–	-3%	-4%	-1	-6%	-10%
	S_1_0.30_0.50	–	-1%	-6%	-1	-3%	-13%
	S_1_0.40_0.60	–	-9%	-12%	-1	-9%	-20%
Strategy 2 - Reorganization	S_2_0.20	-1	-32%	-56%	-2	-28%	-48%
	S_2_0.30	-1	-24%	-42%	-2	-23%	-45%
	S_2_0.40	-1	-22%	-40%	-2	-23%	-46%
	S_2_0.20_0.40	-1	-21%	-36%	-2	-22%	-41%
	S_2_0.30_0.50	-1	-17%	-36%	-2	-20%	-42%
	S_2_0.40_0.60	-1	-19%	-39%	-2	-21%	-45%
Strategy 3 - Expansion	S_3_0.20	1	6%	31%	2	27%	38%
	S_3_0.30	1	5%	28%	2	19%	20%
	S_3_0.40	1	7%	19%	1	14%	4%
	S_3_0.20_0.40	1	27%	53%	3	34%	52%
	S_3_0.30_0.50	1	16%	36%	2	26%	28%
	S_3_0.40_0.60	1	11%	22%	1	18%	9%

4.6 Conclusions

In this chapter, we examined the challenge faced by Poste Italiane in reconfiguring its last-mile self-collection network to enhance the efficiency of this process. In particular, the study aims to evaluate the economic and social dimensions associated with the envisaged redefinition in terms of pick-up points activation costs and distance-based accessibility.

To this end, an extensive spatial analysis is performed on a sample of the most-populated Italian cities, considering the current (AS-IS) and the potential self-collection network already identified by the company. The analysis leads to the question of whether the AS-IS conditions can be obtained by making the network more efficient and whether some accessibility improvements may be reached with contained investments.

To answer these questions, different self-collection network redefinition strategies are proposed. *Strategy 1 - Network contraction* and *Strategy 2 - Network reorganization* shape the problem of minimizing the number of located pick-up points while preserving the current customers' accessibility conditions. *Strategy 3 - Network expansion* points at the same objective but simultaneously maximizes customers' accessibility (i.e., tries to attain the potential conditions).

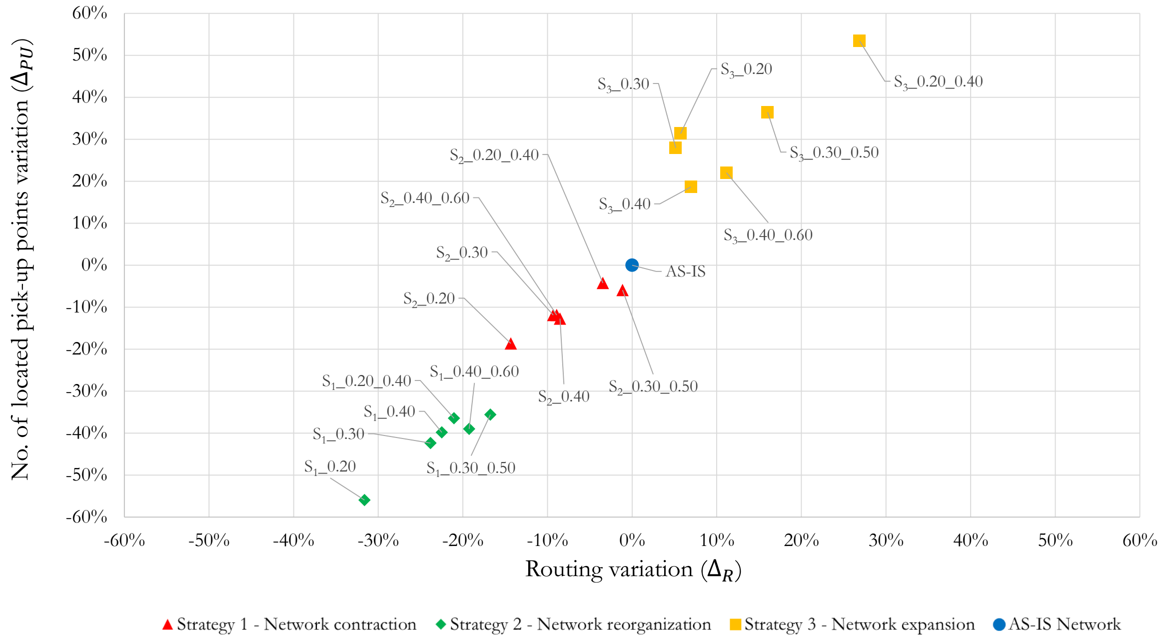


Figure 4.8: Correlation between routing costs variation (Δ_R) and number of located pick-up points variation (Δ_{PU}) (Bologna)

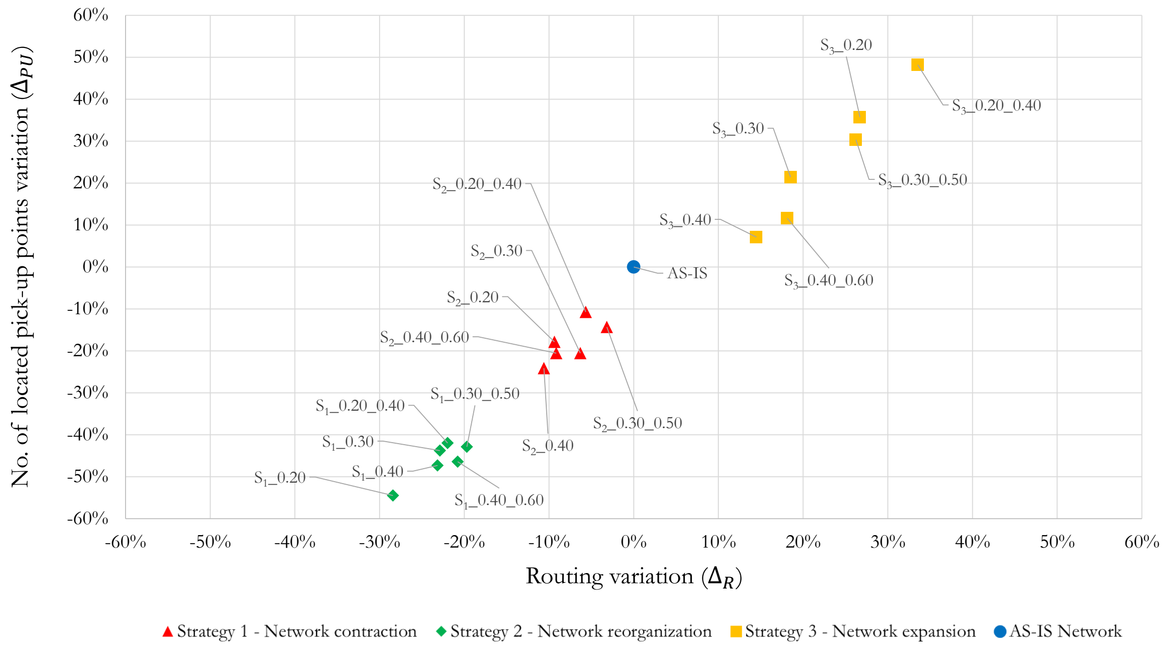


Figure 4.9: Correlation between routing costs variation (Δ_R) and number of located pick-up points variation (Δ_{PU} (Napoli)

The strategies are applied through the resolution of tailored mathematical models taking two main Italian cities as case studies. Experimental results provide a range of alternative network configurations the company may look at depending on its strategic orientation toward costs and customers' accessibility. In particular, we note that significantly reducing located pick-up points would be possible without compromising the current customers' accessibility. This fact makes Strategy 1 and 2 solutions worth considering for a cost-attentive decision-maker. Besides, it also denotes an inefficient AS-IS network design, given the presence of numerous active pick-up points that do not improve customers' accessibility. In addition, Strategy 3 shows that improvements in accessibility are achievable with much fewer activations than the full potential network, allowing for a balance between expansion costs and accessibility benefits. Finally, an in-depth analysis of operating costs supports these observations and proves that the number of points is an effective proxy for routing costs.

The limitations and insights arising from our study create opportunities for future research. The application of the three strategies, in fact, could be extended to other Italian cities in order to generalize and/or particularize the emerging managerial implications in dependence on the characteristics of the urban network being considered. Furthermore, in this chapter, we solely rely on distance-based measures (specifically, the distance from the closest facility) to proxy customers' propensity to self-collection. Hence, as specified, the study was placed within the deterministic approach literature. Although this makes sense from an accessibility perspective, other factors may influence customers' decisions. This calls for integrating explicit customers' choices into the network design decision, switching to a probabilistic perspective.

CHAPTER 5

Pick-up points network design with customers' choice considerations

5.1 Summary

In this chapter, we analyze different solutions to determine the position of pick-up points in order to obtain a delivery system in which the probability of self-collecting parcels is maximized. In particular, we propose a model based on a MultiNomial Logit (MNL) to represent customers' choices. Specifically, in the MNL, parameters reflecting customers' behaviors are included to represent their preferences for the two strategies. The model is applied to the case study Poste Italiane in the city of Bologna, and various scenarios are produced by varying the calibration of the parameters. The results demonstrate the relevance of customers' behavior in affecting decisions and provide numerous managerial insights, thus classifying the proposed model as an effective support tool for the design of self-collection networks.

5.2 Introduction and contribution

In this chapter, we face the problem of designing a self-collection network by explicitly including a customer choice model in the decision. In particular, we propose a facility location model for the optimal location of pick-up points, with the objective of maximizing the proportion of customers opting for self-collection. The latter is computed through a MultiNomial Logit (MNL), which is used to model preferences and choice mechanisms.

In the model, specific parameters reflecting customers behaviours are included. In particular, the choice is regulated by an attractiveness function associated with each potential location, decreasing over the distance and influenced by an impedance factor representative of customers' sensitivity to travel. In addition, home delivery is also included in MNL, and a parameter reflecting the attractiveness of this solution is considered. This way, customers' relative preferences for the two delivery strategies are simultaneously considered. Clearly, in the need to find cost-effective solutions, the proposed model constrains the number of pick-up points to be located, considering it as a proxy of costs. In practice, the model addresses the problem of designing a last-mile self-collection network trading off increased service attractiveness for customers and related investments.

The model is again applied to the case study of Bologna, and various scenarios are produced by varying parameters. In the study, the Poste Italiane network is assumed to be designed "ex-novo", and both current and potential pick-up points (see Table 3.3 are considered as candidate locations. The results demonstrate the relevance of customers' behaviors in affecting decisions and provide numerous managerial insights, thus classifying the proposed model as an effective support tool for the design of self-collection networks.

The study is placed in the literature dealing with the probabilistic approach in network design. It aims to make a twofold contribution to the literature: (i) it proposes a mathematical programming model for the location of pick-up points that incorporates parameters reflecting customers behavior influencing their choices; (ii) it demonstrates that the model yields meaningful solutions and serves as a valid decision-support tool, showing how the combination of different customers behaviors impacts the design of the pick-up points network.

The remainder of the chapter is organized as follows. In Sections 5.3 and 5.4, we formally describe the problem and present its mathematical formulation. The results obtained from the application to the case study are given in Section 5.5. Finally, Section 5.6 summarizes the work done in this chapter, its main conclusions, and outlines potential future research directions.

5.3 Customers' choice representation: MultiNomial Logit model

Of course, an essential aspect of our problem is the formalization of the spatial interaction between customers and pick-up points. In line with the literature, an MNL is adopted (Ben-Akiva and Lerman, 1985). In order to show its application to our case, some helpful notation is introduced.

Let J be the set of potential pick-up point locations and I the discrete set of potential customers' nodes. Additionally, we denote by d_{ij} the customers-to-pick-up-points distances for each pair $(i, j), i \in I, j \in J$, and by r the maximum threshold distance that customers are willing to travel to reach a pick-up point. Accordingly, we indicate by N_i the subset of potential pick-up points within reach of customers in $i \in I$ ($N_i = \{j \in J : d_{ij} \leq r\}$). In other words, we assume that customers in $i \in I$ are only attracted by facilities located within the radius r (that is, $j \in N_i$), and the intensity of such attraction depends on the related distances. Moreover, according to previous studies on the topic, we posit that the attractiveness of a pick-up point j for a given customer i, say α_{ij}, decades with the distance according to a negative exponential function, formulated as follow:

$$\alpha_{ij} = e^{-\beta_i d_{ij}} \quad i \in I, j \in N_i \tag{5.1}$$

with $\beta_i \geq 0$ being an impedance factor representing customers' sensitivity to travel distances.

Figure 5.1 depicts an example of the attractiveness function (α_{ij}) for the generic customer location $i \in I$, showing its variation by the distance (d_{ij}) and the sensitivity parameter (β_i). Note that, the attractiveness is maximal (i.e., equal to 1) if distances equal zero. This means that the most attractive pick-up points are those ideally located where the customer is. On the contrary, the attractiveness decreases with the distance becoming equal to zero outside the radius. Finally, we note that attractiveness decreases by β_i: at equal distances, a given pick-up point turns out to be less attractive for customers less willing to travel. We observe that $\beta_i = 0$ yields the ideal case of a customer being completely insensitive to distances and, thus, fully attracted by a pick-up point located within the radius ($\alpha_{ij} = 1, i \in I, j \in N_i$). Instead, when β_i increases, customer's sensitivity to travel distances becomes higher, and, for the same distance, a pick-up point becomes less attractive.

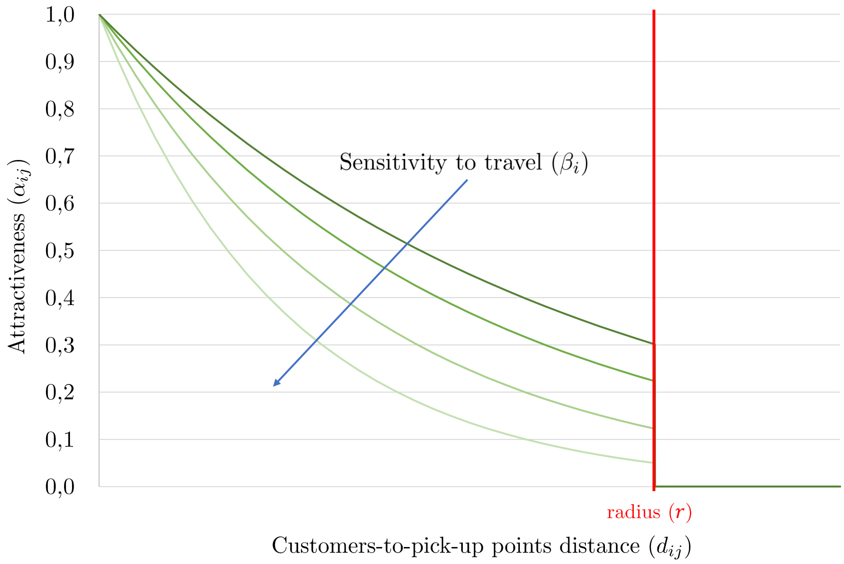


Figure 5.1: An example of attractiveness function

Besides, recall that self-collection is just one of the two potential delivery options available to customers. The latter, in fact, are always free to opt for traditional home delivery (even within the radius r). Hence, its attractiveness is another aspect to be accounted for in order to comprehensively describe customers' behavior. To this end, we define by $\phi_i > 0$ the attractiveness of the home delivery associated with customers in $i \in I$. Thus, we can now derive the rule expressing the proportion p_{ij} of customers in $i \in I$ opting for self-collection at pick-up point $j \in N_i$:

$$p_{ij} = \frac{\alpha_{ij}}{\sum_{k \in N_i} \alpha_{ik} + \phi_i} = \frac{e^{-\beta_i d_{ij}}}{\sum_{k \in N_i} e^{-\beta_i d_{ik}} + \phi_i} \quad i \in I, j \in N_i \tag{5.2}$$

Observe that such proportion is computed as the ratio between the attractiveness of pick-up point j and the attractiveness of the full-set of alternatives available to the customers, given by the sum of the attractiveness of pick-up points within the radius ($\sum_{k \in N_i} \alpha_{ik}$) and the home delivery (ϕ_i). Of course, it follows that $p_{ij} \in [0, 1]$.

Besides, the proportion opting for home delivery, say p_i^{HD}, is given by:

$$p_i^{HD} = \frac{\phi_i}{\sum_{k \in N_i} \alpha_{ik} + \phi_i} = 1 - \sum_{j \in N_i} p_{ij} \quad i \in I \tag{5.3}$$

From equations (5.2) and (5.3), it is easy to notice that customers' choice is affected by the attractiveness of home delivery (ϕ_i) and their sensitivity to travel distances (β_i). In particular, according to (5.2), p_{ij} decreases with both β_i and ϕ_i. In other words, the more customers are sensitive to distances and prefer home delivery, the lower the probability they opt for self-collection. Also, the number of pick-up points within the radius has an impact. From (5.3), in fact, we observe that it reduces the proportion of customers choosing home delivery.

Note that the value of ϕ_i provides an indication of the relative importance of the two strategies for customers in $i \in I$. For instance, $\phi_i = 1$ means that home delivery produces the same attractiveness for customers in i as one pick-up point located exactly at node i (i.e., at zero distance from i). In this ideal case, in fact, the resulting proportions computed by means of (5.2) and (5.3) would be the same (equal to 50%). Clearly, the above observation can be extended to any value of ϕ_i. In practice, we are somehow evaluating a sort of "substitution rate" between two delivery modes. In this view, pick-up points location decisions become crucial as they can strongly affect customers' preferences towards self-collection in dependence on their attitudes (i.e., parameters β_i and ϕ_i).

The mathematical model we use to provide this decision-support is provided next.

5.4 Problem description and formulation

As previously highlighted, we consider a decision-maker interested in locating/activating pick-up points to *maximize the proportion of customers opting for self-collection* to promote the adoption of this strategy over home delivery. We assume the proportion to be represented by the above-introduced MNL. Besides, we assume the number of pick-up points to be located is given. In practice, it is an exogenous (i.e., decision-maker-defined) parameter to account for a *proxy of the investment* borne. With this, the *trade-off underlying our problem* emerges: on the one hand, we wish to maximize service attractiveness; on the other, to constrain investments. To avoid an undesirable proliferation of pick-up points within very short distances that do not really increase users' propensity to self-collect, we consider that a *dispersion criterion* also comes into effect as an additional practical condition. The latter forbids any two pick-up points from being simultaneously located if their mutual distance falls below a given (decision-maker-defined) threshold.

To formulate the model, some further notation is needed. In particular, we denote by n the number of facilities to be located and by u_i the number of potential customers associated with each node $i \in I$. Moreover, we denote by c_{jk} the distances for any pair $(j, k \in J)$ of pick-up points and by $\bar{c}$ the threshold value for the dispersion criterion. Finally, we introduce a family of binary decision variables y_j, equal to 1 if a self-collection facility is activated at node $j \in J$, 0 otherwise.

Based on the above notation, the mathematical model for the *Pick-up Points Location Problem* (*PuP-LP*) can be formulated as follows:

$$\text{maximize} \quad \sum_{i \in I} \sum_{j \in N_i} u_i p_{ij} \tag{5.4}$$

$$\text{subject to} \quad p_{ij} = \frac{\alpha_{ij} y_j}{\sum_{k \in N_i} \alpha_{ik} y_k + \phi_i} \qquad i \in I, j \in N_i \tag{5.5}$$

$$\sum_{j \in J} y_j = n \tag{5.6}$$

$$y_j + y_k \leq 1 \qquad j,k \in J : j \neq k, c_{jk} \leq \bar{c} \tag{5.7}$$

$$y_j \in \{0,1\} \qquad j \in J \tag{5.8}$$

$$p_{ij} \in [0,1] \qquad i \in I, j \in N_i \tag{5.9}$$

Objective function (5.4) maximizes the overall number of customers opting for self-collection. This number is computed by means of proportions p_{ij}, calculated as the relative attractiveness of pick-up point j for node i, related to the total attraction felt by node i from active pick-up points within the radius and the home delivery (Constraints (5.5)). Note that these proportions are now decision variables depending on location decisions (Constraints (5.9)). Constraint (5.6) states that n pick-up points must be located, while Constraints (5.7) impose the minimum dispersion criterion between any two located pick-up points. Finally, Constraints (5.8) – (5.9) define the domain of the introduced decision variables.

It is worth noting that the above model is nonlinear due to the presence of Constraints (5.5). A linear formulation is therefore obtained by adapting a well-known scheme from the extant literature (Aros-Vera et al., 2013). The resulting linear model ($PuP\text{-}LP_L$) then reads as follows, with the introduction of a new set of decision variables, reflecting the proportion of customers opting for the home delivery (p_i^{HD}):

$$\text{maximize} \quad (5.4),$$

$$\text{subject to} \quad (5.6) - (5.9)$$

$$p_{ij} \leq y_j \qquad i \in I, j \in N_i \tag{5.10}$$

$$\sum_{j \in N_i} p_{ij} + p_i^{HD} = 1 \qquad i \in I \tag{5.11}$$

$$p_{ij} \leq \frac{\alpha_{ij}}{\alpha_{ik}} p_{ik} + (1 - y_k) \qquad i \in I, j,k \in N_i : j \neq k \tag{5.12}$$

$$p_i^{HD} \leq \frac{\phi_i}{\alpha_{ij}} p_{ij} + (1 - y_j) \qquad i \in I, j \in N_i \tag{5.13}$$

$$p_{ij} \leq \frac{\alpha_{ij}}{\phi_i} p_i^{HD} \qquad i \in I, j \in N_i \tag{5.14}$$

$$p_i^{HD} \in [0,1] \qquad i \in I \tag{5.15}$$

In the above model, Constraints (5.10) – (5.15) are equivalent to Constraints (5.5). For the proof, we refer the reader to Appendix C.

5.5 Application and results

We apply the model to the case study of the city of Bologna (see Section 3.4.1). We discretized the location space into 2,073 territorial units corresponding to the city census tracts, and we assumed that all consumers located in a census tract are concentrated in its centroid (i.e., $|I| = 2,073$ - see Figure 3.3a). As for the pick-up points, we consider both current and potential ones as candidate locations (i.e., $|J| = 217$, see Table 3.3). Their locations are displayed in Figure 3.4a. All the necessary distances (customers-to-facilities - d_{ij} and the reciprocal distances between facilities - c_{jk}) were determined as the shortest paths on the road network. The described representation of the problem was performed using the open-source software QGIS.

The goal of our experiments is to understand how three main problem's parameters affect the produced location scenarios and the quota of customers propending for self-collection delivery mode: (i) the sensitivity to travel distances, β_i (ii) the attractiveness of home delivery, ϕ_i (iii) the number of located pick-up points, n. In particular, we aim at assessing the specific impact of customers' behavior (β_i and ϕ_i) and, on top of that, the extent of the decision-maker's interventions (n). This way, we intend to quantify – in a cost-benefit analysis fashion – the expected gains in terms of attracted demand (which are highly dependent on exogenous customers' behaviors) against increased investments for network expansion.

To this end, we tested the model by varying $\beta \in \{0.5, 1.0, 2.0\}$ and $\phi \in \{0.5, 1.0, 2.0\}$. Note that both parameters are assumed equal for all the customers ($\beta_i = \beta$ and $\phi_i = \phi$, $i \in I$). Any stratification could be applied but would require a deep analysis of customers' habits. The combination of the chosen test values reflects customers' different typologies. By way of example, $\beta = \phi = 0.5$ denotes the case of users that are most keen on self-collection, having scarce sensitivity to distances and propensity for home delivery. Meanwhile, $\beta = 0.5$ and $\phi = 2.0$ denote the case of customers who prefer the home delivery option. The other relevant parameters, i.e., the radius r and the dispersion distance $\bar{c}$ were set, respectively, equal to 0.50 and 0.10 km. For the former, we follow the papers by Kim and Wang (2022) and Luo et al. (2022b). The latter, instead, was chosen in agreement with the company as a reasonable threshold to avoid a proliferation of pick-up points within very short distances. Finally, for all the considered combinations of the above parameters (β and ϕ, various experiments were realized by varying the number of located facilities n. In order to appropriately set this parameter, we first computed the maximum number of pick-up points that can be located in the city under the imposed dispersion constraint ($\bar{c} = 0.10$ km), say n_{max}. To this end, it suffices to solve a mathematical model that maximizes the number of located pick-up points ($\sum_{j \in J} y_j$), subject to the dispersion criterion, i.e., Constraints (5.7). In our case, we found $n_{max} = 205$. Recall that the number of potential locations ($|J|$), is 217 (the sum of current and potential pick-up points, see Table 3.3, which means that at most 94% of them can be potentially activated (i.e., $n_{max} = 0.94 \times |J|$). Then, we set n as a given percentage γ of $|J|$, and varied γ from 10% to 94% (the maximum possible value), with a pace equal to 10%. This means, in practice, that we varied $n \in \{22, 43, 65, 87, 109, 130, 152, 174, 195, 205\}$. Table 5.1 summarizes the discussed settings used for our empirical tests.

In total, 90 experiments were performed, combining three values for β, three values for ϕ, and ten values for n. All the experiments were performed on an 11th Gen Intel(R) Core (TM) i7-1165G7 CPU at 2.80 GHz, with 16 GiB of RAM running Windows 10 64 bits operating system, using IBM ILOG CPLEX v12.10 as the optimization solver. A three-hour time limit was imposed as the maximum running time for each experiment. Most instances were optimally solved within such limit. In a few instances, optimal solutions were not attained. Nevertheless, such solutions presented very limited optimality gaps (slightly above 1%, on average), which seem more than acceptable given the computational effort required to solve the model and the strategic nature of the investigated problem.

Table 5.1
Parameters' settings

Parameter	Definition	Value(s)
r	Covering radius (in km)	0.50
$\bar{c}$	Threshold distance for the dispersion criterion (in km)	0.10
β	Customers' sensitivity to travel distances	{0.5, 1.0, 2.0}
ϕ	Attractiveness of home delivery	{0.5, 1.0, 2.0}
γ	Proportion of potential pick-up points to activate (in %)	{10, 20, 30, 40, 50, 60, 70, 80, 90, 94}
n	Number of pick-up points to activate	{22,43,65,87,109,130,152,174,195, 205}

5.5.1 Main findings

We start the analysis of the results from the solutions obtained by fixing the attractiveness of the home delivery equal to 1.0 ($\phi = 1.0$). Figure 5.2 shows the proportions of customers opting for self-collection (i.e., the value of our objective function expressed in percentage of the total number of customers) by the percentage of located pick-up points γ. Recall that the maximum tested value of γ is 94% (highlighted in red). In particular, three curves are depicted, one for each tested value of the customers' sensitivity to distances β. For instance, if we consider the curve obtained for $\beta = 1.0$, we observe that the proportion of customers grows with γ and, hence, with the number of located pick-up points. This result is far from unexpected since a higher number of pick-up points increases customers' propensity to self-collection. Interestingly, as the Figure highlights, such improvements seem to reduce as the number of located pick-up points increases. This suggests a deeper look into the marginal growth of the objective function by γ, which we provide in Table 5.2. From the Table, we notice that the marginal increase is progressively lower. For instance, locating 20% of the total potential pick-up points yields 8.8% more customers using self-collection. Instead, such a value becomes close to zero when $\gamma = 90\%$.

Table 5.2
Marginal increases in the fraction of customers opting for self-collection by γ and β ($\phi = 1.0$)

Proportion of pick-up points to activate (γ)	Sensitivity to travel (β)		
	$\beta = 0.5$	$\beta = 1.0$	$\beta = 2.0$
10%	15.3	13.9	11.2
20%	9.6	8.8	7.4
30%	7.3	6.8	5.9
40%	4.9	4.7	4.2
50%	3.8	3.6	3.4
60%	2.8	2.8	2.7
70%	2.0	2.1	2.1
80%	1.1	1.2	1.2
90%	0.4	0.4	0.5
94%	0.0	0.0	0.0

This analysis allows to understand whether the cost deriving from network expansion pays

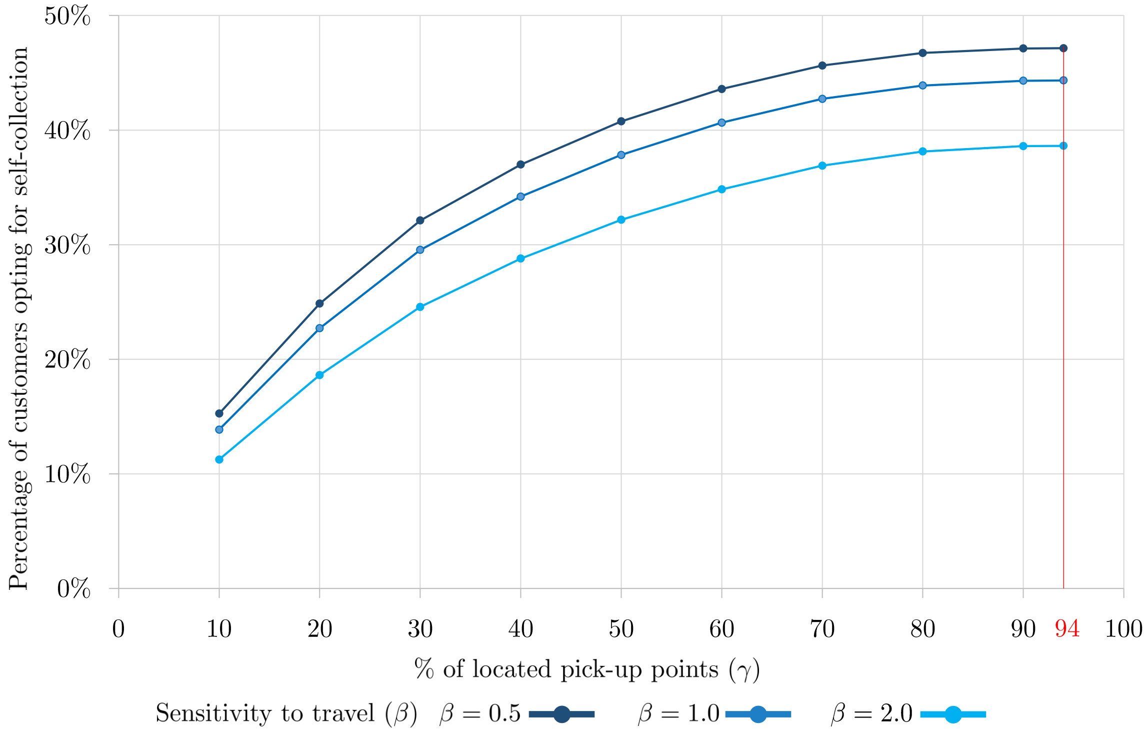


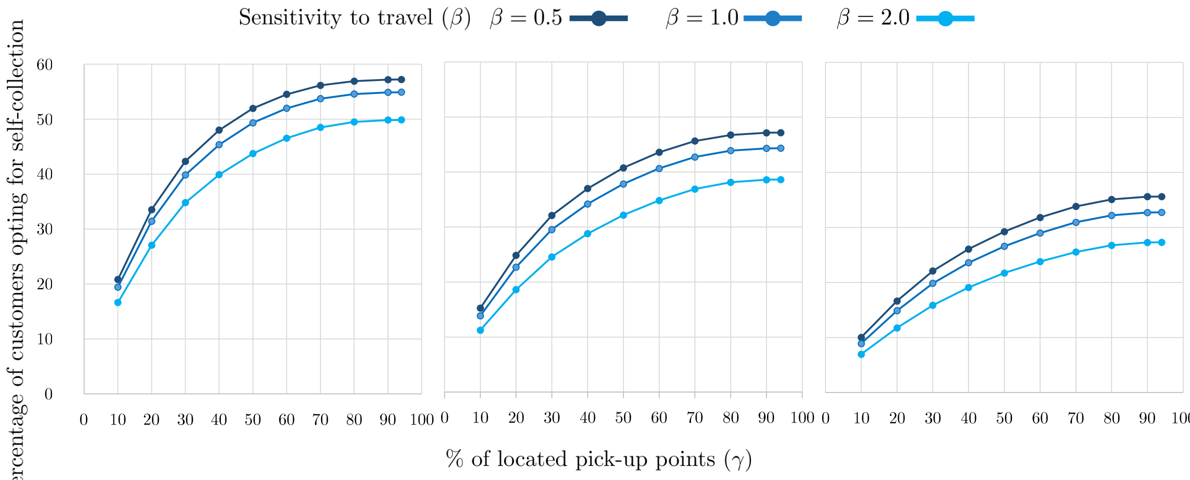
Figure 5.2: Proportion of customers opting for self-collection by γ and β ($\phi = 1.0$)

off in terms of attracted demand for the service. In our example, results would discourage the decision-maker from locating more than 80% of the potential pick-up points, given the negligible improvements resulting from any extra investment. Rather, the analysis of marginal increases suggests that he should consider solutions in the range of 20-60% of potential pick-up points, where the values of the extra benefits justify paying the extra investments deriving from more locations.

When comparing the curves yielded by the three considered values of β, we can see that the ones obtained for $\beta = 0.5$ "dominate" the others. In practice, for an equal number of located pick-up points (i.e., γ), low sensitivity to distances reflects a higher propensity for self-collection. Similar considerations previously detailed on the marginal increases can be applied for $\beta = \{0.5, 2.0\}$.

The full set of performed experiments is summarized in Figure 5.3, which shows a comparison of the results obtained for each tested value of ϕ (i.e., the attractiveness of home delivery). For clarity, the objective function's values (on the y-axis) are also reported in the three tables at the bottom of the picture for each combination of parameters β and ϕ.

From the picture, the effect of ϕ is clear. Indeed, ceteris paribus, the proportion of customers using self-collection almost halves when increasing ϕ from 0.5 to 2.0. For instance, for $\beta = 1.0$ and $\gamma = 50\%$, it reduces by almost 22 percentage points, i.e., from 49% to 27%. Again, these results are fully consistent with the meaning of ϕ. Indeed, customers preferring home delivery are less inclined to self-collect parcels. Also, the Figure confirms that the considerations concerning the marginal increase of the proportion of customers hold regardless of ϕ. However, it is interesting to note that such parameter plays a role in these trends. We see that when the number of located facilities is relatively low (i.e., $\gamma \leq 30\%$), the marginal increase reduces with



β \ γ	10	20	30	40	50	60	70	80	90	100
0.5	21%	34%	42%	48%	52%	55%	56%	57%	57%	57%
1.0	19%	31%	40%	45%	49%	52%	54%	55%	55%	55%
2.0	17%	27%	35%	40%	44%	47%	49%	50%	50%	50%

$\phi = 0.5$

β \ γ	10	20	30	40	50	60	70	80	90	100
0.5	15%	25%	32%	37%	41%	44%	46%	47%	47%	47%
1.0	14%	23%	30%	34%	38%	41%	43%	44%	44%	44%
2.0	11%	19%	25%	29%	32%	35%	37%	38%	39%	39%

$\phi = 1.0$

β \ γ	10	20	30	40	50	60	70	80	90	100
0.5	10%	17%	22%	26%	29%	32%	34%	35%	36%	36%
1.0	9%	15%	20%	24%	27%	29%	31%	32%	33%	33%
2.0	7%	12%	16%	19%	22%	24%	26%	27%	27%	27%

$\phi = 2.0$

Attractiveness of home delivery (ϕ)

Figure 5.3: Extensive results: proportion of customers opting for self-collection by the calibration parameters γ, β, and ϕ

ϕ (at equal values of β). For example, if $\beta = 1.0$, locating 20% of the potential pick-up points yields an increase of 12 percentage points for $\phi = 0.5$, which doubles that obtained for $\phi = 2.0$. In practice, the impact of a higher number of located pick-up points is far more significant if home delivery is less attractive for customers (i.e., for lower values of ϕ). In general, concerning the marginal increases of a given curve (i.e., a combination of β and γ), the values of γ whose extra benefits are relevant compared to the extra investments range between 20% and 60%. The detailed results are reported in Appendix C, Table C1.

Actually, from a more in-depth analysis of the obtained solutions, another interesting insight related to the impact of ϕ seem to emerge. To explain it, we now focus our attention on two particular solutions produced by the model, i.e., those obtained by setting $\gamma = 50\%$ and $\beta = 1.0$, but with different values of ϕ (0.5 and 2.0). The corresponding maps are in Figure 5.4, where the positions of the located pick-up points are displayed. The pictures evidence that the spatial distribution of such facilities appears more clustered in areas with denser customers' presence when the attractiveness of home delivery is higher ($\phi = 2.0$).

To confirm this finding, we compare the two solutions by analyzing the percentage of customer nodes having a given number of located pick-up points within the radius r. To this end, Figure 5.5 displays two series of bars, one for each considered value of ϕ. Each bar reports the percentage of customer nodes having m located pick-up points within r, with m varying from 1 to 7 (the maximum value found in these particular cases). The blue dots at the end of the bars (right side of the picture) report the percentage of customers' nodes having at least one pick-up point within r.

As the Figure shows, the latter is higher for $\phi = 0.5$ (62.6% vs 57.8%). Also, the percentages of nodes with one and two pick-up points in the radius (i.e., the blue and orange bars) are higher for $\phi = 0.5$. Conversely, we see higher percentages of customers' nodes with more facilities (i.e., from 3 to 7) for $\phi = 2.0$.

In practice, our results indicate that, in order to face the higher attractiveness of home delivery, the model tends to foster pick-up points' concentration to increase customers' propensity for self-collection (i.e., our objective function). Hence, higher values of ϕ yield more clustered pick-up points' distributions, as Figure 5.4 suggests.

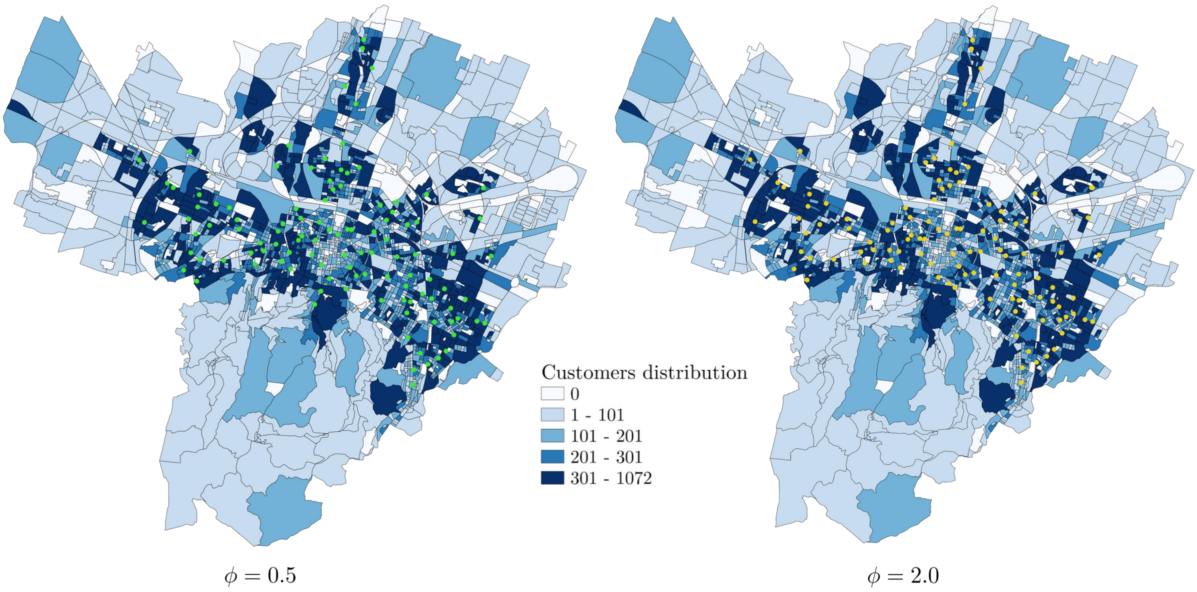


Figure 5.4: Maps of the solutions obtained for different values of ϕ ($\beta = 1.0$, and $\gamma = 50\%$).

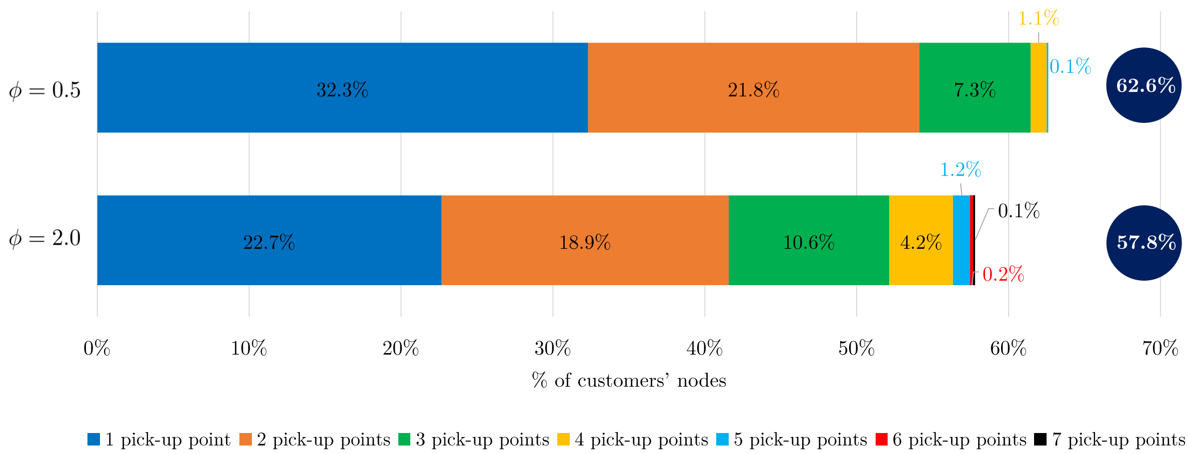


Figure 5.5: Customers' nodes having a given number of located pick-up points within the radius for different values of ϕ ($\beta = 1.0$, and $\gamma = 50\%$)

5.5.2 Sensitivity analysis

The above-discussed results highlight that the location scenarios greatly depend on the calibration parameters of the model. Therefore, this section presents additional insights concerning the *stability* of the produced solutions. In particular, we evaluate their *sensitivity* w.r.t. (i) customers' behavior parameters (β, ϕ), and (ii) the number of located pick-up points (n). After that, (iii) a sensitivity analysis of the joint effects of the discussed parameters is also performed.

(i) Sensitivity to customers' behavior

Here, the idea is to analyze whether some pick-up points' locations are less sensitive to customer behavior changes. Clearly, the latter is hard to predict, and the associated parameters may be natural sources of uncertainty in our problem. To this end, we examined all the produced scenarios to detect those pick-up points that, for a fixed size of the network (i.e., the value of n), recurred in the solutions obtained by varying parameters β (sensitivity to travel) and ϕ (attractiveness of home delivery). These can be regarded as a sort of *robust locations* since their activation is irrespective of the uncertainty associated with behavioral models' parameters and their proper estimation.

Table 5.3 summarizes the outcomes of this analysis. Specifically, for each tested value of n (γ), that is, the number (percentage) of pick-up points to be located, it shows:

- The *robust locations* with respect to the variation of the home delivery attractiveness (columns 2-4), i.e., the number and percentage of pick-up points recurring in the solutions obtained for all the value of ϕ and by fixing β (0.5, 1.0, 2.0);
- The *robust locations* with respect to the variation of the sensitivity to travel (columns 5-7), i.e., the number and percentage of pick-up points recurring in the solutions obtained for all the value of β and by fixing ϕ (0.5, 1.0, 2.0);
- The *robust locations* with respect to the variation of both the parameters (columns 8), i.e., the number and percentage of pick-up points recurring in the solutions obtained for all the combinations of β and ϕ.

By way of example, if 22 pick-points are located (i.e., 10% of the total), we observe that 16 (79%) pick-up points recur in the three solutions obtained by fixing $\beta = 0.5$ and varying $\phi \in \{0.5, 1.0, 2.0\}$. These values equal 15 (68%) and 14 (64%) for $\beta = 1.0$ and $\beta = 2.0$. Besides, we note that 18 pick-up points (82% of 22) recur in the three solutions obtained by fixing $\phi = 0.5$ and varying $\beta \in \{0.5, 1.0, 2.0\}$. Finally, nine pick-up points (41% of 22) are always present in the nine solutions produced for each combination of β and ϕ.

From the table, two main aspects emerge as relevant for our analysis. First, the reported percentages are very high, meaning that a non-negligible fraction of pick-up points tend to recur in the produced solutions. In fact, other than for $n = 22$ $(\gamma = 10\%)$, the percentage of recurring locations across all the tested combinations of the other relevant parameters always exceeds 50% (most of the time even significantly - see the last column in the table). Second, at equal values of n (γ), these percentages are higher for fixed values of ϕ rather than β. In other words, the chosen locations appear "more sensitive" to the varying attractiveness of home delivery (ϕ). This means that the attractiveness of home delivery induces location scenarios that are generally more invariant irrespective of the customers' sensitivity to travel (β).

Overall, location scenarios are proven relatively stable by varying parameters. Thus, the performed analysis provides insight into pick-up points the decision-maker can safely locate regardless of the uncertainties in estimating one or more parameters reflecting customers' behavior. Therefore, in a context where attitudes change rapidly, and behaviors are difficult to predict, this aspect confirms that the model can represent an appropriate tool to support self-collection network design decisions.

Table 5.3
Robust locations: number and percentage of recurring pick-up points by the calibration parameters n (γ), ϕ, and β

n	All ϕ-values			All β-values			All (ϕ, β)
(γ)	$\beta = 0.5$	$\beta = 1.0$	$\beta = 2.0$	$\phi = 0.5$	$\phi = 1.0$	$\phi = 2.0$	combinations
22 (10%)	16 (73%)	15 (68%)	14 (64%)	18 (82%)	18 (82%)	15 (68%)	9 (41%)
43 (20%)	31 (72%)	28 (65%)	26 (60%)	35 (81%)	34 (79%)	35 (81%)	24 (56%)
65 (30%)	51 (78%)	51 (78%)	51 (78%)	52 (80%)	55 (85%)	58 (89%)	43 (66%)
87 (40%)	62 (71%)	63 (72%)	70 (80%)	72 (83%)	75 (86%)	80 (92%)	56 (64%)
109 (50%)	83 (76%)	85 (78%)	78 (72%)	97 (89%)	93 (85%)	96 (88%)	71 (65%)
130 (60%)	113 (87%)	110 (85%)	111 (85%)	119 (92%)	120 (92%)	119 (92%)	101 (78%)
152 (70%)	141 (93%)	141 (93%)	137 (90%)	151 (99%)	146 (96%)	147 (97%)	136 (89%)
174 (80%)	169 (97%)	170 (98%)	169 (97%)	173 (99%)	172 (99%)	173 (99%)	168 (97%)
195 (90%)	189 (97%)	189 (97%)	191 (98%)	192 (98%)	194 (99%)	195 (100%)	188 (96%)
205 (94%)	203 (99%)	203 (99%)	203 (99%)	205 (100%)	(205 (100%)	205 (100%)	203 (99%)

(ii) Sensitivity to the number of located pick-up points

We now change the perspective of our analysis. So far, we have assumed the number of located pick-points (n) to be fixed and evaluated changes depending on customer behavior-related parameters. However, if the latter can be accurately estimated (e.g., based on survey data), it may also be reasonable to assess the stability of the produced solutions by varying n. Notably, this is a decision that may be adapted and changed over time. Likely, decision-makers may dynamically expand the network following the growing e-commerce trend and further promoting the self-collection strategy. Therefore, we went through all the produced scenarios again but, differently from the previous case, we sought pick-up points that, for fixed customers' behavior parameters (β, ϕ), recurred in all the solutions obtained by increasing the size n of the network. We now call these *permanent locations*; once located, in fact, these pick-up points remain active in successive network expansion.

To better understand this idea, Figure 5.6 illustrates the permanent pick-up points we found across the solutions gained by setting $\beta = \phi = 1.0$. In particular, each bar shows the composition of the produced solutions (in terms of pick-up points) for each tested value of n, with the number of permanent locations indicated in the double-edge-border rectangle. For instance, in the first solution ($n = 22$), we see 18 permanent locations; these pick-up points, in practice, are located in all the configurations gained by increasing n. The remaining (non-permanent) four are highlighted in red. Accordingly, the second solution ($n = 43$) comprises

38 permanent locations, which are the 18 just mentioned, plus 20 new ones that will also recur onwards.

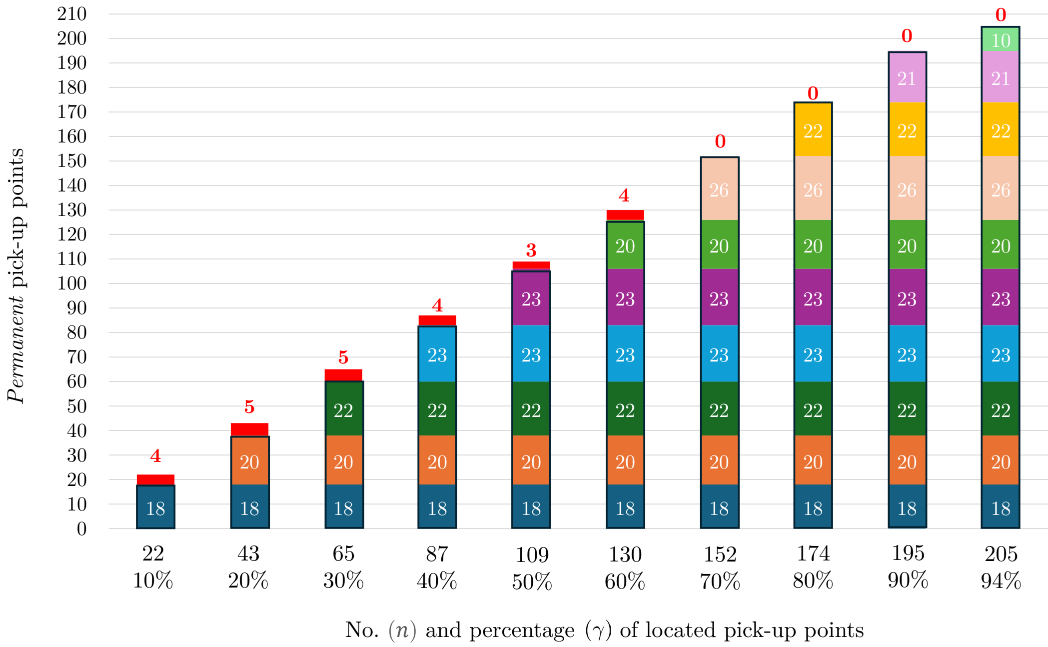


Figure 5.6: *Permanent locations*: number and percentage of recurring pick-up points by n ($\beta = 1.0$, $\phi = 1.0$)

In other words, we see a significant stability in the composition of the produced solutions. The extensive results reported in Table 5.4 confirm this first insight. In general, in fact, the number and percentages of permanent locations are relatively high for all the considered scenarios. As the results prove, the structure of the optimal solutions (in terms of pick-up point locations) is relatively stable by varying n at equal combinations of the other relevant parameters (β, ϕ). In conclusion, this analysis can provide intriguing insights for a service provider interested in broadening its network. As a practical implication, our findings reveal that an initial network can be expanded at negligible reorganization costs, that is, by keeping most of the located facilities active. Indeed, in doing so, we are sure that the optimal solution obtained by creating the expanded network from scratch is well-approximated by the (heuristic) solution obtained by progressive adjustments. This is equally true even if customers' behavior cannot be accurately predicted. For instance, if we consider $n = 65$ (see the third column in the table), we note that the percentage of permanent locations equals at least 80%. This fact suggests a closer look into the joint variation of the considered parameter that we discuss next.

(iii) Sensitivity to joint parameters' variations

The above analysis is now further extended to examine how the model reacts to joint-occurring variations in the considered parameters. This means searching for pick-up points that are invariant to any changing settings or, in our terminology, for simultaneously *robust* and *permanent locations*.

Hence, Table 5.5 displays the number and the percentage of recurring as well as permanent locations. For each value of n in the row, the permanent pick-up points that recur for the combination of ϕ and β in the column are identified. The table has the same structure as Table

Table 5.4
Permanent locations: number and percentage of recurring pick-up points by the calibration parameters n (γ), ϕ, and β

		n (γ)									
		22 (10%)	43 (20%)	65 (30%)	87 (40%)	109 (50%)	130 (60%)	152 (70%)	174 (80%)	195 (90%)	205 (94%)
$\phi = 0.5$	$\beta = 0.5$	12 (55%)	31 (72%)	54 (83%)	78 (90%)	105 (96%)	129 (99%)	151 (99%)	174 (100%)	195 (100%)	205 (100%)
	$\beta = 1.0$	14 (64%)	31 (72%)	52 (80%)	79 (91%)	105 (96%)	128 (98%)	151 (99%)	174 (100%)	195 (100%)	205 (100%)
	$\beta = 2.0$	16 (73%)	35 (81%)	56 (86%)	80 (92%)	103 (94%)	124 (95%)	151 (99%)	174 (100%)	195 (100%)	205 (100%)
$\phi = 1.0$	$\beta = 0.5$	16 (73%)	39 (91%)	61 (94%)	84 (97%)	107 (98%)	129 (99%)	152 (100%)	174 (100%)	195 (100%)	205 (100%)
	$\beta = 1.0$	18 (82%)	38 (88%)	60 (92%)	83 (95%)	106 (97%)	126 (97%)	152 (100%)	174 (100%)	195 (100%)	205 (100%)
	$\beta = 2.0$	18 (82%)	38 (88%)	61 (94%)	81 (93%)	103 (94%)	127 (98%)	152 (100%	174 (100%)	195 (100%)	205 (100%)
$\phi = 2.0$	$\beta = 0.5$	20 (91%)	38 (88%)	59 (91%)	84 (97%)	107 (98%)	129 (99%)	152 (100%	174 (100%)	195 (100%)	205 (100%)
	$\beta = 1.0$	19 (86%)	40 (93%)	61 (94%)	84 (97%)	105 (96%)	128 (98%)	152 (100%)	174 (100%)	195 (100%)	205 (100%)
	$\beta = 2.0$	21 (95%)	41 (95%)	61 (94%)	84 (97%)	106 (97%)	128 (98%)	152 (100%	174 (100%)	195 (100%)	205 (100%)

5.3, but, in this case, it indicates the permanent locations that are also robust to customers' behavior, depending on the uncertainty in estimating one or both of the considered parameters ϕ and β. In particular, the last column shows the "safest" deemed locations, i.e., those remaining unaffected by changes across all parameters. Indeed, these locations are permanent, independent of budget constraints, and robust to all possible combinations of behavior parameters. It is worth noticing that many locations are robust and permanent. For instance, with $n = 65$, 38 pick-up points (i.e., the 58%) are insensitive to all the parameters, confirming high model stability across parameters.

This evidence is an interesting contribution to decision-makers (especially to risk-averse ones) in making informed decisions about investing in self-collection services. In fact, it allows for a "safe" gradual expansion of the network by first locating solely pick-up points that make service attractive to customers, irrespective of their varying behavior.

5.6 Conclusions

This chapter addressed the problem of designing an effective self-collection network, including customers' choices in the decision.

To tackle the problem, we proposed a mathematical model for the optimal location of pick-up points in urban areas seeking to maximize the attracted demand, i.e., the proportion of customers opting for self-collection. The model constrains the number of pick-up points to locate, hence strucks a balance between the envisaged network expansion and the deriving costs. Customers' behavior was modeled using a MultiNomial Logit model, and their propensity for self-collection depends on the number of pick-up points, their relative distances, their sensitivity to travel, and their attraction to home delivery.

The model was applied to the case of Poste Italiane in the city of Bologna, and various scenarios were produced by varying crucial parameters. The obtained results provide insightful managerial implications. First, we observed that the marginal increase in the fraction of customers opting for self-collection stabilized by the number of located pick-up points. This

Table 5.5
Robust-permanent locations: number and percentage of recurring pick-up points by the calibration parameters n (γ), ϕ, and β

n	All ϕ-values			All β-values			All (ϕ, β)
(γ)	$\beta = 0.5$	$\beta = 1.0$	$\beta = 2.0$	$\phi = 0.5$	$\phi = 1.0$	$\phi = 2.0$	combinations
22 (10%)	9 (41%)	9 (41%)	8 (36%)	10 (45%)	13 (59%)	14 (64%)	5 (23%)
43 (20%)	25 (58%)	23 (53%)	24 (56%)	28 (65%)	23 (74%)	33 (77%)	21 (49%)
65 (30%)	45 (69%)	44 (68%)	47 (72%)	44 (68%)	53 (82%)	54 (83%)	38 (58%)
87 (40%)	61 (70%)	61 (70%)	66 (76%)	66 (76%)	73 (84%)	77 (89%)	54 (62%)
109 (50%)	83 (76%)	84 (77%)	77 (71%)	94 (86%)	92 (84%)	94 (86%)	70 (64%)
130 (60%)	113 (87%)	110 (83%)	108 (85%)	119 (92%)	118 (91%)	119 (92%)	101 (78%)
152 (70%)	141 (93%)	141 (93%)	137 (90%)	151 (99%)	146 (96%)	147 (97%)	136 (89%)
174 (80%)	169 (97%)	170 (98%)	169 (97%)	173 (99%)	172 (99%)	173 (99%)	168 (97%)
195 (90%)	189 (97%)	189 (97%)	191 (98%)	192 (98%)	194 (99%)	195 (100%)	188 (96%)
205 (94%)	203 (99%)	203 (99%)	203 (99%)	205 (100%)	(205 (100%)	205 (100%)	203 (99%)

evidence indicated the existence of practical upper bounds in the number of pick-up points beyond which expansion strategies are no longer convenient, as the deriving advantage in service usage does not pay off the occurring costs. Moreover, the solutions highlighted the presence of significant portions of the so-called *robust* and *permanent locations*, i.e., pick-up points that kept being located despite changing parameters' settings (irrespective of customers' behavior and budget constraints). These locations suggested the possibility of designing robust networks able to hedge against sources of uncertainty and prone to potential future expansion in a gradual and multi-period fashion. Overall, the obtained results confirmed that the proposed model could effectively support the decision-maker process. Indeed, in a context where customer attitudes are difficult to predict, this model offers an appropriate tool to produce location scenarios by combining parameters that reflect different customers' behavior.

Of course, this study is not free from limitations, which, together with its insights, open to various research opportunities. Although extant literature suggests that distance from home is the most relevant factor, enhanced attractiveness functions should also account for other reasonable drivers (e.g., proximity to places of work or interest and parking availability, to name a few). Also, further empirical work is necessary to fine-tune the model's calibration parameters. To this end, an ad-hoc data collection campaign or extensive surveys on customers' habits and behaviors could be conducted. This also calls for refined demand segmentation based on socioeconomic characteristics (e.g., age, income).

CHAPTER 6

Delivery areas design in urban contexts: a probabilistic approach

Summary

This chapter explores the challenge of redesigning delivery areas for last-mile logistics in response to the development of pick-up point networks. We introduce an innovative districting approach that groups urban areas into delivery areas, each managed by a specific operator. Our method ensures balanced workloads across districts, maintaining efficiency and meeting delivery time requirements. A key feature of this approach is the integration of visit probabilities, which captures the uncertainty of customers' preferred delivery modes. This enables an evaluation of how pick-up points power consolidation, reducing reliance on home delivery and, consequently, lowering operational costs. The approach is applied to a real-world case study involving Poste Italiane in the city of Bologna, leveraging detailed customer data and historical delivery records. The results yield robust planning solutions, showcasing the operational advantages of incorporating self-collection options into last-mile logistics and offering valuable insights for more informed decision-making.

6.1 Introduction and contribution

In previous chapters, we have addressed the strategic problem of locating pick-up points in urban areas, utilizing both deterministic accessibility-based measures and probabilistic approaches involving discrete customers' choice models. We now move forward in our analysis. Indeed, once an effective network is established, reorganizing delivery operations becomes crucial to align tactical aspects with strategic decisions. As previously argued, pick-up points play a significant role in encouraging customers to adopt self-collection. Consolidating parcel deliveries at these points reduces reliance on home delivery and decreases the number of locations operators need to visit; therefore, it is expected to lower their daily workload and generate cost savings. Accordingly, (i) the reorganization of delivery operations based on pick-up point location scenarios and (ii) the quantification of the associated economic impacts emerge as two relevant issues.

To address these, this chapter presents a practical methodological proposal for the *design of delivery areas* in last-mile contexts. Notably, the organization of service areas in distribution logistics is a consolidated practice. This is commonly approached by resorting to *territory design/districting* methodologies (Kalcsics and Ríos-Mercado, 2019). In the literature, several successful examples of districting applications in distribution logistics are found (see also our discussion in Section 2.4.1). Nevertheless, studies that include explicit routing considerations are limited, and, to the best of our knowledge, none of the available works account for the uncertainties associated with daily visit probabilities at customer nodes and pick-up points. In fact, creating stable and robust territories may be a preferable alternative to solving operational routing. As routes to visit all the customers requiring a parcel may vary from day to day, a more tactical posture is convenient. The overall area to be served (e.g., a city) can be grouped into a given number of delivery areas (the *districts*), each assigned to a specific operator. This way, operators may follow a predefined routing plan—which they adjust dynamically based on customers' daily appearances (skipping those that must not be served)—or organize their daily tours from scratch based on deterministic customer information. Furthermore, such a districting approach enhances operators' *familiarity* with their zones, which improves their performance and heightens customer satisfaction in the mid-to-long run. In fact, as the operator becomes familiar with his zone, he enhances his ability to find customers and, ultimately, his overall performance.

In this context, our research introduces a novel districting procedure that, alongside other typical planning criteria, accounts for *workload requirements*. As a practical condition, the latter ensures that the expected workload in each district remains within specified limits—namely, that daily deliveries are completed in a maximum amount of time. The workload includes the time required to travel, stop, and serve all points within the district (i.e., customers and pick-up points). Thus, it reflects the day-to-day operators' effort under a combination of home delivery and self-collection strategies. The approach also accounts for uncertainty associated with customer preferences toward the strategies with the aim of assessing the impact of different pick-up points network configurations on delivery costs. The procedure is applied to the case study of the city of Bologna, using fine-grained information on customers' locations and historical data on delivery volumes. Results from the performed experiments highlight the value of self-collection, showing the impact of pick-up points' presence in reducing the workforce required to perform daily deliveries and, hence, the associated costs. In addition, we also demonstrate the robustness of the obtained reorganization solutions against varying operational settings and projected delivery volumes. This way, we intend to propose a methodological approach that, beyond its scientific contributions, provides actionable insights enhancing the decision-making practice.

The remainder of the chapter is organized as follows. In Section 6.2, we formally describe the problem at hand and provide its mathematical formulation. The heuristic procedure devised to solve the problem is then formalized in Section 6.3, while the empirical results follow in Section 6.4. Finally, Section 6.5 summarizes the work done and outlooks potential directions for future improvements.

6.2 Problem description and formulation

The problem we investigate involves a logistic provider facing the need to identify an efficient and effective solution to organize parcel delivery services.

To illustrate it, we refer to a generic geographical area divided into a finite set of indivisible elements, hereafter denoted by *Territorial Units* (*TUs*—e.g., city blocks, census tracts, etc.). Within each TU, we consider the presence of a discrete set of nodes, where potential *customers* reside. We assume each node is associated with a daily probability of receiving a parcel. In addition, we consider the presence of a pre-defined set of *pick-up points* where customers may collect parcels (*self-collection*) instead of being served at home (*home delivery*). Moreover, we hypothesize that customers' preferences for self-collection are known and that an explicit model is available to compute their propensity to patronize pick-up points. This ultimately depends on the network configuration (see Chapter 5), which in turn influences the points' visit probabilities. Indeed, as the network becomes denser, more users are willing to utilize these points, which consequently reduces the probability of visiting them at home. Finally, we assume that the size of the *workforce*, i.e., the number of *operators* to carry out the day-to-day deliveries, is given and that the tour of each operator starts [ends] from [at] a specified depot.

In this context, the logistic provider seeks to cluster TUs into *delivery areas* (the *districts*) such that the following *planning criteria* are met:

- *Compactness*: districts must be generally round-shaped and with relatively small territorial extensions. This should help limit the distances that assigned operators need to cover.
- *Integrity*: each TU must be assigned to only one district. Hence, all customers in a TU must always be served by the same operator. In turn, this increases customers' familiarity with the operators (and, hopefully, their satisfaction).
- *Contiguity*: districts must not contain enclaves/exclaves. This implies that districts must be non-overlapping, which assures a clear distinction among the delivery zones assigned to each operator. In principle, contiguity also ensures that it is possible to visit all the nodes in a district without crossing any other district.
- *Maximum workload*: districts must be created to ensure that their workload—i.e., the time to visit customers' nodes and pick-up points, plus the time to stop and serve them—does not exceed a given upper bound. In other words, all daily deliveries should be completed in a maximum amount of time. Possibly, a lower bound can also be considered to convey a more balanced distribution of workloads across the districts. Clearly, points are characterized by visit probabilities that influence the workload measure. To account for this feature, we consider the *expected workload* within each district in the requirements.

The discussed scenario conveys a Districting Problem (DP) in which the peculiarity resides in the workload constraints. In fact, unlike traditional demand balancing—for which exact or approximate linear representations also exist under uncertain conditions (see, e.g., Diglio et al., 2020, 2023)—these requirements are non-trivial to be treated as they involve probabilistic routing aspects. The latter adds further complexity to the problem, and its explicit mathematical formulation would easily yield an intractable-to-solve model, even for small test cases. For this reason, a tailored heuristic procedure is presented in Section 6.3.

To ease the presentation of the problem, a simplified mathematical model is presented in Section 6.2.1. Details on workload considerations and how we cast this feature based on points visit probabilities are given in Section 6.2.2.

6.2.1 Optimization model

We start by introducing some notation to model the problem. Note that most aspects considered here are already in Appendix A—specifically, Section A.2. Still, we prefer resuming them to ensure the current section is self-contained.

Let I be the set of TUs and n the districts we want to create (i.e., the number of available operators). We also denote by c_{ij} the distances between the pair of centroids of the TUs i and j. In addition, let A be the adjacency matrix that includes all direct links between the TUs (one link exists for each pair of adjacent TUs $(i, j) \in I$, i.e., $a_{ij} = 1$). Consequently, for each TU $i \in I$, we denote by A_i the set of nodes adjacent to i, which is: $A_i = \{j \in I : a_{ij} = 1\}, i \in I$.

To model the problem, we use the well-known location-allocation scheme, according to which we first identify n "special" TUs act as the *center* (or *representative*) of a district and then assign each TU to only one of them. To this end, we use binary variables x_{ij}, equal to 1 is TU i is assigned to TU j and 0 otherwise. We note that x_{jj} denotes that TU j is assigned to itself (hence, the *center* of the district). The problem consists of identifying n contiguous districts with the aim of maximizing their compactness, expressed as the average distance of each TU from its assigned center. To ensure that deliveries are completed on time, we impose that the associated expected workload ($E[W_j]$, for each district j) remains within the limit defined by an upper bound (UB). This measure depends on visit probabilities of points included in the districts and can be computed only once the district is formed. This makes the problem solvable solely with an ad-hoc heuristic procedure.

The model can be formulated as follows:

$$\begin{aligned}
\text{minimize} \quad & \sum_{i \in I} \sum_{j \in I} c_{ij} x_{ij} && && (6.1)\\
\text{subject to} \quad & \sum_{j \in I} x_{ij} = 1 && i \in I && (6.2)\\
& x_{ij} \leq x_{jj} && i, j, \in I && (6.3)\\
& \sum_{j \in I} x_{jj} = n && && (6.4)\\
& \sum_{i \in S} x_{ij} - \sum_{i \in \cup_{v \in S}(A_v \setminus S)} x_{ij} \leq |S| - 1 && j \in I, S \subset [I \setminus (A_j \cup \{j\})] && (6.5)\\
& E[W_j] \leq UB && j \in I : x_{jj} = 1 && (6.6)\\
& x_{ij} \in \{0, 1\} && i, j \in I && (6.7)
\end{aligned}$$

The objective function (6.1) minimizes the sum of TUs' distances from the centers of the districts and, thus, optimizes *compactness*. Constraints (6.2), due to the binary nature of the

x-variables expressed by (6.7), ensure *integrity* by forcing that each TU i is assigned to only to one district. Constraints (6.3) are logical conditions guaranteeing that each TU i can only be assigned to a TU j selected as the center of a district. Equalities (6.4) define the number of districts to be devised. Inequalities (6.5) model *contiguity*. This formulation, introduced by Drexl and Haase (1999) and inspired by the sub-tour elimination constraints for the *Traveling Salesman Problem*, assures that for any given subset S of TUs assigned to representative TU j not containing TU j, there must be an arc between S and the set containing i. Finally, Constraints (6.6) state that the expected workload in each district must be lower or equal to the imposed UB, that is, *workload requirements* are met.

6.2.2 The problem of workload requirements

The peculiarity of the described model lies in the presence of the workload requirements. To deeply analyze this feature and facilitate its full understanding, we present an example of a possible solution, i.e., a districting plan. Figure 6.1 depicts a study area consisting of 16 square-shaped TUs, clustered into four districts. TUs belonging to the same district are represented by the same color, with district borders highlighted using double-edged lines.

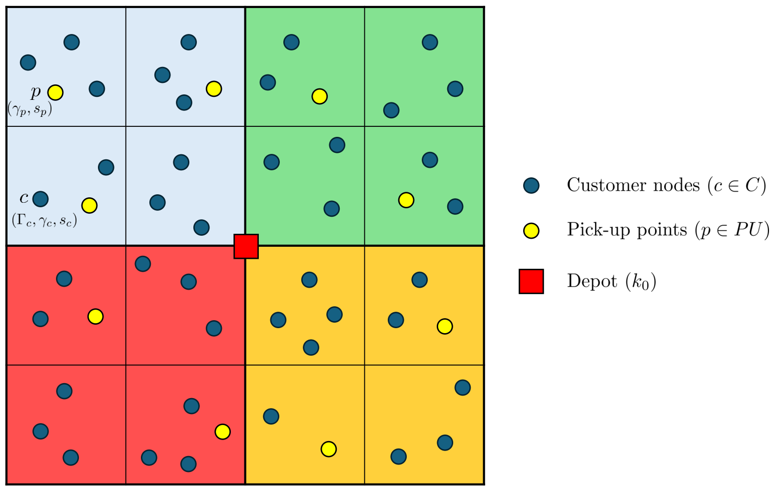


Figure 6.1: An example of a districting solution to our problem

Observe that each TU belongs only to one district (*integrity*), and no enclaves/exclaves are present (*contiguity*). Blue and yellow dots represent customers' nodes (C) and pick-up points (PU), respectively. Dots within each square identify the subset of nodes K_i belonging to TU $i \in I$. The set of nodes belonging to the district j is indicated with K_j. Each customer node $c \in C$ is associated with the tuple $(\Gamma_c, \gamma_c, s_c)$, specifying its probability of requiring a parcel (Γ_c), its probability of being visited at home, and the time needed by the operator to serve that node (s_c). Similar information is given for pick-up points $p \in PU$, i.e., their visit probabilities (γ_p) and service times (s_p). The depot k_0, identified by the red square, is conveniently located in the center of the area.

In this setting, the problem is understanding how to estimate the expected workload within a district, given the visit probabilities of each point. To this aim, we first focus on the way we represent them.

Customers' choice and visit probabilities

Customers in a generic node c have two delivery options: self-collection and home delivery. Following assumptions made in Chapter 5, we suppose that the behavioural model is represented by the *Multinomial Logit* discussed in Section 5.3. Accordingly, the probability of patronizing a pick-up point depends on (i) a parameter reflecting customers' sensitivity to the distances (β), (ii) the attractiveness for the home delivery (ϕ), and (iii) the number of points within a predefined radius (p), defining the set N_c. Hence, relying on Eq. 5.2 and Eq. 5.3, this probability (p_{ck}) is equal to:

$$p_{ck} = \frac{e^{-\beta_c d_{ck}}}{\sum_{h \in N_c} e^{-\beta_c d_{ch}} + \phi_c} \tag{6.8}$$

With this in mind, from Figure 6.1, we noticed that each customer node is associated with a daily probability of receiving a parcel (known beforehand), say Γ_c, and a probability of being visited at home, say γ_c. Now, let's consider two explicative cases, as in Figure 6.2.

(a) Case 1: Home delivery

(b) Case 2: Home delivery and self-collection

Figure 6.2: Customers' choice representation

In the first case (Figure 6.2a), we suppose that no pick-up points are located in the neighborhood c. Hence, customers can only be served via home delivery, and the daily probability of being visited coincides with that of receiving a parcel ($\gamma_c = \Gamma_c \, c \in C$).

In the second case (Figure 6.2b), customers can opt for self-collecting parcels from any of the two located pick-up points k. Here, the probability γ_c of visiting them at home depends on their choices, and, according to Eq. 6.8, can be expressed as:

$$\gamma_c = \Gamma_c(1 - \sum_{k \in N_c} p_{ck}) \tag{6.9}$$

As shown by this example, the impact of pick-up points on customers' choices is evident. In fact, wider availability of points increases the probability of choosing the self-collection service, as expressed by the term $\sum_{p \in N_c} p_{ck}$. This leads to a corresponding reduction in the probability of home delivery (Eq. 6.9).

Naturally, the visit probability of pick-up points γ_p also depends on customers' choices. In particular, it can be expressed as:

$$\gamma_p = 1 - \prod_{c \in M_p} (1 - p_{cp}) \tag{6.10}$$

where M_p is the subset of customers' nodes within distance r from p (Figure 6.3).

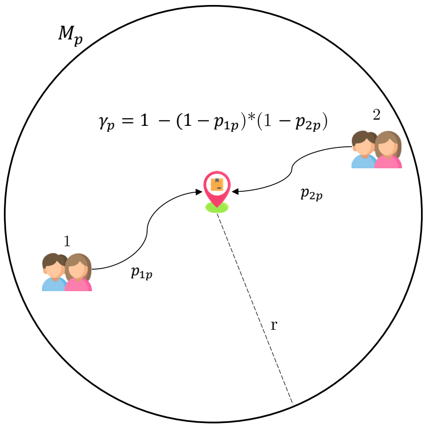


Figure 6.3: Pick-up point visit probability

The above expression can be derived by observing that $\prod_{c \in M_p}(1 - p_{cp})$ expresses the probability that no customers $c \in M_p$ self-collect at pick-up point p (these events are assumed to be statistically independent). Hence, $1 - \prod_{c \in M_p}(1 - p_{cp})$ represents the probability that at least one customer receives a parcel at pick-up point p, and, hence, that p must be visited.

Expected workload estimation

Now, based on visit probabilities, the expected workload must be estimated. In our setting, the expected workload $E[W_j]$ of the generic district j (Figure 6.4) is the sum of two terms: (i) the *expected service time* $E[S_j]$ to serve all the nodes in the district (whose set is indicated with K_j); (ii) the *expected visit time* $E[V_j]$ to route through these nodes.

$$E[W_j] = E[S_j] + E[V_j] \tag{6.11}$$

The expected service time $E[S_j]$ is computed by considering all the nodes belonging to the district weighted by their visit probabilities. In particular, if s_k is the time needed by an operator to serve a generic node k, the expected service time for district j can be easily expressed as:

$$E[S_j] = \sum_{k \in K_j} \gamma_k s_k = \sum_{c \in K_c} \gamma_c s_c + \sum_{p \in K_p} \gamma_p s_p \tag{6.12}$$

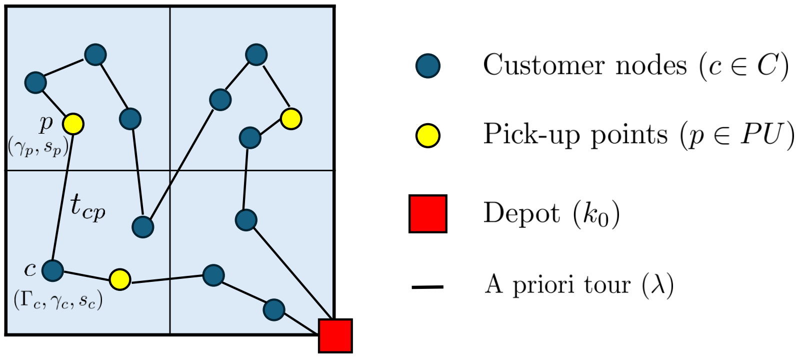


Figure 6.4: An example of workload estimation in a district

where K_c and K_p are the set of customers and pick-up points, while s_c and s_p their respective service times.

Being dependent on visit probabilities, Eq. 6.12 highlights the role of pick-up points in reducing the total expected service time. A dense network decreases the visit probabilities of customer nodes, thereby lowering their expected service times ($\sum_{c \in K_c} \gamma_c s_c$) while increasing the contribution from pick-up points ($\sum_{p \in K_p} \gamma_p s_p$). However, since customer nodes are more numerous than pick-up points, this significantly reduces the overall expected service time in the district ($E[S_j]$).

As for the expected visit time $E[V_j]$, a possible solution to measure it emerges upon observing that we are challenged with a stochastic routing problem. In particular, the problem of determining the optimal route to visit a set of nodes, each with a specific visit probability, is known in the literature as the *Probabilistic Traveling Salesman Problem (PTSP)*—see, e.g., Bertsimas and Howell, 1993; Bianchi et al., 2002, 2005; Laporte et al., 1994). The solution to this problem is commonly obtainable by first determining a priori tour of minimal length (λ in Figure 6.4, where t_{cp} denotes the travel time between any two nodes). This must visit all nodes starting and ending at the depot. Then, assuming that actual nodes are visited in the same order as they appear in the a priori tour, the so-called *skipping strategy* is implemented, "bypassing" certain nodes based on their probabilities. Grounded on this and following the notation already introduced, the expected visit time of the district can be calculated using the closed formula (demonstrated by Jaillet, 1985):

$$E[V_j] = \sum_{k=1}^{|K_j|} \sum_{l=k+1}^{|K_j|} t_{kl} \gamma_k \gamma_l \prod_{m=k+1}^{l-1} (1-\gamma_m) + \sum_{l=1}^{|K_j|} \sum_{k=1}^{l-1} t_{lk} \gamma_l \gamma_k \prod_{m=l+1}^{|K_j|} (1-\gamma_m) \prod_{m=1}^{k-1} (1-\gamma_m) \quad (6.13)$$

In the above expression, t_{kl} denotes the time to move between any two generic nodes k and l in the district (without any distinction between customer nodes and pick-up points). For the sake of clarity, we specify that the probability of visiting the depot equals 1, as the tour starts and ends at the depot itself. The first term in the formula accounts for the expected visit time contribution when moving forward in the a priori tour. It considers a scenario where node k is visited before node l, weighted by their respective visit probabilities γ_k and γ_l. The product term $\prod_{m=k+1}^{l-1}(1-\gamma_m)$ represents the probability that all intermediate nodes between k and l are skipped, meaning the operator travels directly between these two nodes. The second term captures the contribution when moving backwards along the tour, meaning the operator visits node l before node k, which can occur due to the probability of skipping other nodes. The product $\prod_{m=l+1}^{|K_j|}(1-\gamma_m)$ ensures that no nodes are visited between l and the end of the tour, while $\prod_{m=1}^{k-1}(1-\gamma_m)$ accounts for skipping all nodes before k.

In general, the formula calculates the expected visit time based on the dynamic skipping of nodes, reflecting how the probabilistic nature of the problem "reshapes" the optimal a priori tour. Again, the contribution of pick-up points is clear. In fact, lowering the visit probabilities of customer nodes increases the "skipped nodes" contribution, thereby significantly reducing the total expected visit time within the district.

A feasible solution to our problem verifies that this expected workload remains within the given UB.

6.3 A heuristic solution approach

In order to solve the described problem, a heuristic procedure is proposed. The main steps of the procedure are depicted in Figure 6.5. A description of each of them follows.

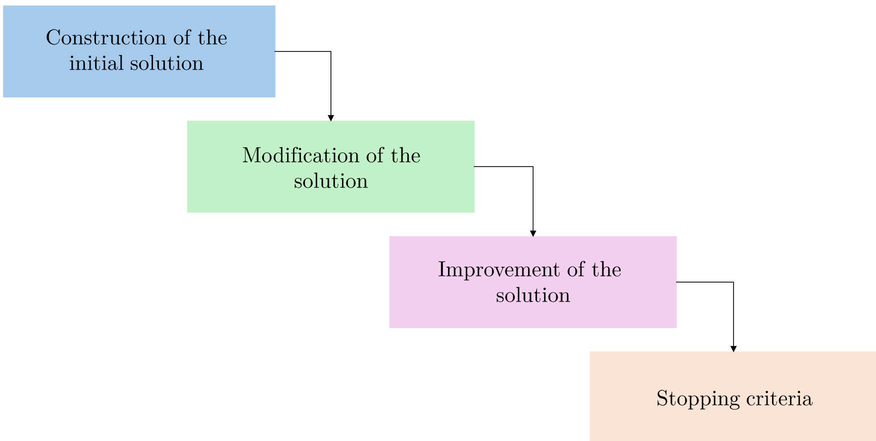


Figure 6.5: Heuristic procedure

- *Construction of the initial solution*

  The first step of the heuristic is to devise an initial districting plan X as a starting point to find a feasible solution to our problem. For this phase, we use the procedure briefly described below and formalized in Appendix D, Section D.1.1. Specifically, the algorithm starts by solving an uncapacitated p-median problem to identify n centers to which TUs are assigned without considering contiguity constraints. Then, using an ad-hoc procedure, contiguity is corrected.

- *Modification of the solution*

  After obtaining an initial districting plan (X), we check its feasibility by considering the workload requirements. This is done by evaluating the expected workload $E[W_j]$ in each district. In this step, we calculate the deviation from the upper bound, identifying the violations. The process returns the highest violation (*maxViolation*), and if this value equals zero, the solution is considered feasible, otherwise we need to change it. To this end, we identify the most unbalanced district (namely *target district*, i.e., that with the highest maxViolation) and attempt to adjust it. Specifically, we try to "unload" it by reassigning one of its TUs to an adjacent district. In the routine, the most underloaded district is prioritized for receiving additional workload. TUs are also sorted in descending order based on their expected service time, meaning that the TU with the highest value is tried to be reassigned first. If the target district cannot be unloaded due to neighboring ones being too full, an adjacent one is randomly selected, and a TU is removed from it. This creates space for future adjustments. Details and the algorithmic schemes are in Appendix D, Section D.1.2.

- *Improvement of the solution*

  If a feasible solution to our problem is found ($X^\star$), we start a local search phase to improve its compactness (details are given in Appendix D, Section D.1.3). In particular, we evaluate the reassignment of any TU to any other district. Specifically, we accept the change if (i) it reduces the current objective function value, (ii) it does not break contiguity, and (iii) the resulting solution remains feasible. Once all TUs have been analyzed, we further improve compactness by changing the center of the districts. This is done by solving a 1-median problem in each district. If centres are changed, we re-evaluate TUs' reassignments.

- *Stopping criteria*

  The procedure runs until a specified `timeLimit` is reached. It either returns the best feasible solution to the problem (in terms of compactness) or the districting plan with the lowest *maxViolation*—i.e., the "least unfeasible" solution found. Clearly, if no further improvements are possible (in the improvement phase), the procedure stops and returns the solution.

Algorithm 1 provides an overview of the entire described procedure.

6.4 Application and results

The city of Bologna was again selected as a representative case for our tests. Specifically, we considered its 2,334 census tracts as the reference TUs and identified set I with their centroids ($|I| = 2,334$). Accordingly, we calculated the pairwise distances c_{ij} for each pair of TUs $(i, j) \in I$ as the Euclidean distances between their centroids, along with the adjacency matrix A. To represent the set of customer nodes C ($|C| = 40,235$), we used publicly available data on street numbers in Bologna (accessible at https://opendata.comune.bologna.it/). In total, $|K| = 40,452$ nodes were considered. Additionally, the position of the depot (k_0) was given. Figures 3.3 and 3.4a offer a graphical representation of the case study, distinguishing the main sets involved.

Using these data, we calculated the Euclidean distances d_{kl} for each pair of nodes $(k, l) \in K$. Following Seghezzi et al. (2022), the corresponding travel times (t_{kl}) were obtained by

Algorithm 1 Overall solution procedure (`maxIter`, `timeLimit`)

maxViolation $\leftarrow +\infty$; // current solution's maximal workload violation.
bestViolation $\leftarrow +\infty$; // lowest maximal violation so far.
$X \leftarrow$ CONSTRUCTINITIALDISTRICTING(`maxIter`); // current solution—Algorithm D1.
$X^\star \leftarrow X$; // best solution.
Let UB^+ the vector storing the districts' violations w.r.t. the bound in (6.6);
maxViolation $\leftarrow$ EVALUATEVIOLATION(X, UB^+); // Algorithm D2.
while `timeLimit` is not reached **do**
  if maxViolation > 0 **then**
    $X \leftarrow$ CHANGETHESOLUTION(X, maxViolation, UB^+); // Algorithm D3.
    maxViolation $\leftarrow \max_{j \in I: x_{jj}=1}\{UB_j^+\}$; // changed solution's maximal violation.
    if maxViolation $<$ bestViolation **then**
      bestViolation $\leftarrow$ maxViolation; // update best violation.
      $X^\star \leftarrow X$; // update best solution.
    end if
  else
    $X^\star \leftarrow$ IMPROVECOMPACTNESS($X^\star$); // Algorithm D5.
  end if
end while
return $X^\star$; // the best feasible solution (if any) or that with the lowest maximal violation.

considering a standard vehicle speed equal to 15 km/h. We also fixed the same service time—three minutes—for all nodes (i.e., $s_k = 3$ min., $k \in K$). In agreement with Poste Italiane, the daily likelihood of a customer receiving a parcel (Γ_c) was estimated as the ratio of the (average annual) number of daily delivered parcels, denoted as $\overline{V}$, to the total customer's nodes. In practice, we have: $\Gamma_c = \frac{\overline{V}}{|C|}$, $c \in C$, with $\overline{V} = 3011$ in our case. This results in a daily probability of approximately 7.5%, indicating that, on average, a customer receives a parcel roughly once every 13 days. For our tests, we varied the maximum time limit (UB) to perform a sensitivity analysis of the produced scenarios.

Since our case study involves a very high number of customer nodes, to ease the computational effort, we employed a methodology to reduce the size of the problem. Details on this are given in Appendix D, Section D.2. Instead, the setting of technical parameters for the heuristic is reported in Appendix D, Section D.3.

Preliminary assessment: the impact of pick-up points on customers' visit probabilities

As the number of pick-up points is expected to reduce the probability of visiting customers at home according to the mechanism described above, we perform our experiments by varying the number (p) of located points. This allows us to evaluate and quantify the impact of different network sizes and configurations on customer choices and, consequently, on delivery operations. In particular, we considered the location scenarios produced in Chapter 5 with the customer's behaviour parameters set to 1 ($\phi = \beta = 1$) and varied the network size p up to the entire potential pick-up points network ($|PU| = 217$—see also Section 3.4.1).

As a preliminary assessment, Figure 6.6 illustrates the average visit probabilities of customer nodes as the number of pick-up points increases. As expected, in the initial scenario without any pick-up points, all customers have a visit probability of 7.5%, corresponding to the likelihood of receiving a parcel (Γ_c). As the pick-up point network expands, the average visit probability decreases significantly, ultimately dropping to 3.1% (approximately half the initial value) when the entire network is utilized.

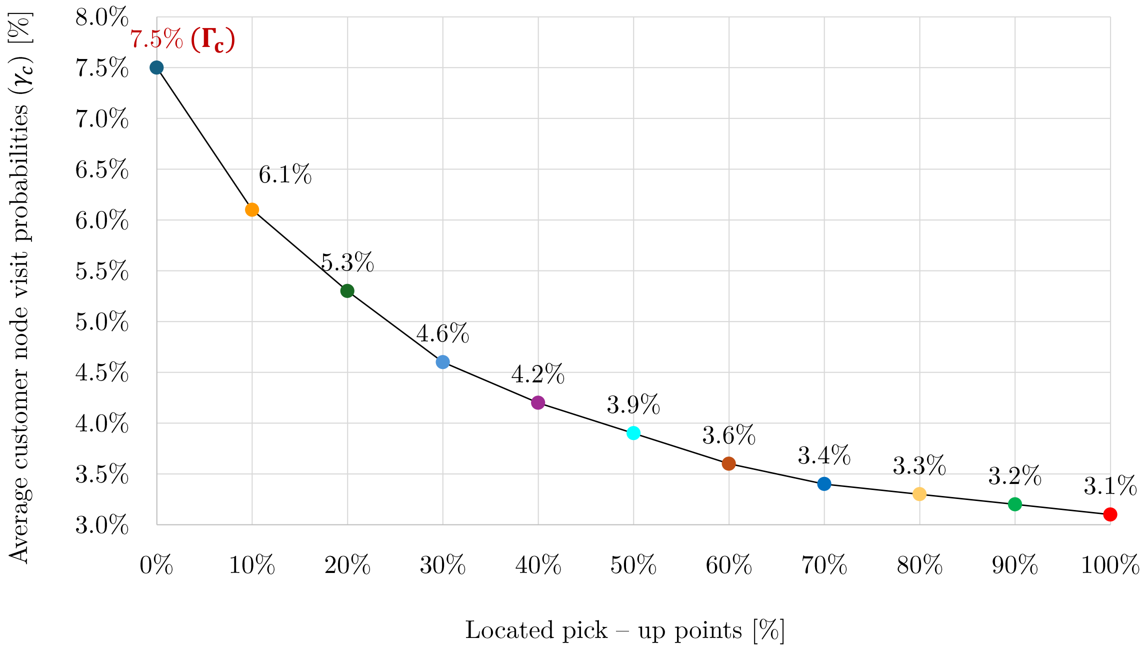


Figure 6.6: Average customer node visit probabilities by percentage of located pick-up points

From this result, it is evident that a dense network of pick-up points can significantly reduce home deliveries. Following these outcomes, we applied the procedure to effectively evaluate the cost savings resulting from the integration of the pick-up point network in a last-mile delivery system.

6.4.1 Main findings

In this section, we present the results obtained from the application of the proposed algorithm to the case of Bologna. The objectives of our analysis are manifold.

First, we seek to assess the impact of integrating self-collection into delivery operations. With this aim in mind, we first characterize the so-called *baseline scenario*, i.e., the case in which no pick-up points are located, and home delivery is the only available option to serve customers. Next, we benchmark the baseline scenario against several optimized design configurations for the self-collection network. Through this comparison, we provide an evaluation of how network design decisions, particularly the dimensioning of the network, influence key factors such as workforce sizing and daily workloads. Furthermore, these effects are analyzed under diverse operational conditions, primarily focusing on variations in the allowed time windows for completing daily deliveries. This analysis captures the dynamic nature of delivery operations and highlights how operational constraints interact with delivery zone design.

Finally, we assess the effects of increased delivery volumes to demonstrate the robustness of the proposed solutions. By testing the optimized districting configurations under scenarios of higher-than-expected demand, we evaluate their resilience and practicality in real-world settings. This step illustrates how the proposed tactical approach applies effectively to an operational-level framework, particularly under uncertain conditions.

Baseline scenario: home delivery strategy

In the *baseline scenario*, no pick-up points are available, and customers are served exclusively via home delivery. In this case, they are visited with a daily probability of 7.5% (once every two weeks).

We start by presenting the results assuming that daily deliveries are expected to be completed in 4 hours. Figure 6.7 reports the average workload for solutions spanning from the first feasible (with 62 districts) until that with 70 districts, with a peace of two. Also, table 6.1 presents the relative standard deviations of the workloads and the percentage of districts with a workload exceeding 95% of the maximum (i.e., the *saturated districts*). The first indicator measures the balance of operators' activities within a districting plan, while the second quantifies the number of zones where the available time window is nearly fully utilized.

We notice that 62 districts (hence operators/vehicles) are the minimum required to complete all the home deliveries in Bologna within 4 hours. Although, on average, each operator works for 3.3 hours, more than 30% of the districts are saturated, meaning that operators use almost the whole delivery window for completing deliveries. As expected, the average workload decreases with n, and the relative standard deviations remain consistently around 20% across all cases. This indicates that as the number of operators increases, they can complete deliveries in less time. The nearly similar relative standard deviations suggest that this reduction is evenly distributed among all. Additionally, the percentage of saturated districts decreases significantly, almost halving (from approximately 30% to 15%). Therefore, there are more operators working without fully utilizing their time window, allowing for a greater margin of flexibility to complete their tasks comfortably.

Hence, although 62 is the minimum required to complete deliveries on time, solutions with more operators can be particularly appealing to a *risk-averse* decision-maker. Indeed, this could be willing to "pay" the cost of a larger workforce size to ensure a safety buffer within the window. A similar approach provides operators with the flexibility to complete deliveries even when unforeseen events occur, such as traffic or changes in road viability.

Table 6.1
Relative Standard Deviation (RSD) of workloads and percentage of saturated districts (Baseline Scenario)

	Number of districts (n)				
	62	64	66	68	70
RSD workloads [%]	20%	23%	22%	22%	22%
Saturated districts [%]	31%	32%	26%	21%	16%

As an example, Figure 6.8 illustrates the districting plan with $n = 62$. In the figure, the districts are tematized with different colours. These are all contiguous and as compact as possible. Naturally, the compactness largely depends on the characteristics of the basic territorial units, which are not always "round-shaped". However, it is clear that the smallest districts are concentrated in the central area, where the highest density of customers is located (see Figure 3.3b).

A decision-maker might be interested in completing deliveries in less time to increase the

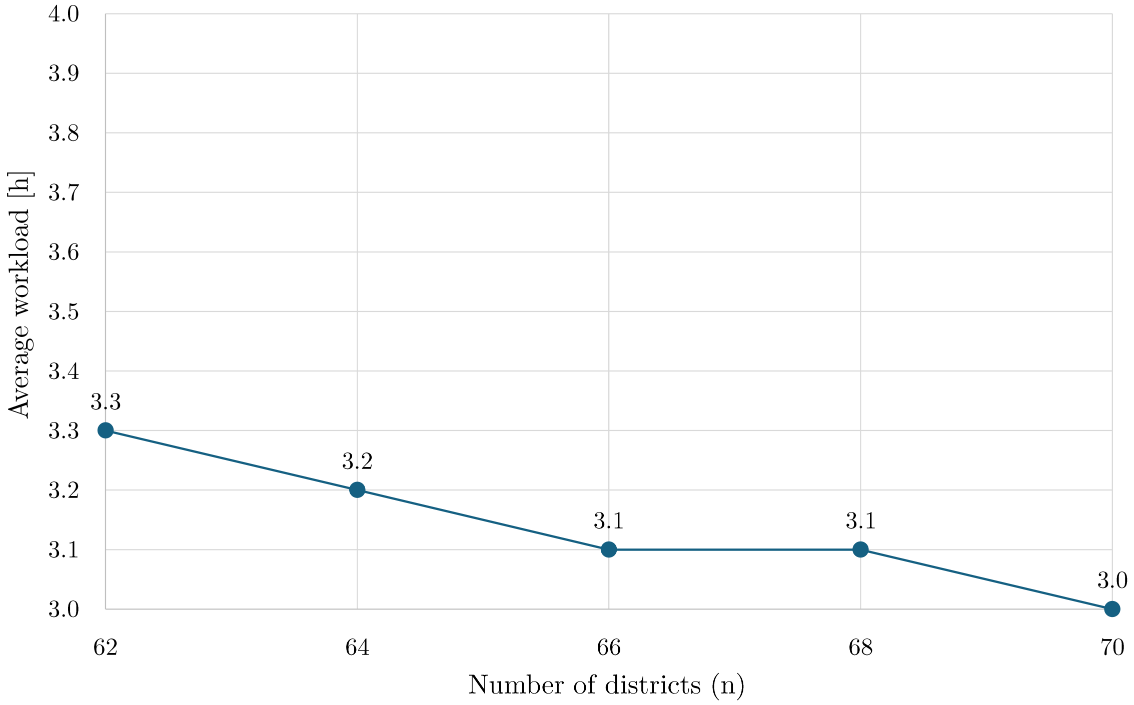


Figure 6.7: Average workloads per number of districts (Baseline Scenario)

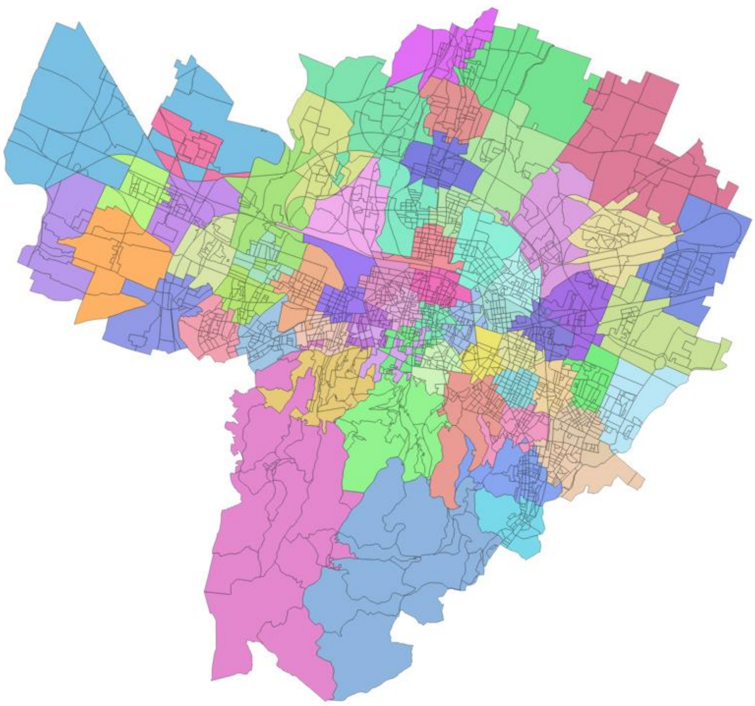
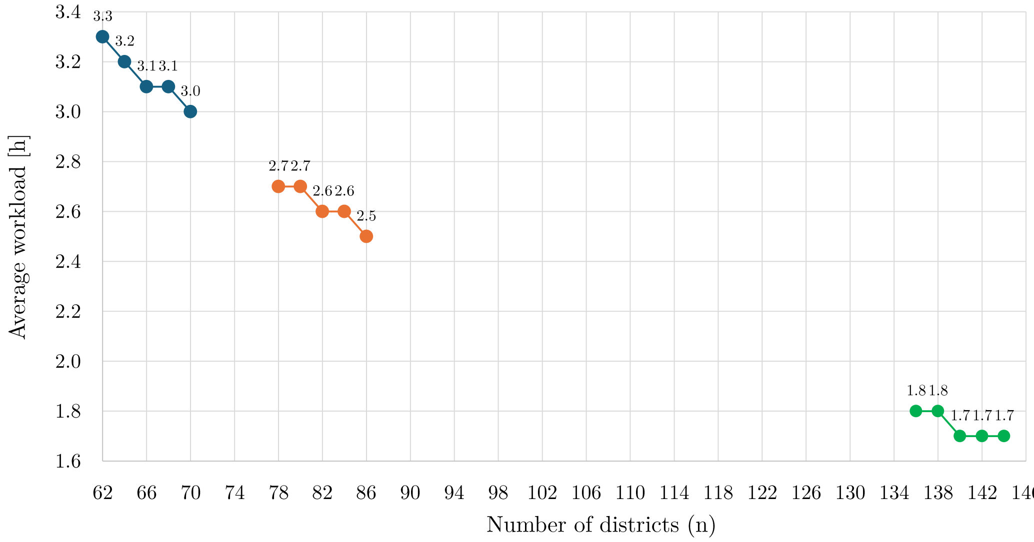


Figure 6.8: Map of Bologna: baseline scenario with 62 districts

efficiency of the service. To this end, it could be valuable to analyze the impact of reducing the maximum workload and, thus, the delivery window on the district design. Figure 6.9 presents the average workloads for the first five feasible solutions under different maximum available times (4, 3, and 2 hours). The accompanying table provides the RSD of the workloads and the percentage of saturated districts.



4 h	Number of districts (n)				
	62	64	66	68	70
RSD workloads [%]	22%	23%	22%	22%	22%
Saturated distr. [%]	31%	32%	26%	24%	16%

3 h	Number of districts (n)				
	78	80	82	84	86
RSD workloads [%]	13%	16%	17%	18%	18%
Saturated distr. [%]	59%	58%	51%	49%	40%

2 h	Number of districts (n)				
	136	138	140	142	144
RSD workloads [%]	17%	18%	19%	19%	19%
Saturated distr. [%]	60%	63%	56%	50%	56%

Figure 6.9: Average workload and minimum number of districts by maximum available times

As expected, shrinking the delivery window significantly increases the number of districts required to complete the activity on time. Specifically, reducing the time window from 4 to 2 hours more than doubles the minimum number of districts needed to produce a feasible solution (from 62 to 136). It is interesting to note that, in the case of 2 hours, the average workload value is high (1.8) and remains almost constant even for solutions with a higher n. Almost the same occurs for the percentage of saturated districts. Hence a higher number of operators work at full capacity throughout the available time window in all the proposed solutions. In this case, a risk-averse decision-maker would be advised to significantly increase the number of n beyond the minimum required to maintain a buffer for unforeseen events, with a substantial increase in associated costs.

The baseline scenario with home delivery serves as the starting point for the evaluation of the benefits achievable, in a comparative fashion, with an integrated strategy involving self-collection, as we discuss next.

Integrated strategy: the effect of pick-up points

Now, we take the analysis a step further by integrating self-collection in the delivery solutions. We consider the network design scenarios of pick-up points proposed in Chapter 5 and compare them with the baseline. This way, we can evaluate the savings achievable from different network configurations on delivery districts and workforce size.

The results of this application are shown in Figure 6.10, which illustrates the minimum number of districts n to achieve a feasible solution with a maximum workload of 4 hours by varying the number of located pick-up points. With just 10% of the pick-up points, n decreases from 62 to 46. This further lowers as the locations increase, reaching 32 with the full network. Interestingly, the marginal decrease is not constant. In fact, it smooths as the number of locations increases. The expansion from 60% to 70% of pick-up points results in a reduction of only two districts (from 34 to 32). Beyond this point, further increasing the number of pick-up points provides no additional benefit in terms of workforce savings. In practice, in line with those shown in Section 5.5, these results again would discourage the decision-maker from locating more than 70% of the potential pick-up points, given the nonexistent savings attainable by further expanding the network. For this reason, from now on, the analysis will focus on the network configuration with 152 pick-up points (70%), considered the most significant among those evaluated.

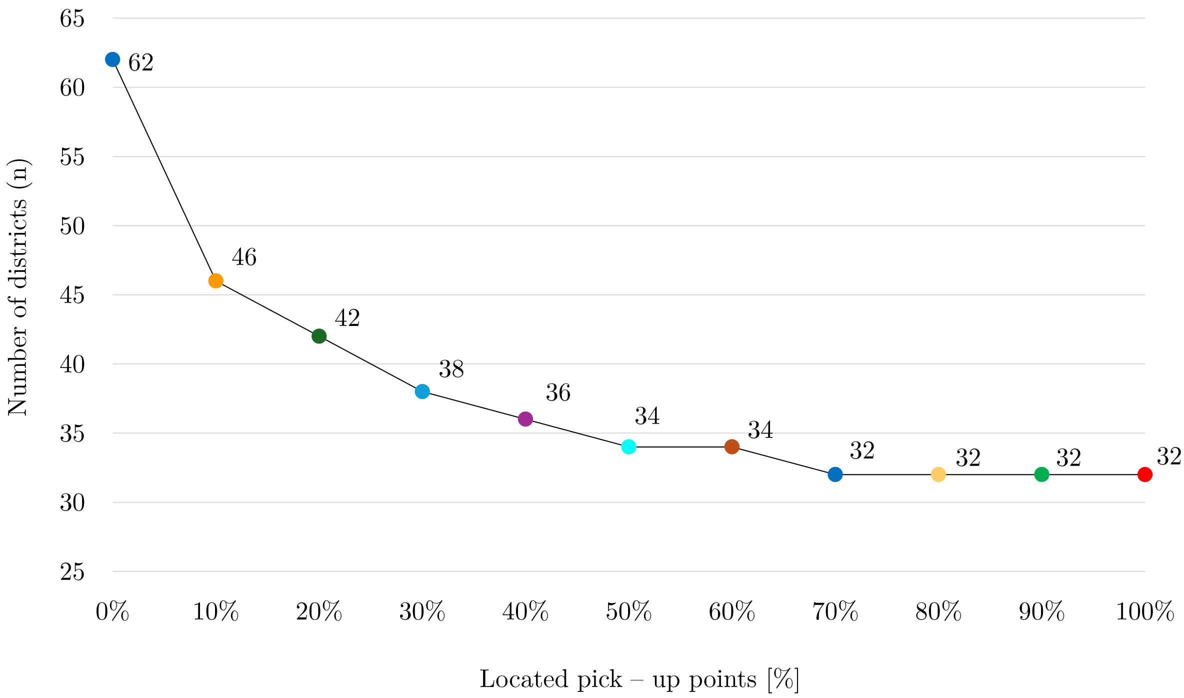


Figure 6.10: Minimum number of districts by percentage of located pick-up points ($UB = 4h$)

Even in this case, the decision-maker may be interested in evaluating how the territorial design changes and how many additional districts are required when the delivery time window is reduced. Table 6.2 presents the minimum number of districts, the average, the RSD of workloads and the percentage of saturated districts for maximum time windows of 4, 3, and 2 hours. These indicators are provided for both the home delivery-only scenario (baseline) and the integrated strategy, facilitating a comparison between the two.

Table 6.2
Comparison between the baseline scenario and integrated strategy: minimum number of districts, average and RSD of workloads

	Maximum workload	Minimum no. of districts	Δ w.r.t. 4h	Avg. Workload [h]	RSD Workloads [%]	Saturated districts [%]
Baseline scenario - Home delivery	4h	62	-	3.3	22%	31%
	3h	78	+16	2.7	13%	59%
	2h	136	+58	1.8	18%	60%
Integrated strategy - 152 pick-up points	4h	32	-	3.7	10%	47%
	3h	44	+12	2.8	11%	68%
	2h	82	+38	1.7	18%	48%

In the table, Δ indicates the increase in the minimum number of districts required to complete deliveries within the time window compared to the 4-hour scenario. It is interesting to note that, by reducing the time window to 3 hours, 12 additional districts are required in the integrated strategy compared to 16 in the home delivery-only scenario. Conversely, when halving the time window to 2 hours, the increase amounts to 38 districts versus 58. This demonstrates that the integrated strategy also leads to a smaller increase in workforce size to complete deliveries in a shorter time. Regarding the workloads, with 4 hours, in the integrated scenario, the average value is higher than that related to home delivery alone (3.7 and 3.3, respectively), with a significantly lower RSD (10% versus 22%). Similarly, the percentage of saturated districts is significantly higher (47% versus 31%). These differences flatten out when the maximum workload decreases. In general, these results suggest that the presence of pick-up points reduces the minimum number of districts, creating areas where operators tend to completely utilize their available time window.

So far, we have seen that the integrated strategy helps reduce delivery costs compared to an approach based solely on home delivery. However, e-commerce is characterized by an ever-growing expansion that is continuously increasing the volume of parcels. Furthermore, the associated seasonality or periodic sales events can lead to fluctuations in the daily number of deliveries. This highlights the importance of evaluating the robustness of the proposed scenarios accounting for potential parcel volume variations. It is worth remembering that the growth in volumes impacts the likelihood of receiving a parcel (Γ_c). For example, a 20% increase leads to a rise of Γ_c from 7.5% to 8.9%. This means that if a customer previously received a parcel every 13 days on average, he would now receive one every 11 days. Consequently, this evidently impacts workloads, potentially compromising the timely completion of deliveries unless adjustments are made to the districts.

Therefore, to compare the robustness of the solutions for the baseline and integrated scenarios, we assess whether the districts obtained with the *AS-IS* volumes can still meet the time window, even with an increase in delivered parcels. To do this, we calculate the workloads with new volumes and estimate the *maxViolation* indicator, which quantifies the maximum exceedance of the upper bound across the plan's districts.

Table 6.3 shows the *maxViolation* of the solutions as the estimated volume increases by 10%, 20%, and 30%.

As can be observed, no district plan is robust enough to ensure perfect compliance. However, with reference to a maximum workload of 4 hours, a volume increase of up to 20% results in a maximum exceedance for integrated strategies that does not surpass 5 minutes. This reaches 7 minutes in the scenario with a 30% growth, remaining relatively contained. A similar trend is observed for 3 and 2 hours, proving that robustness is not strongly dependent on the imposed time window. A very different situation occurs with home delivery, where even a 10% increase causes an overrun exceeding fifteen minutes in two out of three cases (14 and 18 minutes with 4h and 3h, respectively). The exceedance reaches 20 minutes with 30% more parcels when considering 3 hours.

Interestingly, these results clearly show that the benefit of an integrated strategy is evident not only in terms of costs but also in robustness. Although it leads to greater utilization of the time window by operators (as we see from Table 6.2), a sufficiently dense network of pick-up

Table 6.3
Maximum violation [%] (minutes) by volumes increases

		Volumes increase [%]		
	Maximum Workload	+10%	+20%	+30%
Baseline Scenario - Home delivery	4h	6% (14)	6% (14)	7% (17)
	3h	10% (18)	10% (18)	11% (20)
	2h	7% (8)	8% (10)	8% (10)
Integrated strategy - 152 pick-up points	4h	1% (2)	2% (5)	3% (7)
	3h	2% (4)	3% (5)	4% (7)
	2h	1% (1)	1% (1)	4% (2)

points ensures robust delivery areas capable of handling parcel volume fluctuations without significant operational delays. This represents an additional significant advantage that the integrated strategy brings in terms of efficiency in a highly dynamic context such as last-mile delivery.

6.5 Conclusions

In this chapter, we addressed the problem of designing delivery areas for daily operations in last-mile logistics.

Specifically, we proposed a novel districting approach to define delivery areas, ensuring that the expected workload remains within predefined limits. This guarantees that daily deliveries can be completed on time. The workloads were calculated considering the time necessary for travel and service at all points within each district, thus including routing measures. This metric reflects the daily effort required from operators to satisfy deliveries. Furthermore, the approach accounted for uncertainties stemming from fluctuations in parcel demand and variations in customer preferences. Indeed, each point, whether a customer's location for home delivery or a pick-up point for self-collection, was assigned a probability of being visited. This probability impacts the expected workload of the district and is determined by considering the likelihood of receiving a parcel and the preference for delivery strategy. To model the latter, we employed a Multinomial Logit model, enabling predictions of the probabilities of visits to both customer locations and pick-up points on any given day.

The procedure was applied to a case study of Poste Italiane in the city of Bologna, leveraging detailed information about customer locations and historical data on delivery volumes. The experimental results underscored the significant advantages of integrating self-collection networks into delivery operations. In particular, the availability of pick-up points had a notable effect on reducing the workforce required to manage daily deliveries, thereby optimizing labour resources and lowering operational costs. Moreover, the study revealed that a dense network of pick-up points enhanced the robustness of the proposed districting solutions. Indeed, an integrated strategy with self-collection is able to adapt seamlessly to varying projected delivery volumes, maintaining efficiency across districts despite fluctuations in demand. These findings are particularly important in the ever-evolving landscape of urban logistics, where parcel volumes can shift rapidly due to external factors such as seasonality, market trends, or unforeseen disruptions.

The study has some limitations, which present opportunities for further research. From an applied perspective, a potential extension could focus on rural areas to investigate whether the impact of an integrated delivery strategy varies across different socio-economic and geographical contexts. In addition, various operational conditions can be taken into account. For instance, it may be valuable to consider not only the maximum workload but also to introduce a minimum threshold. This could help create more balanced districts, ensuring that resources are distributed more equitably and that no one is underutilized. Finally, the choice of the basic territorial unit can be reconsidered. While census tracts have the advantage of being recognized territorial bases by national statistical agencies, creating ad-hoc "round-shaped" units may offer the benefit of generating more compact districts. This, in turn, can facilitate the minimization of distances that an operator needs to cover, enhancing the efficiency of the activities.

General conclusions

The expansion of e-commerce has reshaped the logistics landscape, introducing significant challenges in managing the surge in parcel volumes. This shift has fundamentally transformed consumer behavior, creating unprecedented demand for faster, more flexible, and highly customized delivery options. Customers started to expect not only quick turnaround times but also a wide range of methods tailored to their specific schedules and preferences, such as same-day delivery and time-slot selection. This growing pressure has compelled logistics operators to reassess the entire parcel supply chain in order to maintain (and enhance) competitiveness in an increasingly dynamic market. A key focus, in this context, is last-mile logistics, often regarded as the most critical and challenging segment. Its complexities arise from factors such as high transportation costs, operational inefficiencies, and the economic burden of failed delivery attempts requiring re-scheduling.

In addition to operational challenges, this phenomenon has been raising environmental concerns in urban areas. In fact, the growing number of delivery vehicles contributes to traffic bottlenecks, noise pollution, and greenhouse gas emissions. In response, local governments are actively developing sustainable urban logistics strategies to address these broader societal implications.

The convergence of consumer expectations, operational efficiency for providers, and public policy priorities underscores the multifaceted nature of last-mile logistics challenges, highlights the necessity for innovative solutions and advanced decision-making approaches.

In this thesis, we implemented tailored approaches to face the reorganization of last-mile logistics based on opportunities provided by self-collection. Specifically, we proposed a decision-making pathway to face logistic challenges, starting with the strategic network design and moving progressively toward the definition of the tactical delivery area. In doing this, multiple perspectives and stakeholders' interests were considered. First and foremost, it focused on the standpoint of logistics providers, as the study has been developed in collaboration with Poste Italiane, the leading logistics provider in Italy. Additionally, it considered the customer perspective, recognizing that individuals are willing to adopt self-collection only if the network is efficient, convenient, and integrated with their daily routines and habits. Finally, the output of the research also met the interests of central policymakers keen to promote and incentivize self-collection as a sustainable delivery strategy.

The thesis was organized into six chapters as follows. Chapter 1 contextualizes last-mile logistics, discussing trends, challenges, and solutions like self-collection, with a focus on Italy's initiatives for sustainable urban mobility. Chapter 2 reviews the literature on last-mile logistics, highlighting key research gaps and clarifying the contributions of the thesis. Chapter 3 examines Poste Italiane's case, describing its transformation into a fully flagged logistics operator and detailing its self-collection initiatives and case studies. Chapter 4 addresses the strategic problem of pick-up points network design using spatial analysis and facility location models to optimize cost-efficiency and customer accessibility. Chapter 5 introduces a probabilistic approach to integrating customer preferences into network design, aiming to enhance self-collection adoption. Chapter 6 proposes a novel probabilistic approach for designing urban delivery districts, offering robust solutions that account for the uncertainty associated with customers' preferences.

Contributions

The contributions of the thesis can be seen from two main standpoints: academic and managerial.

From the *academic standpoint*, the work advances the literature by proposing novel methodologies for decision-making problems related to self-collection, integrating optimization approaches with customers' behavioural modeling. The methodologies provide a comprehensive framework for optimizing pick-up point network design and defining delivery districts, accounting for uncertainties arising from customer choices.

In particular, concerning the strategic network design problem, we proposed data-driven location methods that incorporate accessibility measures and customer behaviour factors in the decision, identifying practical solutions to promote the innovative delivery option. We tackled the problem using both a deterministic and a probabilistic perspective. In the deterministic, we introduced a methodology based on spatial analysis to implement strategies for reconfiguring Poste Italiane's pick-up points network. In the probabilistic, we proposed a facility location model to design the network, including customer choices in the decision-making process. These approaches highlighted how service accessibility and the interaction of different customer behaviours can shape the optimal network design and proposed insightful scenarios to support the decision-making process.

At the tactical level, we tackled the challenge of designing delivery areas by introducing an innovative approach to define districts for daily operations. This ensures that the workload in each area remains within specified limits while accounting for uncertainties related to customer preferences. This approach highlighted the benefits of a dense network of pick-up points in promoting parcel consolidation and reducing reliance on home deliveries. This, in turn, significantly decreases the number of operators required for daily delivery activities.

The application of the proposed methods to partner provider case studies allows for a thorough analysis of real-world variability and complexities, driving practical and impactful advancements also from a *managerial standpoint*. By leveraging detailed geographical and operational data, the findings support the design of cost-effective, adaptable networks that enhance the efficiency of delivery operations. Moreover, the proposed solutions are robust to changes in customer behavior and scalable to accommodate future service expansions. Therefore, although developed in the context of Poste Italiane, the presented approaches offer versatile solutions applicable to a wide range of stakeholders involved in developing and implementing more efficient parcel delivery systems, generating tangible and cross-cutting benefits.

Further Developments

Despite the described cues and insights, the present thesis calls for future research directions.

From a methodological perspective, future research may focus on developing explicit multi-period and multi-criteria extensions of the models, allowing for a more dynamic and comprehensive representation of real-world decision-making processes. This would enable the analysis of network evolution over time, accounting for changes in demand patterns, service levels, and operational constraints. In parallel, the development of advanced heuristic solution approaches could significantly enhance the scalability and computational efficiency of these models, making them more applicable to large-scale, complex case studies. Additionally, further refinements to the proposed districting procedures could be explored with a dual objective: improving computational performance to ensure faster solution times and incorporating additional planning criteria of practical relevance.

From an applicative perspective, future extensions may explore additional factors influencing customers' acceptance of self-collection. While distance remains a key aspect, the multi-faceted concept of attractiveness could be enriched by considering further elements (i.e. actual travel times, proximity to workplaces and points of interest, and availability of parking facilities). Further empirical research, including targeted data collection and customer surveys, would help refine the model calibration and enable the segmentation of customer demand based on socioeconomic characteristics. Expanding the computational analysis to include real-world case studies from different cities and logistics providers could further demonstrate the versatility of the proposed models in generating meaningful managerial insights across diverse contexts. Additionally, extending the application to rural areas represents a promising research avenue, given the distinct logistical challenges that these environments present. Also, future studies could enhance the assessment of environmental impacts by integrating detailed emission estimation models.

Finally, future studies could focus on redefining the decision-making framework in city logistics by adopting an explicit public interest-oriented perspective. This approach envisions the development of integrated and cooperative delivery solutions, where multiple logistics operators share (self-collection) networks and resources to optimize efficiency and sustainability. Central to this vision is the role of a public authority acting as the primary decision-maker, responsible for coordinating activities, setting regulatory frameworks, and safeguarding the social, environmental, and community interests of urban residents. By shifting from fragmented, operator-driven strategies to a more centralized and collaborative model, future studies could explore how a cooperative approach may not only enhance urban freight efficiency but also assure operative sustainable conditions.

Appendices

Hereafter, we report some additional material for the models and the computations reported in the manuscript. Specifically, Appendix A refers to Chapter 2. Appendix B reports further results from Chapter 4. Appendix C extends materials from Chapter 5, while Appendix D refers to Chapter 6.

Appendix A—Additional material for Chapter 2

This appendix reports the mathematical formulations used for the two main classes of problems discussed in Section 2, i.e., *Facility Location* (Section A.2) and *Districting* (Section A.2).

A.1 Facility Location Problems

In the following, we refer to discrete problems, i.e., problems in which the location space is discrete and customers are concentrated in a finite number of demand nodes.

In order to present the basic facility location models, we introduce the following notation:

Sets

I Set of demand nodes, where customers are located;

J Set of candidate site for locating facilities;

Parameters

p Number of facilities to locate;

d_i Demand (weight) associated to node $i \in I$;

c_{ij} Distance between demand node $i \in I$ and candidate site $j \in J$;

Decision variables

y_j Binary variable equal to 1 if a facility is located at candidate site $j \in J$, and 0 otherwise;

x_{ij} Binary variable equal to 1 if customers from demand node $i \in I$ are allocated to a facility located at candidate site $j \in J$, and 0 otherwise.

A.1.1 p-Median problems

The p-median problem aims to find the optimal location of a fixed number of facilities p, usually called medians, among the candidates, so that the weighted (by the demand) sum of the distances between customers and their assigned facilities is minimized.

A p-median model is a *minisum* problem, in which the objective to minimize depends on the costs associated with each of the users in equal measure.

The first formulation of the p-median problem is attributable to Hakimi (1964) and is the following:

$$\min \sum_{i \in I} \sum_{j \in J} d_i c_{ij} x_{ij} \tag{A.1}$$

$$\text{s.t.} \sum_{j \in J} x_{ij} = 1 \qquad \forall i \in I \tag{A.2}$$

$$x_{ij} \leq y_j \qquad \forall i \in I, j \in J \tag{A.3}$$

$$\sum_{j \in J} y_j = p \tag{A.4}$$

$$x_{ij} \in \{0,1\} \qquad \forall i \in I, j \in J, \tag{A.5}$$

$$y_j \in \{0,1\} \qquad \forall j \in J \tag{A.6}$$

Constraints (A.2) ensure that the (whole) demand from each node is assigned to only one facility. According to constraints (A.3), customers can be assigned to candidate site j if there is an open facility in that location. Constraint (A.4) sets the number p of facilities that must be located. Finally, constraints (A.5) and (A.6) define the domain of the decision variables.

The minimum average weighted distance between customers and facilities is obtained by dividing the value of the objective function (A.1) by $\sum_{i \in I} d_i$ (known).

Starting from the above formulation, several extensions have been proposed in the literature to include practical features or to target specific applications.

For instance, one of the first applications of p-median is clustering, which aims to gather a large set of elements into mutually exclusive smaller groups based on their similarities Klastorin (1985). Holmes et al. (1972) introduced the *capacitated p-median* problem by imposing a maximum capacity level for facilities to locate. Moreover, in order to avoid strong inefficiencies or obtain a more balanced distribution of customers between facilities, *balancing requirements* may be introduced, as in Carreras and Serra (1999).

A.1.2 Covering problems

Covering location problems, initially introduced by Toregas et al. (1971), constitute a major class of problems in facility location analysis, with numerous applications in a wide range of domains. The "coverage", in fact, is one of the classical objectives within location modelling. The goal is to ensure that customers are covered, i.e. served by (at least) one facility whose distance is lower than a certain value r, typically indicated as *covering radius*.

Two major types of covering models were proposed in the early relevant literature:

- The *Location Set Covering Problem* (LSCP) seeking to determine the minimum number of facilities and their location to fully cover all the demand nodes in a given location space. The seminal papers are Toregas et al. (1971) and ReVelle et al. (1976);

- The *Maximum Covering Location Problem* (MCLP) aiming to maximize the covered demand, given a limited number (p) of facilities to locate or a budget (B). It was formally introduced by Church and ReVelle (1974)

In order to formulate the basic LSCP and MCLP models, let us consider the notation above and denote the covering set N_i as the set of all candidate sites j within the covering radius r from demand node i, i.e., $N_i = \{j \in J : c_{ij} \leq r\}$.

The LSCP can be formulated as follows:

$$\min \sum_{j \in J} y_j \tag{A.7}$$

$$\text{s.t. (A.6)} \tag{A.8}$$

$$\sum_{j \in N_i} y_j \geq 1 \qquad i \in I \tag{A.9}$$

Objective function (A.7) aims to minimize the number of facilities to locate. Constraints (A.9) guarantee that each demand node i finds at least one located facility j within distance r; thus, every node is covered within radius r. Constraints (A.6) explain the binary nature of decision variables.

According to the above notation and considering binary decision variables z_i, $i \in I$ equal to 1 if customers at demand node i are covered, and 0 otherwise, the MCLP formulation is formulated as follows:

$$\max \sum_{i \in I} d_i z_i \tag{A.10}$$

$$\text{s.t. (A.4), (A.6)} \tag{A.11}$$

$$\sum_{j \in N_i} y_j \geq z_i \qquad i \in I \tag{A.12}$$

$$z_i \in \{0, 1\} \qquad i \in I \tag{A.13}$$

Objective function (A.10) maximizes the total demand covered by a fixed number p of facilities to locate (A.4). Constraints (A.12) guarantee that a demand node i is considered as covered whether at least one facility is located within covering radius r. Finally, constraints (A.6) and (A.13) define the domain of decision variables.

The wide applicability of covering models stimulated strong interest in the research community, testified by a huge number of publications over the last 50 years. Indeed, the coverage concept allows for modelling problems involving ordinary services whose access by consumers should be guaranteed within a maximum distance.

A.2 Districting Problems

Formulations for DPs resort to the seminal contribution of Hess et al. (1965). To present it, we consider a set I of territorial units that we want to divide into a fixed number, say p, of districts. Each district will have a TU representing it. Hence, when some other TU is assigned to the district we abuse the language by saying that we are assigning a TU to the representative of the district. We note that single-assignment (i.e. *integrity*) is assumed for the TUs as customary in districting problems.

We consider the following parameters defining the problem:

d_i, demand of TU i ($i \in I$);

c_{ij}, cost for assigning TU i to TU j $(i, j \in I)$;

α, maximum desirable deviation of the demand in a district w.r.t. the reference value μ;

μ, average demand per district ($\mu = \frac{\sum_{i \in I} d_i}{p}$);

and the following decision variables:

$$x_{ij} = \begin{cases} 1, & \text{if TU } i \text{ is assigned to TU } j; \\ 0, & \text{otherwise.} \end{cases} \qquad (i, j \in I)$$

In this case, $x_{jj} = 1$ indicates that TU j is assigned to itself which also indicates that it is selected as the "representative" TU of its district.

Using these decision variables, Hess et al. (1965) proposed the following mathematical model for the territorial districting problem with balancing constraints in the context of political districting:

$$\text{minimize} \quad \sum_{i \in I} \sum_{j \in I} d_i c_{ij}^2 x_{ij} \tag{A.14}$$

$$\text{subject to} \quad \sum_{j \in I} x_{ij} = 1 \qquad i \in I \tag{A.15}$$

$$\sum_{j \in I} x_{jj} = p \tag{A.16}$$

$$(1 - \alpha)\mu x_{jj} \leq \sum_{i \in I} d_i x_{ij} \leq (1 + \alpha)\mu x_{jj} \qquad j \in I \tag{A.17}$$

$$x_{ij} \in \{0, 1\} \qquad i, j \in I \tag{A.18}$$

The objective function (A.14) quantifies the total cost to be minimized. Constraints (A.15) ensure that each TU is assigned to exactly one district whereas Constraints (A.16) guarantee that exactly p districts will be designed. Constraints (A.17) are the balance constraints. Finally Constraints (A.18) define the domain of the decision variables.

In districting problems, the costs c_{ij} are typically related to the distances. In particular, denoting by ℓ_{ij} the distance between i and j $(i, j \in I)$, a common cost to consider is $c_{ij} = \ell_{ij}$ or $c_{ij} = \ell_{ij}^2$. This turns the above objective function into a so-called compactness measure known as the moment of inertia. Finally, we note that euclidean distances are often considered (Bergey et al., 2003; Bard and Jarrah, 2009).

A close look into the above model proposed by Hess et al. (1965) reveals that it does not solve exactly a districting problem but only a relaxation of it; it solves a location-allocation model with a demand balancing requirement. In fact, the model ignores one important aspect of districting: contiguity (and, consequently, no enclaves). Therefore, apparently, a solution provided by the model may yield contiguity solutions only by chance. Nevertheless, it should be noted that when we seek to optimize a compactness measure in a districting problem, the resulting solution is typically strong in terms of the districts' contiguity. It is also true that the introduction of balancing constraints may disfavor compactness and, accordingly, contiguity. In other words, balancing and compactness measures may easily become conflicting. Despite these facts, various authors do not explicitly address contiguity in their models Kalcsics and Ríos-Mercado (2019), and thus, the model proposed by Hess et al. (1965) is still the basic model for researchers working on districting problems.

Different approaches have been proposed in the literature to model contiguity. A few additional notation is introduced to present some of them. In particular, let $G = (I, A)$ be the graph underlying our problem, where I represents the set of nodes corresponding to our TUs, and A is the adjacency matrix that includes all direct links between the TUs (one link exists for each pair of adjacent TUs $(i, j) \in I$, i.e., $a_{ij} = 1$). Consequently, for each TU $i \in I$, we denote by A_i the set of nodes adjacent to i, which is: $A_i = \{j \in I : (i, j) \in A\}, i \in I$.

To treat contiguity as a hard constraint, the formulation provided by Drexl and Haase (1999) can be used. The resulting constraints are:

$$\sum_{i \in S} x_{ij} - \sum_{i \in \cup_{v \in S}(A_v \setminus S)} x_{ij} \leq |S| - 1 \qquad j \in I, S \subset [I \setminus (A_j \cup \{j\})] \tag{A.19}$$

which ensures that for any subset S of nodes assigned to the representative TU j not containing TU j itself, there must be an arc between S and the set containing i. These inequalities draw on an analogy with the sub-tour elimination constraints in the Traveling Salesman Problem and are exponential in number. However, as demonstrated by Salazar-Aguilar et al. (2011), they can be efficiently applied within an exact *row-generation* approach, where contiguity constraints are introduced dynamically during the solution process. In that study, the authors also show that the following valid inequalities accelerate the convergence of the procedure:

$$\sum_{l \in A_i} x_{il} \geq x_{ij}, \qquad i \in I, j \in I \setminus (\{i\} \cup A_i). \tag{A.20}$$

The above constraints state that if a TU i is assigned to a center j it is not adjacent to, a necessary condition for contiguity is that at least one TU l adjacent to i is also assigned to j.

An alternative approach involves constructing a model with a linear number of constraints, following the formulation introduced by Shirabe (2009). In this approach, an analogy to network flow problems is applied: each territorial unit (TU) is treated as a source generating a unit of flow, while the district representatives function as sinks or flow attractors. A district is considered contiguous if there exists a path allowing the flow to travel from each TU within the district to its representative, passing only through TUs belonging to the same district. To implement these constraints, an additional set of variables is introduced:

$y_{mij} \geq 0$, flow of district j sent from m to i with $i, j, m \in I$, and $(m, i) \in A$.

Accordingly, the following constraints can now be written:

$$\sum_{m\in I\,|\,(m,i)\in A} y_{mij} \leq (|I|-p-1)x_{ij}, \qquad i,j\in I, \tag{A.21}$$

$$\sum_{m\in I\,|\,(i,m)\in A} y_{imj} - \sum_{m\in I\,|\,(m,i)\in A} y_{mij} = x_{ij}, \qquad i,j,\in I,\ i\neq j, \tag{A.22}$$

$$y_{mij} \geq 0, \qquad i,j,m\in I,(m,i)\in A. \tag{A.23}$$

Constraints (A.21) ensure that flows associated with district j are directed to node i only if node i is assigned to that district. The right-hand side expression reflects that each district can include up to $(|I|-p)$ TUs that are not representatives. Constraints (A.22) ensure that any node assigned to a district but not acting as a center will contribute at least one unit of flow within that district.

Appendix B—Additional material for Chapter 4

This appendix reports the detailed results obtained from the implementation of the proposed strategies in the city of Napoli. The structure of the Tables follows that already described for Bologna in Section 4.4 (Tables 4.4–4.8). Specifically, in what follows, Table B1 refer to Strategy 1—Network contraction, Tables B2–B3 to Strategy 2—Network reorganization, while Tables B4–B5 to Strategy 3—Network expansion.

Table B1
Strategy 1 solutions vs. AS-IS in Napoli

AS-IS		$\bar{d}$ [km]												
		0.10	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**		d_{avg} [km]	$\lvert J_{PU}^{c}\rvert$
	γ	4.0	20.7	40.4	57.2	69.5	77.2	83.0	87.7	90.3	92.1		0.46	222
Strategy 1 – Contraction		$\bar{d}$ [km]												
		0.10	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**	$\Delta_{\gamma_{\text{avg}}}$	$\Delta_{d_{\text{avg}}}$ [km]	Δ_{PU}
S_1_0.20		-0.3	–	-1.2	-2.0	-2.4	-2.7	-2.9	-2.9	-2.0	-1.4	-1.8	+0.02	-50
S_1_0.30	Δ_{γ}	-0.7	-1.2	–	-0.8	-1.4	-1.3	-1.2	-1.7	-1.1	-0.9	-1.0	+0.00	-52
S_1_0.40		-1.2	-3.3	-2.4	–	-0.9	-0.5	-0.5	-0.7	-0.4	-0.4	-1.0	+0.00	-67
S_1_0.20_0.40		-0.3	–	-0.1	–	-0.4	-0.3	-0.4	-0.7	-0.3	-0.2	-0.3	+0.00	-28
S_1_0.30_0.50	Δ_{γ}	-0.6	-1.1	–	-0.2	–	-0.1	-0.2	-0.5	-0.2	-0.2	-0.3	+0.00	-37
S_1_0.40_0.60		-1.2	-2.9	-2.0	–	-0.5	–	-0.1	-0.5	-0.1	-0.1	-0.7	+0.00	-58

Table B2
Strategy 2 solutions vs. AS-IS in Napoli

AS-IS		$\bar{d}$ [km]												
		0.10	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**		d_{avg} [km]	J^c_{PU}
	γ	4.0	20.7	40.4	57.2	69.5	77.2	83.0	87.7	90.3	92.1		0.46	222
Strategy 2 – Reorganization		$\bar{d}$ [km]												
		0.10	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**	$\Delta_{\gamma_{\text{avg}}}$	$\Delta_{d_{\text{avg}}}$ [km]	Δ_{PU}
S_1_0.20		-0.8	–	-6.8	-12.1	-15.7	-15.6	-14.4	-12.7	-10.5	-8.6	-9.7	+0.13	-141
S_1_0.30	Δ_γ	-1.3	-3.0	–	-4.1	-7.0	-7.8	-7.9	-6.8	-6.3	-5.3	-5.0	+0.08	-132
S_1_0.40		-1.7	-5.6	-4.8	–	-2.4	-3.8	-3.5	-4.0	-4.0	-3.7	-3.4	+0.06	-135
S_1_0.20_0.40		-0.9	–	-1.4	–	-3.0	-4.6	-4.9	-5.2	-4.5	-3.9	-2.8	+0.05	-121
S_1_0.30_0.50	Δ_γ	-1.3	-3.9	–	-0.5	–	-0.8	-0.7	-1.8	-1.8	-1.7	-1.3	+0.02	-123
S_1_0.40_0.60		-1.7	-5.9	-5.5	–	-0.2	–	-0.0	-0.8	-1.0	-1.1	-1.6	+0.02	-132

Table B3
Strategy 2 solutions in Napoli: deactivated and new activated pick-up points

Instance	Δ_{PU}	Deactivated pick-up points	New activated pick-up points
S_2_0.20	-141	-187	46
S_2_0.30	-132	-175	43
S_2_0.40	-135	-170	35
S_2_0.20_0.40	-121	-169	48
S_2_0.30_0.50	-123	-172	49
S_2_0.40_0.60	-132	-169	37

Table B4
Strategy 3 solutions vs. AS-IS in Napoli

AS-IS		$\bar{d}$ [km]												
		0.10	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**		d_{avg} [km]	$\lvert J^c_{PU}\rvert$
	γ	4.0	20.7	40.4	57.2	69.5	77.2	83.0	87.7	90.3	92.1		0.46	222
Strategy 3 – Expansion		$\bar{d}$ [km]												
		0.10	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**	$\Delta_{\gamma_{\text{avg}}}$	$\Delta_{d_{\text{avg}}}$ [km]	Δ_{PU}
S_1_0.20		2.6	12.8	12.7	8.7	5.9	4.6	3.6	1.4	1.5	1.7	5.6	-0.07	112
S_1_0.30	Δ_γ	1.2	7.7	14.4	10.4	7.1	6.3	5.4	3.3	2.9	2.5	6.1	-0.08	60
S_1_0.40		0.1	1.9	7.6	11.7	7.4	7.0	6.4	4.3	3.6	3.2	5.3	-0.07	13
S_1_0.20_0.40		2.8	12.8	14.1	11.7	8.3	7.6	6.4	4.3	3.7	3.2	7.5	-0.09	152
S_1_0.30_0.50	Δ_γ	1.3	8.2	14.4	11.0	8.7	7.6	6.4	4.3	3.6	3.2	6.9	-0.09	83
S_1_0.40_0.60		0.2	2.1	7.5	11.7	7.9	7.8	6.5	4.3	3.6	3.3	5.5	-0.07	26
Potential	Δ_γ	3.7	12.9	14.4	11.7	8.7	7.8	6.7	4.6	3.8	3.4	7.8	-0.10	260

Table B5
Strategy 3 solutions in Napoli: deactivated and new activated pick-up points

Instance	Δ_{PU}	Deactivated pick-up points	New activated pick-up points
S_2_0.20	112	-62	174
S_2_0.30	60	-84	144
S_2_0.40	13	-109	122
S_2_0.20_0.40	152	-45	197
S_2_0.30_0.50	83	-74	157
S_2_0.40_0.60	26	-100	126

Appendix C—Additional material for Chapter 5

C.1 Model linearization

In this Appendix, we prove that Constraints (5.10) – (5.15), are equivalent to (5.5). To this end, and for simplicity, let us consider a generic node $i \in I$, and two generic pick-up points $j, k \in N_i$. Let us also assume that these pick-up points are both active (i.e., $y_j = y_k = 1$). Accordingly, based on (5.12), we have:

$$p_{ij} \leq \frac{\alpha_{ij}}{\alpha_{ik}} p_{ik} \tag{A.24}$$

$$p_{ik} \leq \frac{\alpha_{ik}}{\alpha_{ij}} p_{ij} \tag{A.25}$$

Inequalities (A.24) and (A.25) are equivalent to the following:

$$p_{ij} = \frac{\alpha_{ij}}{\alpha_{ik}} p_{ik} \tag{A.26}$$

$$p_{ik} = \frac{\alpha_{ik}}{\alpha_{ij}} p_{ij} \tag{A.27}$$

Let us now focus on home delivery (p_i^{HD}). From (5.13) and (5.14), it is straightforward to demonstrate that the following equalities hold:

$$p_i^{HD} = \frac{\phi_i}{\alpha_{ij}} p_{ij} \tag{A.28}$$

$$p_i^{HD} = \frac{\phi_i}{\alpha_{ik}} p_{ik} \tag{A.29}$$

Of course, from (5.11) we have:

$$p_{ij} + p_{ik} + p_i^{HD} = 1 \tag{A.30}$$

which, due to (A.26), (A.27), and (A.28) (or, equivalently, (A.29)), can be now rewritten as:

$$\frac{\alpha_{ij}}{\alpha_{ik}}p_{ik} + \frac{\alpha_{ik}}{\alpha_{ij}}p_{ij} + \frac{\phi_i}{\alpha_{ij}}p_{ij} = 1 \tag{A.31}$$

By leveraging (A.27), we can also express (A.31) as a function of the sole p_{ij}:

$$p_{ij} + \frac{\alpha_{ik}}{\alpha_{ij}}p_{ij} + \frac{\phi_i}{\alpha_{ij}}p_{ij} = 1$$

and, hence,

$$p_{ij} = \frac{\alpha_{ij}}{\alpha_{ij} + \alpha_{ik} + \phi_i} \tag{A.32}$$

Note that (A.32) can be written for each user node $i \in I$ and for each pick-up point $j \in N_i$, thus proving the equivalence with (5.5).

C.2 Further computational results

In this Section, we report on extended results for the computation in Section 5.5. In particular, Table C1 displays the marginal increases of the objective function (5.4) by the attractiveness of home delivery (ϕ), the percentage of pick-up points to activate (γ), and customers' sensitivity to travel (β).

Table C1
Marginal increases in the proportion of customers opting for self-collection by the calibration parameters ϕ, γ, and β

ϕ	γ	$\beta = 0.5$	$\beta = 1.0$	$\beta = 2.0$
0.5	10	20.8	19.4	16.6
	20	12.7	12.0	10.4
	30	8.8	8.4	7.7
	40	5.7	5.5	5.1
	50	4.0	4.0	3.8
	60	2.6	2.7	2.8
	70	1.6	1.8	2.0
	80	0.8	0.8	1.0
	90	0.3	0.3	0.3
	94	0.0	0.0	0.0
1.0	10	15.3	13.9	11.2
	20	9.6	8.8	7.4
	30	7.3	6.8	5.9
	40	4.9	4.7	4.2
	50	3.8	3.6	3.4
	60	2.8	2.8	2.7
	70	2.0	2.1	2.1
	80	1.1	1.2	1.2
	90	0.4	0.4	0.5
	94	0.0	0.0	0.0
2.0	10	10.0	8.9	7.0
	20	6.6	6.0	4.8
	30	5.5	5.0	4.1
	40	4.0	3.8	3.2
	50	3.2	3.0	2.6
	60	2.6	2.4	2.1
	70	2.0	2.0	1.7
	80	1.3	1.3	1.2
	90	0.5	0.5	0.5
	94	0.0	0.0	0.0

Appendix D—Additional material for Chapter 6

In this Appendix, we report details on the main algorithms of the heuristic procedure in Sections D.1. Afterwards, in Section D.2, we detail the so-called *coarsening procedure* used for reducing the size of the case study at hand. Finally, in Section D.3, we report the setting for technical parameters of the heuristic procedure.

D.1 Heuristic procedure: main algorithms

In this Section, we present and formalize the main algorithmic schemes of the heuristic procedure. In particular, in Section D.1.1, we describe the construction of the initial districting plan, while Section D.1.2 formalizes the procedure to obtain a feasible solution. Finally, Section D.1.3 provides details on the improvement phase.

D.1.1 Construction of the initial solution

In this Section, we describe the procedure to contract the initial districting scheme. To this end, we solve the following problem:

$$
\begin{aligned}
&\text{minimize} && (6.1) \\
&\text{subject to} && (6.2)-(6.5), (6.7) \\
& && \sum_{i \in I} E[S_i] x_{ij} \leq UB \qquad j \in I
\end{aligned}
\tag{A.33}
$$

Constraints (A.33) state that the expected service time of each district is lower or equal to the UB. Our experiments demonstrated that an initial districting obtained in this way results in faster and more consistent convergence of the heuristic compared to other explored approaches (e.g., relaxing Constraints (6.6)). The likely reasons are twofold. First, service time proxies the expected workload of each district. Second, it tends to avoid the creation of districts with too many nodes, whose workload estimation may become particularly time-consuming (see also Section D.1.2).

Algorithm D1 formalizes the procedure used to devise our initial districting plan.

The algorithm begins by solving an uncapacitated p-median problem (n in our case) as a means to obtain a compact n-partition of the TUs (line 1). To this end, we use the heuristic by Resende and Werneck (2004). Contiguity constraints are ignored at this stage; therefore, we need to check if the current solution, say X, is contiguous. This control can be efficiently done through a Breadth-First Search or Depth-First Search algorithm (line 2). If the check fails,

Algorithm D1 CONSTRUCTINITIALDISTRICTING (`maxIter`)

1: Solve an uncapacitated p-median problem. Let X be the resulting (current) solution;
2: Check the contiguity of X. Let $\overline{I}$ be the set of non-contiguously assigned TUs;
3: **if** $|\overline{I}| > 0$ **then**
4:     $X \leftarrow$ ENSURECONTIGUITY$(X, \overline{I})$;
5: **end if**
6: maxViolation $\leftarrow +\infty$; // current solution's maximal violation w.r.t. Constraints (A.33).
7: bestViolation $\leftarrow +\infty$; // lowest maximal violation so far.
8: $X^\star \leftarrow X$; // best solution.
9: counter $\leftarrow 1$; // number of iterations so far.
10: Let UB^+ the vector storing the districts' violations w.r.t. the bound in (A.33);
11: maxViolation $\leftarrow$ EVALUATEVIOLATION(X, UB^+); // Algorithm D2.
12: **while** maxViolation > 0 **or** counter $\leq$ `maxIter` **do**
13:     $X \leftarrow$ CHANGETHESOLUTION(X, maxViolation, UB^+); // Algorithm D3.
14:     maxViolation $\leftarrow \max_{j \in I : x_{jj}=1}\{UB_j^+\}$; // changed solution's maximal violation.
15:     **if** maxViolation $<$ bestViolation **then**
16:         bestViolation $\leftarrow$ maxViolation; // update best violation.
17:         $X^\star \leftarrow X$; // update best solution.
18:     **end if**
19:     counter $\leftarrow$ counter $+ 1$;
20: **end while**
21: Update the centers of the districts in $X^\star$; // solve a 1-median problem in each district.
22: **return** $X^\star$; // an initial contiguos

contiguity is restored by employing a procedure proposed by Diglio et al. (2021). In essence, the routine ENSURECONTIGUITY$(X, \overline{I})$ in line 4 reassignes TUs $i \in \overline{I}$ such that contiguity in X is achieved while limiting the deriving increases in the objective function. We address the reader to the referenced paper for further details on the algorithm.

At the end of these steps, X is a contiguous districting plan. Yet, explicit considerations on the UB have been omitted. Hence, as for Algorithm 1, we check whether X respects the UB and calculate its associated *maxViolation* w.r.t. the requirements (line 11). If not, we modify X to reduce infeasibility and update the corresponding *maxViolation* (line 13). It is important to underline that the EVALUATEVIOLATION() and CHANGETHESOLUTION() functions are also utilized in Algorithm 1; however, they are slightly adjusted here to focus on service times rather than workloads. We refer the reader to Section D.1.2 for their description (and adaptions to the above case).

The procedure stops either if (i) a solution respecting the UB is found or (ii) the maximum number of iterations `maxIter` is attained. Finally, the compactness of $X^\star$ is improved by solving a 1-median problem within each district. This improved solution is returned as the output of Algorithm D1.

D.1.2 Modification of the solution

In this Section, we give details on the procedure to check the feasibility of the solution X w.r.t. workload upper bound (Algorithm D2) and to correct the solution if not feasible (Algorithm D3).

Evaluate Violation

As discussed in Section 6.2.2, this step involves solving a *Probabilistic Traveling Salesman Problem (PTSP)* in each district. Although specialized but more time-consuming approaches can be used, we determine the a priori tour in district j as the solution to a deterministic *Traveling Salesman Problem (TSP)* through all its nodes and the depot (K_j and k_0—line 3). Specifically, we use the LHK-3 heuristic proposed in Helsgaun (2017). Afterward, the expected workload $E[W_j]$ is evaluated according to Equation (6.11). At this point, we can calculate the relative deviation from the upper bound of the workload requirements (UB_j^+ —line 5). In particular, we have:

$$UB_j^+ = \max\left\{0, \frac{E[W_j] - UB}{UB}\right\} \tag{A.34}$$

Note that UB_j^+ is non-negative by definition and, if equal to zero, indicates that the expected workload of district j is within the desired UB. The algorithm iterates these steps for all districts and returns the highest violation (i.e., *maxViolation*) found. Clearly, a null *maxViolation* denotes a feasible solution to our problem.

Algorithm D2 EVALUATEVIOLATION (X, UB^+)

1: **for** $j \in I : x_{jj} = 1$ **do**
2: $\quad K_j \leftarrow \cup_{i \in I: x_{ij}=1} K_i$; // subset of nodes belonging to (the TUs of) the district.
3: $\quad$ Solve a TSP through nodes $K_j \cup \{k_0\}$. Let λ_j be the resulting a priori tour;
4: $\quad$ Using λ_j, evaluate the expected workload $E[W_j]$ according to (6.11);
5: $\quad UB_j^+ \leftarrow \max\{0, \frac{E[W_j]-UB}{UB}\}$; // violations from workload bound.
6: **end for**
7: maxViolation $\leftarrow \max_{j \in I: x_{jj}=1}\{UB_j^+\}$; // maximal violation of current solution X.
8: **return** maxViolation;

Change the solution

To obtain a feasible solution, we use the procedure sketched in Algorithm D3 (inspired by Diglio et al., 2021).

Algorithm D3 CHANGETHESOLUTION(X, maxViolation, UB^+)

1: Let $\hat{j}$ be the target district associated with the maxViolation, and $Adj(\hat{j})$ the set of its adjacent districts;
2: moveFound $\leftarrow$ REASSIGNFROM($\hat{j}$, $Adj(\hat{j})$, X, maxViolation, UB^+); // Algorithm D4.
3: **if** moveFound $= 0$ **then**
4: $\quad$ Randomly select a district $\hat{j}'$ adjacent to $\hat{j}$ (i.e., $\hat{j}' \in Adj(\hat{j})$);
5: $\quad$ maxViolation $\leftarrow +\infty$;
6: $\quad$ moveFound $\leftarrow$ REASSIGNFROM($\hat{j}'$, $Adj(\hat{j}') \setminus \{\hat{j}\}$, X, maxViolation, UB^+);
7: **end if**
8: **return** X; // changed solution.

Specifically, we target the district causing such *maxViolation*, say $\hat{j}$, and try to modify it. Specifically, we attempt to "unload" it by reassigning one of its TUs to an adjacent district to reduce the resulting *maxViolation*. We accomplish this by using the routines REASSIGNFROM(), whose general scheme is given below (Algorithms D4). Regarding such procedure, the following details are emphasized:

- Districts are sorted in non-decreasing order by UB^+ in Algorithm D4. In practice, we try to reassign a TU from the most to the least over-loaded district $\hat{j}$ (line 8). If this is not possible, we try to reassign from $\hat{j}$ to another potential candidate following the sorted sequence.

- Differently from Diglio et al. (2021), TUs are sorted in non-increasing order by their expected service $E[S_i]$ in both procedures. Note that $E[S_i]$ is readily available information for each TU $i \in I$. Accordingly, their reassignment is evaluated following this sorted sequence. In other words, we try to reassign the TU with the highest service time (line 11). As a proxy of each TU's (internal) expected workload, we observed that this sorting criterion led to significant computational benefits (compared, e.g., with a lexicographic ordering).

- Line 8 in Algorithm D4 defines a necessary condition for a move to be potentially accepted. In particular, we do not further evaluate the move of a TU if it leads to a higher *maxViolation* based on expected service times considerations only.

- In a *first-improvement-like* fashion, we accept a move as soon as it yields a lower *maxViolation* (line 19). Alternatively, we could explore the whole neighborhood of the current solution and pick the solution that produces the *best improvement*. However, this would involve the evaluation of numerous new expected workloads (two per potential move), which would be very time-consuming.

The function returns 1 if we succeeded in our attempt and 0 otherwise. Indeed, unlike Diglio et al. (2021), our search may also fail. At some point, we may be unable to "unload" $\hat{j}$ to attain a lower *maxViolation*. Such a circumstance typically happens if the neighboring districts are "too much" loaded. In such cases (line 3 in Algorithm D3), we proceed as follows. We randomly select one adjacent district to $\hat{j}$, say $\hat{j}'$ (line 4). Then, if $\hat{j}$ is over-loaded, we remove a TU from $\hat{j}'$. This creates "some space" to hopefully successfully unload $\hat{j}$ in some subsequent iterations. To this end, we re-apply the REASSIGNFROM() routine with $\hat{j}'$ as the new target district. To ensure that a move is always found, *maxViolation* is set to a very high arbitrary number before calling the function (line 5). The resulting districting plan is therefore accepted, whatever its *maxViolation* might be. One important aspect must be further emphasized. Let $(i, \hat{j}', \hat{j}'')$ the move we performed to obtain a non-improving solution in a generic iteration of Algorithm 1 (i.e., we reassigned i from $\hat{j}'$ to $\hat{j}''$). Note that the "backward" move $(i, \hat{j}'', \hat{j}')$ clearly leads to an improved solution. Hence, if we select this "backward" move in the next iteration of the algorithm, we may risk always alternating between such two districting plans. To escape this situation, we store the above moves and forbid them for a given number of iterations `#iter`.

Remark 1. *Based on the above discussion, it becomes now clear that Algorithm 1 conveys a local search descent method. At each iteration, the algorithm modifies the current solution by creating a new districting plan (obtained by moving one TU between two districts) with a lower maxViolation. If this is not possible, the algorithm produces (and accepts) a non-improving solution in terms of maxViolation. From that point, the descent process is restarted.*

Remark 2. *The* CHANGETHESOLUTION() *function is also utilized in Algorithm D1. To make it applicable in the latter routine, it suffices to subject the evaluation of each move in the* REASSIGNFROMDISTRICT() *only to expected service time considerations (thus avoiding workload estimations in the interested districts—i.e., line 15 in Algorithm D4).*

Algorithm D4 REASSIGNFROM($\hat{j}$, $Adj(\hat{j})$, X, maxViolation, UB^+)

```
Order the districts in non-decreasing order by $UB^+$. Let $[j_{[1]}, j_{[2]}, ..., j_{[n]}]$ be the sorted districts;
Order the TUs in non-increasing order by $E[S_i]$. Let $[i_{[1]}, i_{[2]}, ..., i_{[|I|]}]$ be the sorted TUs;
$OldUB^+ \leftarrow UB^+$;                                         // store $UB^+$.
oldMaxViolation $\leftarrow$ maxViolation;                         // store maxViolation.
moveFound $\leftarrow 0$;
$l \leftarrow 1$;
while moveFound $= 0$ or $l \leq n$ do
    $\hat{j}' \leftarrow j_{[l]}$;                                 // potential district to which we try to reassign a TU.
    if $\hat{j}' \in Adj(\hat{j})$ then
        for $m \in \{1, 2, ..., |I|\}$ do
            if $x_{i_{[m]}\hat{j}} = 1$ then
                if $\frac{E[S_{\hat{j}'}] + E[S_{i_{[m]}}] - UB}{UB} <$ maxViolation then
                    if reassigning $i_{[m]}$ to $\hat{j}'$ does not break contiguity then
                        $x_{i_{[m]}\hat{j}} \leftarrow 0$;  $x_{i_{[m]}\hat{j}'} \leftarrow 1$;       // try to modify the solution.
                        Evaluate $E[W_{\hat{j}}]$ and $E[W_{\hat{j}'}]$;     // new expected workloads in interested districts.
                        Update $UB^+_{\hat{j}}, UB^+_{\hat{j}'}$ according to (A.34);
                        maxViolation $\leftarrow \max_{j \in I : x_{jj}=1}\{UB^+_j\}$;
                        if maxViolation < oldMaxViolaton then
                            moveFound $= 1$;                  // the modified solution is accepted.
                            $m \leftarrow |I|$;               // exit the for loop.
                        else
                            $x_{i_{[m]}\hat{j}} \leftarrow 1$;  $x_{i_{[m]}\hat{j}'} \leftarrow 0$;   // restore the old solution.
                            $UB^+_{\hat{j}} \leftarrow OldUB^+_{\hat{j}}$, $UB^+_{\hat{j}'} \leftarrow OldUB^+_{\hat{j}'}$;
                            maxViolation $\leftarrow$ oldMaxViolation;
                        end if
                    end if
                end if
            end if
        end for
        if moveFound $= 0$ then
            $l \leftarrow l + 1$;
        end if
    end if
    if moveFound $= 0$ then
        $l \leftarrow l + 1$;
    end if
end while
return moveFound;
```

D.1.3 Improvement of the solution

In this Section, we formalize the algorithmic scheme (Algorithm D5) for the procedure developed to improve the compactness of the feasible solution ($X^\star$).

Algorithm D5 IMPROVECOMPACTNESS($X^\star$)

repeat $\leftarrow 1$;
while repeat $= 1$ **do**
  Let I_C be the set of centers in the current solution X';
  Let $z^\star$ the value of the objective function associated with X';
  for each TU $i \in I$ **do**
    Let j_i be the center i is assigned to ($x_{ij_i} = 1$);
    for each $j \in I_C \setminus \{j_i\}$ **do**
      if $z^\star - c_{ij_i} + c_{ij} < z^\star$ **then**
        if reassigning i from district j_i to district j does not break contiguity **then**
          $x_{ij_i} \leftarrow 0$; $x_{ij} \leftarrow 1$; // try to modify the solution.
          Evaluate $E[W_{j_i}]$ and $E[W_j]$; // new expected workloads in interested districts.
          Calculate UB_j^+ according to (A.34);
          if $UB_j^+ = 0$ **then**
            $z^\star \leftarrow z^\star - c_{ij_i} + c_{ij}$; // the modified solution is accepted. Update $z^\star$.
          else
            $x_{ij_i} \leftarrow 1$; $x_{ij} \leftarrow 0$; // the modified solution is discarded.
          end if
        end if
      end if
    end for
  end for
  Update centers in each district (and hence $z^\star$). Let $I^\star$ be the resulting set of centers.
  if $I^\star = I_C$ **then**
    repeat $\leftarrow 0$;
  end if
end while
return $X^\star$;

D.2 Coarsening procedure

In this section, we outline the so-called *coarsening procedure*, i.e., the methodology employed to reduce the size of the case study (specifically, the number of customer nodes $|C|$) introduced in Section 6.4. The idea is straightforward and involves solving a *Location Set Covering Problem* (see Appendix A—Section A.1.2). The latter is slightly adapted to our case by assuming that the sets of demand nodes and facilities (I and J, respectively) coincide with the set of customer nodes C (i.e., $I \equiv J \equiv C$). This way, given a covering radius r, we aim to find the minimum number of customer nodes covering the full set, say $C^{\star}$. We also denote the latter as the set of "covering nodes". To solve this problem, a well-known heuristic is applied, whose scheme is given in Algorithm D6.

The procedure begins by initializing three sets: the set of covering nodes $C^{\star}$, the set of covered nodes $N(C^{\star})$, and the set of uncovered nodes $\overline{N}(C^{\star})$. Note that $N(C^{\star}) = \cup_{c \in C^{\star}} N_c$, where N_c represents the set of nodes covered by c (i.e., within distance r from c) and not covered by any other node ($N_c = \{c' \in C \setminus N(C^{\star}) : d_{cc'} \leq r\}$). Initially, no covering nodes are selected, so the set of uncovered nodes $\overline{N}(C^{\star})$ coincides with C. At a generic iteration of the algorithm, a new node $c^{\star}$ is selected that yields the highest increase in coverage, namely, that covers the highest number of nodes that are uncovered up to that point. Sets $C^{\star}$, $N(C^{\star})$, and $\overline{N}(C^{\star})$ are accordingly updated and a new iteration starts. The heuristic proceeds until all nodes are covered (i.e., $N(C^{\star}) \equiv C$).

Algorithm D6 COARSENINGPROCEDURE(C)

$C^{\star} \leftarrow \emptyset$; $N(C^{\star}) \leftarrow \emptyset$; $\overline{N}(C^{\star}) \leftarrow C$; // initialize relevant sets.
while $N(C^{\star}) \neq C$ **do**
  for $c \in C \setminus C^{\star}$ **do**
    $N_c \leftarrow \{c' \in C \setminus N(C^{\star}) : d_{cc'} \leq r\}$; // set of nodes covered by c that are still uncovered.
  end for
  $c^{\star} \leftarrow \arg\max_{c \in C \setminus C^{\star}} \{|N(c)|\}$; // the node yielding the highest increase in coverage.
  $C^{\star} \leftarrow C^{\star} \cup \{c\}$; $N(C^{\star}) \leftarrow N(C^{\star}) \cup N(c^{\star})$; $\overline{N}(C^{\star}) \leftarrow C \setminus \overline{N}(C^{\star})$; // update sets.
end while
return $C^{\star}$; // the set of covering nodes.

The identified covering nodes ($C^{\star}$) are considered as the "new" customer nodes in the reduced instance. As aggregates of the original customer nodes, their service times and visit probabilities are adapted to ensure consistency between the full and reduced instances. In particular, for each covering node $c^{\star} \in C^{\star}$, we calculated:

- the service time ($s_{c^{\star}}$), as the expected service time computed across the nodes it covers. Mathematically: $s_{c^{\star}} = \sum_{c \in N_{c^{\star}}} \gamma_c s_c$;
- the visit probability ($\gamma_{c^{\star}}$), as the likelihood of visiting at least one of the nodes it covers. Formally, we have: $\gamma_{c^{\star}} = 1 - \prod_{c \in N_{c^{\star}}} (1 - \gamma_c)$.

The reduced instance, in practice, omits routing considerations among the "covered" customer nodes while assuring similarity in service times. Nevertheless, if the covering radius is relatively small, this approximation is expected to be acceptable.

To validate this assumption, we performed some preliminary tests using districting plans generated by relaxing balancing and workload requirements. To this end, we applied Algorithm

D1. In particular, we varied the number of districts $n \in \{25, 50, 75, 100\}$ For each of these solutions, we estimated the (ex-post) expected districts' workload using both the full ($|C| = 40,235$) and the reduced instance. For the latter, three cases are considered by varying the covering radius $r \in \{10, 20, 30\}$ (in meters). Observe that, by applying Algorithm D6, the number of covering nodes $|C^{\star}|$ equals 34,020 for $r = 10$, 23,186 for $r = 20$, and 15,506 for $r = 30$. These values mark a relative decrease of 16%, 43%, and 62%, respectively, compared to the full instance. Hence, the attained reduction in the problem size is significant.

To evaluate the corresponding impact, Table D1 summarizes the key findings obtained from our ex-post assessments. In particular, two main indicators are reported: (i) the average expected workload calculated across all districts (in hours), and (ii) the computational time required for workload estimations (in seconds). These results are included in absolute values for the full instance (*Full*) and in relative deviation terms (w.r.t. the full instance) for the reduced ones (denoted by the value of r).

As the Table shows, computational times can be reduced to a significant extent as r increases, but at the cost of higher estimation errors. Overall, choosing $r = 20$ leads to substantial computational benefit, reducing computational times by almost 80% for all the tested values of n, and with negligible workload errors (1.30% in the worst case—$n = 25$). Our results, therefore, classify the reduced instance obtained by setting $r = 20$ as a safe choice for our experiments.

Table D1
Testing the coarsening procedure: workload estimation errors and computational times

	Avg. Expected Workload				Computational Times			
n	*Full*	$r = 10$	$r = 20$	$r = 30$	*Full*	$r = 10$	$r = 20$	$r = 30$
25	4.34	0.58%	1.30%	8.58%	1,218	-52.71%	-85.06%	-94.17%
50	2.40	0.48%	1.00%	7.77%	319	-24.45%	-77.12%	-90.91%
75	1.78	0.49%	1.16%	7.10%	255	-50.98%	-80.00%	-91.76%
100	1.46	0.24%	0.68%	6.35%	171	-47.37%	-80.70%	-91.81%

D.3 Technical parameters setting

In this Section, we define the setting for some technical parameters of our heuristic. The procedure (Algorithm 1) is allotted a total runtime (`timeLimit`) of 30 minutes. For the construction phase (Algorithm D1), based on some preliminary experiments, we limit the process to at most 1,000 iterations (i.e., `maxIter` $= 1,000$) for obtaining the initial districting plan that meet the UB requirements. Finally, recall that we implement a strategy for handling non-improving moves to avoid cycles and encourage exploration of alternative solutions (see the related discussion in Section D.1.2). Specifically, any non-improving move is recorded and prohibited from being repeated for ten subsequent iterations (`#iter` $= 10$) during the execution of Algorithm 1. The heuristic procedure has been implemented in C using the MinGW compiler on an 11th Gen Intel(R) Core (TM) i7-1165G7 CPU at 2.80 GHz, with 16 GiB of RAM running Windows 10 64-bit operating system.

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