Doctoral Dissertation
Doctoral Program in Computer and Control Engineering (31.st cycle)

Mixing quantitative and qualitative methods for sustainable transportation in Smart Cities

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Politecnico di Torino
July, 2019

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Summary

The transportation system has been subject to significant paradigm shifts over the past decades, as regards both the freight transportation and people mobility. On the one hand, the urbanization and economic development in the mid-'90s have led the rise of faster-growing medium-large-sized companies that have specialized in the delivery of small parcels, giving birth to the Global Courier, Express, and Parcel (CEP) market [64]. Since the 2000s, the advent of e-commerce changed the logistics and freight transportation dramatically, with an increase of the deliveries to the Business-to-Consumer segments in the urban areas and the competition of e-commerce giant platform to cope with the increasing requests for fast and cheap deliveries.

On the other hand, the urbanization and demographic growth increase the need for people mobility with a huge impact on the saturation of transportation infrastructure. Freight vehicles compete with private and public vehicles transporting people for the capacity of the streets and arteries of the city, and contribute significantly to congestion and environmental nuisances, such as emissions and noise [20]. Thus, the urban space needs to be rethought in order to optimize the flow of traffic, but also encourage the use of non-motorized transport to move people and goods (e.g., bikes and cargo bikes), and collaborative business models. Therefore, a different way of improving the performance of the transportation system has to be found to make people and freight transportation more efficient, cost-effective and sustainable, becoming key factors for the economic development of a country and its competition at the international level. A number of new organization and business models have recognized this challenge, leading researchers and practitioners to propose initiatives that jointly optimize the economic, operative, social, and environmental goals of transportation and logistics, mitigating their externalities and inefficiencies.

City Logistics provides a first mean toward this end. Originally, Taniguchi et al. [230] defined as City Logistics as "the process for totally optimizing the logistics and transport activities by private companies in urban areas while considering the traffic environment, the traffic congestion and energy consumption within the framework of a market economy". However, recent phenomena as the on-demand economy, e-commerce, and urbanization, as well as pervasive technologies, lead to enlarge this framework and give the birth to new domains as the Physical Internet, and their convergence into the Hyperconnected City Logistics.

City Logistics has a multi-facet nature, characterized by concepts as multimodality and intermodality, synchronization of information and physical flows, consolidation and coordination, and finally, sustainability of the urban freight transportation and logistics systems (operational, economic, social, and environmental) [185]. Despite the high interest in City Logistics and its influence on urban development, not all initiatives and proposals are successfully implemented. The main reasons of failure lie the lack of support and commitment from the different actors (with different expertise) in the urban areas [156, 203], also as a consequence of the lack of a managerial perspective in designing sustainable policies appropriate for freight transportation and logistics. Indeed, usually implementation and proposal are too focused on the technological aspects as platforms, or optimization tools, missing a global vision and the lack between the business and operational models.

Moreover, another reason comes from the coverage of the urban area. City Logistics solutions can deal with the entire urban area, but very often they are focused on a limited area or subareas of the city characterized by specific socio-economic and demographic patterns, and the need to protect the cultural and historical property.

Much research and state-of-the-art in recent years have focused on technological solutions and interesting developments are still ahead. In fact, City Logistics challenges researchers to develop models, methods and decision support tools [109]. However, the complex system above described involves several critical issues (e.g., large-scale problems with a huge number of deliveries points, uncertainty) and actors that must not be considered individually, and a holistic approach is necessary. This brings new challenges and complexity for urban transportation system that must work as a system integrator, incorporating current structures and, new and future business models (e.g., new delivery options and low-emission transportation modes) in a modular manner. Moreover, due to the on-demand economy, we are witnessing to a contraction in the timing for decision making. In fact, it appears that medium-term "tactical" decisions may involve very short-time horizons, highlighting the need of a flexible system able to represent different behaviors into an overall model. This integration of new business models and the common practice of outsourcing in the parcel delivery and transportation might become sustainable if a negotiation process is done between actors (e.g., between shippers and carriers), and attention is paid to the design of the infrastructure, the capacity planning and the design of the different services. In doing so, negotiations and the decision-making process must be aided by *ad-hoc* methodologies. These methodologies must aim a comprehensive concept of sustainability from economic, operational, environmental and social standpoints, and thus they must be based on a mixture of qualitative and quantitative techniques. In fact, methods and models by the communities of researchers in Operation Research, Management and Business, Transportation Science, Statistics and Computer Science, within new frameworks as the City Logistics must be integrated. However, such an approach is still missing in the literature.

This work contributes to filling this lack in the literature in terms of multi-disciplinary approach and modeling framework for new planning problems. In particular, this thesis starts with the analysis of the recent relevant literature on intermodal freight transportation that is acknowledged as the backbone of international trade, supporting the efficiency of the above discussed emerging operational and business models, such as City Logistics, in achieving sustainable transportation and logistics. For this reason and due to the similarities at the logical level with the urban context, it can provide important insights from which draw inspiration to optimize the urban freight transportation and design a sustainable system. The review conducted on the intermodal freight transportation literature confirms the multi-disciplinary and multi-facet nature of applications in freight transportation. The results highlight the need for incorporating into simulation and optimization tools a managerial perspective and a representation of the business models of the various stakeholders. Thus, the challenge for simulation development is to model the business models of the different actors and their interactions in terms of contracts, pricing and costing schemes, and operational issues.

In this direction, the thesis has two goals:

- investigate if the integration between business and operational models is possible and which could be the value of this type of integration;
- discuss the benefits of the integration of business and operational models in the urban context. In particular, this thesis is focused on the last mile segment of the supply chain that as mentioned, is the most critical segment due to the large scale problems in a small-sized area and the different sources of uncertainties.

Then, two main problems in the transportation context are proposed to highlight how qualitative and quantitative methods and models are used to support the decision-making processes and to extrapolate industrial and public policies. These applications concern the integration of traditional freight transportation modes with low-emissions vehicles and new delivery options (e.g., cargo bikes and lockers), and the tactical capacity planning problem, respectively.

This thesis is organized as follows. Chapter 1 provides an overview of urban freight transportation and logistics, introducing the emerging challenges and proposing a multi-disciplinary approach to deal with them and design a sustainable urban system.

In Chapter 2, we review the recent relevant literature on intermodal freight transportation, to explore the need for linking new business and operational models and incorporate them into decision support systems for new planning problems.

In Chapter 3, we present the first application of the proposed multi-disciplinary approach that concerns the integration of traditional transportation modes (i.e., vans) and new vehicles with a low-environmental impact (i.e., cargo bikes). This study integrates a managerial analysis of the current business models in urban freight transportation and parcel delivery, describing the stakeholders' profiles in terms of their needs and, cost and revenues structures. Then, the integration of business and operational models, is supported by a performance analysis of the traditional and green delivery options, based on the main variables that affect the last-mile logistics in urban areas (e.g., distance, delivery time). Finally, a quantitative analysis of the system is guaranteed through a Monte Carlo simulation, to extrapolate mixed-fleet policies.

In Chapter 4, we extend the prior analysis investigating to what extent the integration of traditional transportation with new delivery options can be sustainable, considering not only vans and cargo bikes, but also the automated pick-up and delivery point "lockers", reflecting the current practice in the market. After introducing the context, we identify a lack in the City Logistics initiatives regarding a standard framework for simulating and studying the impact of optimization to achieve reasonable levels of efficiency in urban freight transportation, limiting the possibility to validate solutions and policies in real settings, and compromising the technology transfer to industry. Thus, we propose a new standard simulation-optimization framework for building instances and assess operational settings. To illustrate the usefulness of the framework, the authors conduct a case study, in order to evaluate the impact of integrating delivery options to face the demand from e-commerce, in an urban context as the city of Turin (Italy).

The integration of different transportation modes and outsourcing practices necessitate complex negotiation, and monitoring of contracts between shipper and carrier. In particular, in Chapter 5, we present a tactical capacity planning problem in freight transportation. This problem considers a shipper who seeks to secure transportation and warehousing capacity of multiple types from a carrier, to meet its demand for deliveries. The medium-term nature of contracts, requires to deal with the uncertainty, that in this study is expressed in terms of the demand of loads to be transported, the availability of contracted capacity, the cost and the availability of additional capacity if required. After introducing the problem, which is relevant in both the first and last mile segments of the supply chain, we formulate a stochastic two-stage model and propose a meta-heuristic based on the Progressive-Hedging (PH) algorithm. We present new instance sets for tackling the problem partially derived by real parcel delivery applications. Then, we discuss the extensive computational campaign conducted to evaluate the impact of considering uncertainty in the first and last extremities of the supply chain (i.e., long-haul shipment and last-mile delivery) and provide managerial insights.

Finally, Chapter 6 reports conclusions and future developments of the research activity.

Acknowledgements

Firstly, I would like to express my sincere gratitude to my advisor Prof. Guido Perboli for the continuous support of my Ph.D study and related research, for his patience and motivation. His advice on both research as well as on my career have been invaluable.

I would also like to thank to all members of the ICT for City Logistics and Enterprises (ICE) Center, the Operations Research and Optimization (ORO) group, Prof. Roberto Tadei and all the colleagues of Laboratory 8 at Politecnico di Torino.

A very special gratitude goes out to Prof. Teodor Gabriel Crainic who welcomed me at Centre Interuniversitaire de Recherche sur les Réseaux d'Entreprise, la Logistique et le Transport (CIRRELT) research center in Montréal and gave me the opportunity to work with him, generously sharing with me his tremendous experience and immense knowledge. I have very fond memories of my time in Montréal.

Besides my advisor, I would like to thank the rest of my dissertation committee members for their invaluable advice and crucial remarks that shape my final dissertation.

I am also grateful to the Istituto Superiore Mario Boella (now LINKS foundation - Leading Innovation & Knowledge for Society) in the person of Ing. Edoardo Calia, for its generous financial and research support.

A special thanks to Roberto. Words can not express how my feelings to you for supporting me for everything, and especially I can't thank you enough for encouraging me throughout this experience.

To you

“The daisies are safe”

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Chapter 1

Introduction to urban freight transportation and logistics

In this chapter, we present, in a systematic way, the urban transportation and logistics context describing the fundamental concepts and its role in the e-commerce era, with emphasis on the notions of sustainability and sustainable transportation (Section 1.1). In Section 1.2, we then identify some of the challenges that urban distribution raises being a complex system. After an overview of the City Logistics initiatives implemented to deal with these challenges and their major lacks (Section 1.3), a new approach mixing qualitative and quantitative methods and models is presented in Section 1.4.

1.1 Urban freight transportation and logistics in the e-commerce era

The growing urbanization and development of megacities make the urban transportation extremely important to the functioning and prosperity of modern economies.

The urban transportation refers to the mobility for people and goods connecting origin and destination points within the urban areas [88, 18]. Thus, it includes, for example, the public and private transportation, pedestrians and non-motorized transport modes (e.g., bikes) and freight distribution.

As highlighted by Bektaş, Crainic, and van Woensel [18], people mobility is well-designed and developed, and it has been a longstanding pursuit in the literature particularly for what concerns the modeling of the urban residents' transport behavior and the definition of smart urban mobility. Unfortunately, the same cannot be said for the movement of goods that although presents similar general patterns (e.g., planning issues) with the people-based transportation, it constitutes both a critical significance for economic growth and a rather disturbing factor for urban life [176]. Indeed, it is well-recognized that urban freight transportation and logistics are vital activities for the dynamism of cities for several reasons as:

- support the procurement and trading activities for firms established within city borders. [7, 55]. Thus, the transportation of goods represents lifeblood for these firms, being the connection with their customers and suppliers;
- improve citizens lifestyle creating job opportunities (2% to 5% of the total labor force according to [222]) and, providing services and supporting their consumption activities.
- enlarging the vision: an efficient urban distribution represents a competitive factor at the national level.

Moreover, the changes in political, economic and social condition, and trends heightened the role of urban freight transportation. Among the most important phenomena, there are:

- the urbanization. According to the Organisation for Economic Co-operation and Development (OECD), in the 1950s the 50% of the population was urban, and by 2050 it is likely to reach the 85% [177];
- the globalization, liberalization of economies and the opening of broad-free trade economic zones. On the one hand, these phenomena increase the competition between firms, which become more cost-oriented. On the other hand, they foster the accessibility of customers and firms to long-distance market to support their purchasing activities, and the procurement of raw materials and selling products, respectively;
- the arise of new management and production principles such as the Just-In-Time and Lean manufacturing that increase the recourse to transportation activities [66];
- the explosive growth of the e-Commerce that changes the entire logistics chain dramatically. As Morganti et al. [165] point out, the 45% of European consumer shop online. Indeed, the e-Commerce increases the product discoverability for the final consumer that is increasingly requesting fast and on-time personalized delivery for free or at least at the lower cost. In fact, the customer becomes less aware of the implications of its delivery on the company and society, and less willing to pay a delivery fee, due to the ubiquitousness that the so-called "free shipping" or "free returns", disregarding the hidden cost of logistics operations in charge of the company. According to the survey in [161], for the 93% of online shoppers, the free shipping affects its shopping habits, while the 58% are willing to spend more on goods, to reach the free shipping thresholds. Incumbent e-Commerce platform such as Amazon and Alibaba are facing the growing requests for fast and cheap deliveries associated with the high-quality service level, and in this direction, the efficiency of logistics becomes vital for their success. This link between e-Commerce and

logistics is highlighted by the fact that e-Commerce counts the 10% of the overall logistics demand, and this projection is expected to grow [98].

All these phenomena increase at a fast rate the volumes of goods moved and consequently, the flow of vehicles that transit within the urban areas. Generally, the freight coming from long-haul shipment is consolidated into urban trucks in distribution centers located at the outskirts of the urban areas and then transferred to the second set of infrastructures named satellite platforms, located within the city borders. At the satellite, the freight is transferred to city-freighters (e.g., urban vans) that perform a designed route inside the city to reach and serve the final customers. This final leg of the logistic process is named the "last mile" and it starts when the loads leave the satellite and finishes with the home delivery. The high volumes increase the complexity of the last mile that becomes the bottleneck in the supply chain as well as the least efficient, and most polluting and expensive, segment [104], accounting the 28% of the transport costs [113]. In particular, Gevaersa, Van de Voorde, and Vanelslandera [103] identify two main problems connected to the cost-inefficiency of the last mile activity: the high failure rate of delivery due the customer is not at home problem (about the 12% of delivery requires a second round [246] and the lack of critical mass due to lack of market penetration and density.

Although its relevant role in urban vitality, the freight transportation and logistics industry generates negative externalities, such as traffic and congestion, environmental nuisances, noise disturbance, with the result of unsafe and unlivable cities. Moreover, the consequence of the traffic and congestion is the loss of about the 1% of the European Gross Domestic Product (GDP) every year, corresponding to 100 billion Euros [18]. Concerning the environmental impact, despite the long distances involved in long-haul transportation, urban freight transport is the most pollutant, due to the inefficiencies of activities, its road-based nature (i.e., it is mainly operated using non-renewable fuels vans) and the large number of stops, with severe consequences in terms of greenhouse-gas (GHG) emissions, noise and visual pollution. Indeed, the transportation sector is responsible for the 72.9% [90]. More in detail, according to the research and innovation roadmap by ALICE Alliance [2], the urban freight emissions account for the 25% of urban transport-related CO2 emissions and 30% to 50% of other transport-related pollutants (e.g., particulate matter, nitrogen oxide N2O, methane CH4). The environmental impact of transportation has harmful effects causing climate changes, global warming and damage to human health (e.g., respiratory and cardiovascular problems). The complexities of these impacts have led public authorities and stakeholders in the city to pursue environmental policies and mitigation strategies. The European Commission sets binding emission targets for the transportation industry, requiring the member states to achieve essentially CO2-free City Logistics in major urban centers by 2030 [87].

Reducing global pollutant emissions and environmental protection are one of the main pillars embraced by the concepts of sustainability and sustainable transportation. In particular, as Ehmke [80] points out, the dilemma of urban freight transportation is to be innovative and competitive, while reducing the environmental externalities.

In general, sustainability is challenging city managers, researchers and practitioners in finding solutions and approaches that go beyond the urban planning activities. The concepts of "sustainability" and "sustainable development" appear for the first time in the report *Our Common Future* by the World Commission on Environment and Development [237]. In the Brundtland report, the sustainable development is defined as:

> the development that meets the needs of the present without compromising the ability of future generations to meet their own needs.

Different contributions aim to express the meaning of sustainable transportation in line with the principle of sustainability outlined previously [195, 253, 158, 16]. In particular, they identify different issues and related objectives of sustainable transportation that can be summarized as follows (Figure 1.1):

- *People*. Sustainable urban freight transportation aims to reduce the unsustainable effects that can generate disease, damage or compromise the public health, safety and security (e.g., traffic accidents, noise, and air nuisance). Moreover, it has to ensure the accessibility offered by the transport system to all citizens, guaranteeing their social inclusion.

- *Environment*. It refers to the reduction of GHG emissions, noise and visual pollution, reducing the connected social costs and improving the air quality.

- *Economy*. Sustainable urban freight transportation has to ensure a profit (particularly to the private stakeholders) reducing the cost-inefficiency due to environmental aspects, regulations and restrictions while improving the cost-effectiveness of the transportation operations.

- *City*. Sustainable urban freight transportation becomes a fundamental requirement to obtain a sustainable development of the city, which becomes competitive and attractive, and well-functioning.

1.2 Emerging challenges

From the global vision presented above, it is clear as the urban area, and particularly the last mile, are represented as a complex system, challenging the city managers and the stakeholders in finding factual solution to improve the efficiency of transport while preserving the quality of life of citizens. In particular, in the following, the most important emerging challenges for urban transportation and logistics are described.

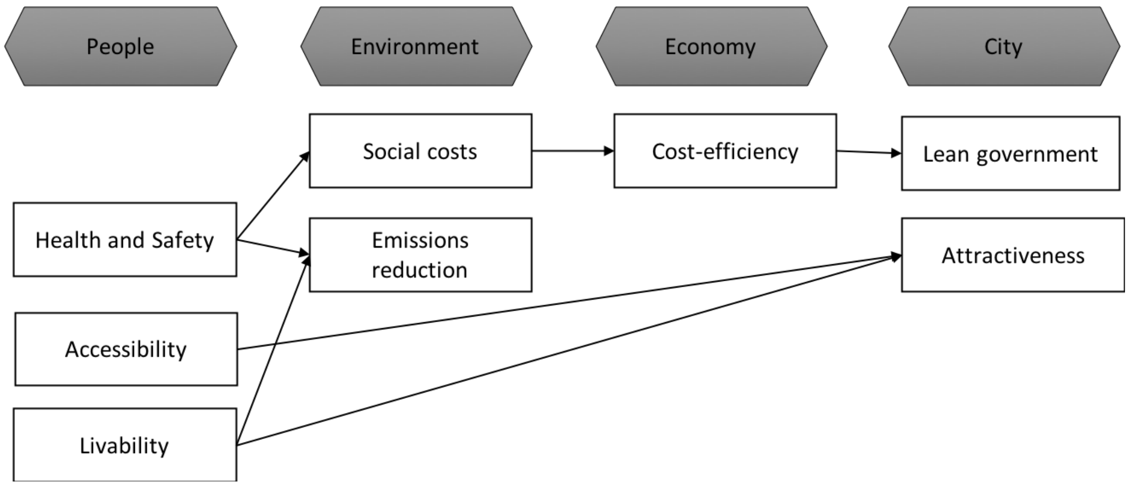

Figure 1.1: Pillars of the urban freight transportation sustainability.

Paradigm shifts In past decades, urban freight transportation and logistics have been interested in different paradigm shifts to face the requirements of the modern economy. In the beginning, urban freight transportation and logistics were more related to the business-to-business and intra-business segments for procurement and selling purposes. The urbanization has rapid growth, starting from the 1950s. According to the estimations of the United Nations [238], the urban population was equal to 746 million in 1950, reached the 7.6 billion in 2017 and additional 2.5 billion people are projected to be urban in 2050. This phenomenon led to benefits to the urban fabric and the economic development of cities. Also, the logistics have benefited from the urbanization and demographic growth, and we saw a first change that has led to the creation of micro-small transport companies with vehicle fleets of reduced size, which provide urban freight services in limited areas of the city. The economic development since the 1990s has led the restructuring of there small business in medium-large companies (e.g., TNT, DHL, etc.) that utilizing city vans or small-medium trucks make consolidation-based delivery tours to serve the last-mile segment of the supply chain. They are the faster-growing urban transport business [64], giving rise to the CEP industry. More recently, the massive adoption of online shopping and the development of e-Commerce giant platforms contribute to another paradigm shift in urban distribution and logistics. Indeed, we see the transition from an offer-driven logistics to a demand-driven logistics, in which the customer obsession and the demand orchestrate the supply chain.

Multiple actors The urban transportation system involves many different actors with sometimes conflicting goals and objectives (Table 1.1). In the literature, it is commonly recognized that the four main actors who affect urban freight domains are briefly described in the following [203, 195, 15, 171, 25]:

- *Shippers*. The shippers aim to reach their customers and suppliers to sell their products and procure raw material and semi-finished products, generating the demand for transportation services. Generally, they engage third-party logistics service providers (3PLs) and carriers to outsource the physical freight movement and the logistics activities. The relationship between shippers and carriers requires a complex decision-process by which the shippers decide the transportation mode, shipment size, frequency, lead-time, delivery precision and flexibility, according to its supply-chain and logistics planning strategies, and additional factors (e.g., freight rates, reliability, transit times, market and carriers considerations, etc.) [15, 168].

- *Carriers*. These companies are responsible for organizing and performing freight transport efficiently (e.g., using different strategies for routing and avoid congestion) and to eventually, provide customized services.
  Since they are private stakeholders, the shippers and carriers are usually interested in picking up and delivering products at the lower costs, but with a high-quality service level and short lead-times [203].

- *Administrators*. This actor refers to the local public authorities responsible for the management of the city and to ensure the livelihood and the welfare of the community. Thus, the administrators aim to reduce the negative externalities related to the transportation activities, reduce the social costs and guarantee the sustainable development of the city, making it more livable, socially inclusive, attractive and competitive [171, 175, 147, 224]. Starting from the beginning of the 21st century, the role of the public authorities is no longer remained closed to restrictive measures but becomes relevant in the design of policies for freight transportation in urban areas.

- *Customers*. They are the final receivers of the goods moved in the city, as well as the citizens, participatory members of the city. Customer's main interest is to receive the purchased good at the desired time and location, and the lower cost. Moreover, they are interested to live in a pleasant, accessible, environmental-friendly and safe city.

Table 1.1: Key actors in urban freight transportation and their objectives.

Actor	**Main interests**	**Objective in the literature**
Shipper	Minimize cost, maximize service level	Service time, time window
Carrier	Minimize cost, maximize service level	Travel cost, distance, travel time, fleet size
Administrators	Sustainable development, minimize externalities	Environmental cost
Citizen	Maximize service level, minimize externalities, minimize transportation costs, maximize quality of life	Environmental cost

In Chapter 2, a detailed description of a complex transportation system, the actors involved and their interaction is provided.

Common and scarce resources In urban areas, the movement of people and freight coexist. Thus, as Crainic, Ricciardi, and Storchi [55] point out, freight vehicles share and compete with public transportation modes and private-citizens cars for the use of infrastructure and resources, e.g., streets, parking spaces, etc., and contribute significantly to congestion, noise, and environmental pollution. Obviously, the city streets and urban spaces have limited capacity making the conciliation of freight with people, and the land-use planning challenges for the cities managers to order and regulate the efficient adoption of commodities.

Large-scale problems As stated in Section 1.1, the home delivery has lead to a rapid increase of the volumes of freight that transit within urban areas increased rapidly, requiring to cope with large-scale problems. In particular, the online shopping generates a fragmented demand composed by more frequent orders of small dimension, i.e., mainly parcels up to 3 kg. Morganti et al. [165] refer to this issue as the "atomization of parcel flows", which has considerable repercussions on the last-mile logistics.

The urban freight is characterized by a phenomenal diversity [64], as cities throughout the world are diverse in terms of social, political, geographical and economic patterns, as well as the different business inside a city generate diverse flows volume and characteristics (e.g., durable products differ from the e-grocery), which vary from city to city. Despite this diversity, some data from contributions in the literature and internal analysis published in [185] can give an idea of the dimension of problems in urban context. These data considers all the good movements related to the business-to-business and business-to-consumer segments as well as the home deliveries from the online shopping and e-Commerce, and the end-consumer private movement flows (i.e., made with private transportation modes) According to different contributions [165, 222, 175, 65, 94, 185], the city generates about:

- 0,1 delivery/collection per capita per day;
- 1 delivery/collection per job per week;
- 30 to 50 tons of goods per capita per year;
- about 4000 delivery/day in a medium-sized city;
- between the 40% and 45% of the total goods traffic in terms of road occupancy rates for economic needs of local businesses;
- between 45% and 55% of the total goods traffic by the business-to-consumer and the private movement flows.

The high volume of transit flows can significantly disturb the urban transportation system, compromising the environmental and economic sustainability of transportation and logistics activities in the city. Indeed, the transportation and parcel delivery companies are dealing with a new phenomenon in this sector: the diseconomies of scale. The high density of deliveries point-to-point and the diversity of destinations lead to an increase in the delivery travel and service times, instead of a decrease, due to traffic and congestion.

Planning issues and uncertainty The above issues demonstrate as the urban context is a complex domain, where people and freight compete for common and shared resources and different actors with conflicting objectives interact. Furthermore, it is characterized by a rapid rate of growth, according to the political, economic and social evolution of the environment, and changes require capital-intensive investment and long implementation times [45]. In this context, accurate planning processes at different decision levels become valuable, challenging researchers to develop appropriate methods, models and Decision-Support Systems (DSS). The papers by Crainic and Gilbert [45] and Benjelloun and Crainic [20] identify three planning levels (i.e., strategic, tactical and operational), which are briefly discussed in the following:

- *Strategic level.* It involves the highest level of management and refers to the decisions related to the logistics system design over a relatively long time horizon that require large capital investments. For example, strategic decisions concern infrastructure aspects (e.g., the location models of urban distribution centers or satellites), the determining of the optimal fleet composition [96], the designing of strategies and policies.

- *Tactical level.* It concerns all the medium-terms horizon decisions, which are usually related to the definition of a transportation plan describing the adequate allocation and utilization of existing resources, that allow achieving the best trade-off between operating costs and service performance [45]. Tactical decisions are the service network design, and the planning of transportation and warehousing capacity.

- *Operational level.* It concerns short term decisions as day-to-day operations. The urban areas are dynamic contexts, thus anticipating future events (e.g., demand, congestion and unfavorable conditions) and reacting in short or even real time is valuable. Operational decisions concern the adjustment of tactical plans, such as daily routing, assignment of delivery requests to vehicles.

It appears, however, that "tactical" may involve very short time horizons, e.g., the next day, in urban freight transportation. In fact, to the classical planning levels, the availability of reliable real-time (or quasi real-time) data streams, the computational capabilities installed on the machines, and the intelligence present in the IoT network, create a new planning level, the so-called "short-term tactical", "pre-tactical" or even "day-before planning" [56]. It is a decision level where, thanks to analytics and data from sensors in the city, we can design a tactical problem ranging over a shorter time horizon (normally one or two days), but incorporating a simplified version of the operational actions. Relative to the management environment and constraints, planning closely to operation-time is beneficial when one has little or no restrictions on mustering facilities and people on very short notice.

The planning process requires to operate in an uncertainty environment. Indeed, usually at the time for decisions, not all the information is available, but some parameters related to random events (e.g., the demand fluctuation) are uncertain. Thus, the decision-marker deals with a stochastic problem and it has to take into account the different sources of uncertainty in urban areas that could have a strong influence on the decisions and performance of the transportation system. Chapter 5 will present a tactical decision-making process under uncertainty that involves shippers and carriers, regarding the capacity planning problem.

1.3 City Logistics

In the last decades, the issues that affect the freight transportation and logistics in urban areas motivate the researchers and practitioners to design and develop solutions to make this complex system more innovative and competitive, while reducing its inefficiencies and environmental impact. In this direction, first attempts of actions came from the City Logistics, which is defined by Taniguchi et al. [230] as:

> the process for totally optimizing the logistics and transport activities by private companies in urban areas while considering the traffic environment, the traffic congestion and energy consumption within the framework of a market economy.

As Crainic, Ricciardi, and Storchi [55] point out, an unequivocal definition of City Logistics does not exist, and several classifications of the initiatives in this field are available in the literature [154, 76, 202, 203, 63, 166]. However, the different contributions converge to the following pillars that characterize a City Logistics measure:

- focus on freight transportation at the urban level;
- emphasis on reaching an integrated logistics system;
- reducing the inefficiency and environmental impact of transportation activities and supporting the sustainable growth of livable cities.

In this subsection, an overview of the City Logistics measures is provided, according to the classification depicted by Figure 1.2. In particular, the different City Logistics initiatives can be grouped in the following categories:

- *Infrastructure*. This category includes the initiatives related to the urban transportation network, as the building of new infrastructure reserved for freight operations or the improvement of the existing infrastructures and their links. Such measures comprise for examples the nearby delivery areas and loading/unloading lay-by zones, which are urban areas reserved for freight loading and unloading purposes, avoiding the problem of double-parking by trucks [215, 65]. Other measures of this type are the multi-use lanes or the preferred freight vehicles lanes for freight distribution. The first case has been adopted in Barcelona [119] and in Bilbao [257], where one of the road lanes is provided for the loading and unloading of goods and their transit at certain time slots, and used for other vehicle activities during the rest of the day. A consistent part of the City Logistics initiatives in this category deal with the installation and allocation of Urban Distribution Centers (UDCs) or Urban Consolidation Centers (UCCs). These are logistics terminals where the goods coming from the long-haul shipments are consolidated into urban vehicles, improving the transported payload, minimizing the logistics costs while alleviating the traffic and congestion within urban areas. For further details about the different UCCs located within Europe and outside, the interested reader could refer to the comprehensive review by Browne et al. [29]. Finally, Crainic and Sgalambro [47] proposed an extended generalization of the UCCs, named two-tier city logistics system, where a second set of infrastructures named satellite platforms are located inside the city. Here, the freight coming from the external UCCs, is consolidated into smaller vehicles named city-freighters, which can travel along the street in the inner city to the final customer. The complexity and the size of the problem at the level of the whole city area pushed the researchers to explore multi-tier logistics frameworks, where a set of depots of small size are located inside the urban area. The size and the location of the depots, usually called satellite depots, require, to be operationally efficient, a strong coordination of the operations between the actors and the vehicles involved in the delivery process. They enable the integration of environmental-friendly vehicles as electric vans and cargo bikes [185]. More recently, the possibility to have mobile satellite depots, as the Mobile Depot by TNT [153], enforces the effect of the synchronization of the operations among the vehicles used at the different levels of the multi-tier system. The usage of the mobile depot can be static, i.e., its position is fixed in the optimization time horizon, or dynamic, i.e., the location changes in the operational time horizon.

- *Regulation and governance*. This category comprises the “positive” measures as the incentives to encourage the supporting of sustainable transportation, as well as the “negative” ones, as restrictions, limitation or monetary impositions set by the local administrators of the city. For example, today most cities have restrictive regulations on time window to access in city centers or low-emission zones, especially historical or pedestrian zones (e.g., Turin, Milan) and requirements of a minimum load factor to avoid empty trips (e.g., Copenhagen and Göteborg). Other types of regulation measure are road-pricing and area-pricing, which impose monetary charges (e.g., tolls) for certain types of freight vehicles (e.g., congestion charging schemes in London and Stockholm). This measure plays an important role in the demand and vehicles fleet management, leading the freight transportation company to rationally use their vehicles, reducing the costs and environmental impacts of operations.

Finally, the last governance measure implemented for example in Barcelona and New York concerns the off-hour delivery or night delivery, which imposes the freight companies to shift deliveries during less congested hours as the night.

- *Technology*. As stated by Taniguchi [225] a key element for promoting City Logistics is the application of innovative Information and Communication Technologies (ICTs) and Intelligent transport systems (ITS). In the projects already implemented, these measures concerned mainly the development of platforms and telematic systems for control and charging the access to regulated areas or for booking the loading/unloading zones. Moreover, these system aimed to gather data and information concerning the truck flows on urban road networks, through on-board units, cameras and sensors spread all over the city, supporting dynamic vehicle routing and scheduling according to the degree of congestion on the transport network [202, 225].

  Another important framework in this category concerns the technical innovation related to the vehicle design, as the alternative vehicles and energy saving-engine, that can be relevant to achieve low-energy and low-emission transportation activities.

- *Collaborative systems*. This last category includes solutions at the planning level that regard how the freight moves within the city, fostering the collaboration among the different actors, transportation modes and integrating people and freight. In these systems, the different actors share not only information, but also the management and coordination rules. Many experiences in different cities (e.g., Turin [184], London [138], Paris [64]) address the potential of multi-modality and intermodality that integrate traditional vans with non-motorized vehicles as cargo bikes, for sustainable urban freight transport, as investigated in Chapter 3.

  Another concept is the "co-modality" or "cargo hitching" that considers the adoption of public transport vehicles such as trains, trams, buses or taxis, which usually have an underutilized capacity, for transporting passengers and goods simultaneously [18, 106, 140, 227, 234].

Although the City Logistics aims to achieve an integrated logistics system as mentioned before, most of the measures in this field are fragmented and mainly address just some of the different aspects in the freight transportation, individually. Thus, a lack of a global vision of this complex system emerges. In fact, as stated by Bektaş, Crainic, and van Woensel [18] the major challenge for City Logistics is to develop models and methods that provide a comprehensive formulation of the system. In this direction, the next subsection will be devoted to analyze the main issues of the current solutions in the City Logistics and to propose a new multi-disciplinary approach that considers the different stakeholders and matters of urban freight transportation to support the decision-making processes.

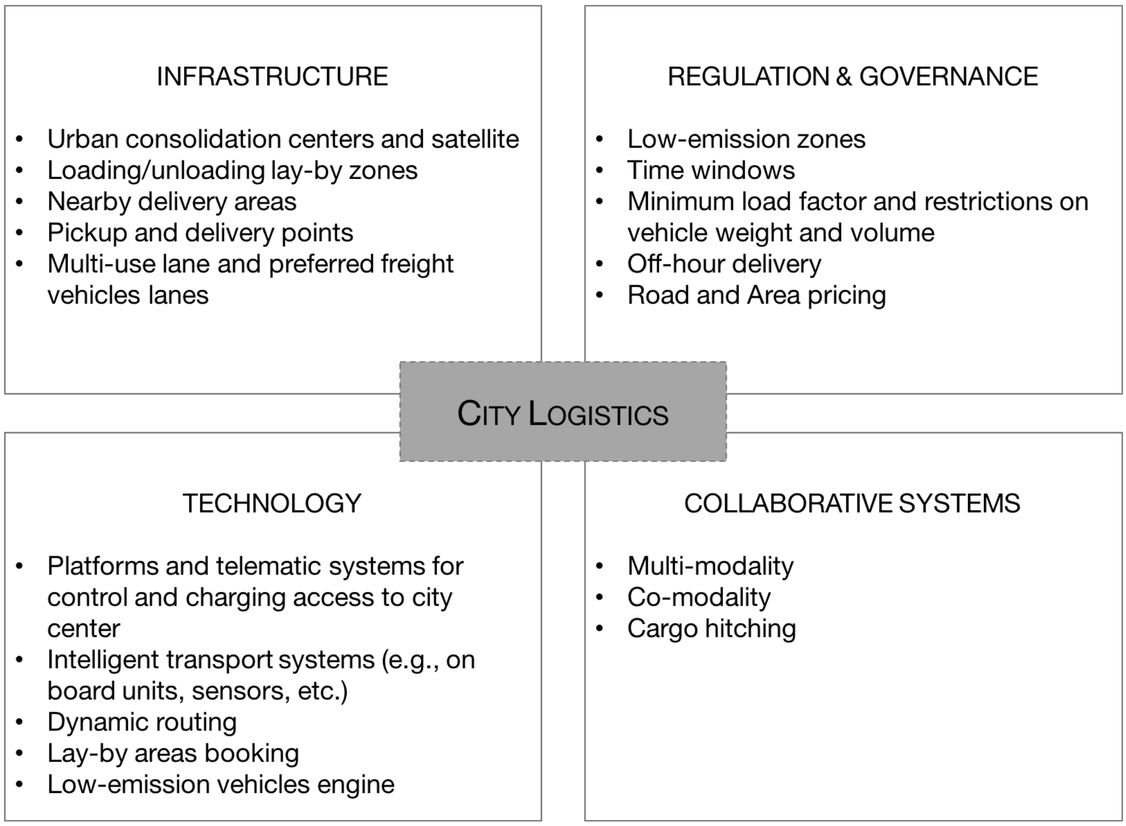

Figure 1.2: A categorization of the main City Logistics measures.

1.4 A new approach to sustainable urban freight transportation

The City Logistics measures presented in Section 1.3 have three main issues. First, despite the good results and performance of their proposed solutions, they are usually related to a limited spatial coverage. In fact, the major part of the City Logistics initiatives is focused on a limited area of the city (e.g., a commercial district or the inner city), where the socio-demographic patterns, occupation density and, cultural and historical values are valuable, disregarding the overall urban context. Thus, it might be difficult to use at a regional or national level. Indeed, they do not consider the complexity and phenomenal diversity of urban logistics, as discussed in Section 1.2, resulting strictly dependent on the environment where they are implemented [149, 15, 137]. Moreover, as Dablanc [64] point out, the success of these initiatives and best practices to improve the sustainability of urban transportation depends on the local government interest and subsidies.

Second, the City Logistics initiatives fail due to the lack of support and commitment from the different actors in the urban areas [156, 203]. Indeed, as emerged in the studies conducted by Behrends [15], Vieira, Fransoo, and Carvalho [243], Marcucci et al. [156], Dablanc [67], and Ville, Gonzalez-Feliu, and Dablanc [245], projects and research on City Logistics address mainly the public authorities perspectives (e.g., dealing with pricing policies, road infrastructure), while private companies are rarely involved. For example, Behrends [15] highlights as in 2013 the public perspective is addressed in the 52% of papers, while only the 5% deals with the shippers and receivers perspectives. As mentioned above, the urban transportation system is characterized by multiple actors involved in complex interaction and with different background and conflicting objectives, causing difficulties in converging to a coordinate and accepted solution. According to [221], there is a lack of qualified expertise in local authorities for the proper conflict resolution among the different participants in City Logistics projects. Modeling efforts considers the importance of engaging the different actors and stakeholders in the city, only within recent years [171, 137, 215, 123]. Thus, it becomes clear the need for designing and deploying strategies for sustainable transportation, which are commonly accepted by all the actors. Hence, authorities should choose the set of measures that receive the best support from the stakeholders [215].

Finally, the third issue of the City Logistics initiatives, which is related to the previous points, refers to the lack of a managerial perspective in designing sustainable policies appropriate for freight transportation and logistics. The proposed solutions are too focused on the technological aspects as platforms, or optimization tools, missing the lack between the business and operational models and causing the ending of the projects when funds and financial supports end [193, 97]. This aspect will be further discussed in the next chapter of this thesis.

To deploy efficient and effective solutions to achieve sustainable urban transportation, it emerges the necessity of a visionary and holistic approach that looks at the system, in its entirety, and not only to the technological and scientific standpoints. For example, this approach must take into account the different actors in the city, the complexity of their interactions and relationships, the different technologies and logistics solutions and the coexistence of freight and people, rarely considered together in City Logistics initiatives.

In this direction, the thesis aims to fill the above-discussed lacks in the literature and to investigate whether a multi-disciplinary approach is valuable to support the decision makers in the assessment of new factual solutions and, industrial and public policies in the urban transportation system. The proposed multi-disciplinary approach integrates qualitative and quantitative methods and model from the research communities of Business and Management, Operation Research, Transportation and Computer Sciences. It could provide the following benefits and contributions to the community:

- an automatic decision-making process because of its technological component, i.e., optimization tools;
- integration of real data from the context;
- integration of methodologies and models that otherwise would remain a niche;
- actor-centric approach capable of allowing the communication and interaction with non-technical staff or among actors with different backgrounds, going to fix the issue related to the lack of stakeholders involvement and convergence.

Figure 1.3 depicts the building blocks of the approach, as following described:

- *Behavior analysis*. The starting phase for evaluating urban freight transport initiatives that aim at improving sustainability concerns an analysis of the context (e.g., urban characteristics, social and political issues) and particularly of the actors involved. It attempts to understand which are the actors involved, and the reason for that involvement, as well as to describe their behaviors under certain conditions and their business models [123, 202, 226]. According to Kritzinger et al. [135], Nilesh et al. [171], and Regan and Garrido [197], urban freight transportation modeling lacks appropriate behavioral approach towards modeling related processes and the planning or policy assessed under such circumstances does not guarantee anticipated results. Moreover, understanding the interactions among different actors is an essential step in the decision-making process to analyze the causes of the urban goods movement and forecast the effects of new policies, overcoming the unexpected consequences due to poor decision making [171]. In this direction, the simulation can be applied to deeply study and reproduce the connections and interactions among the actors. Moreover, qualitative tools (e.g., Value Proposition Canvas, Business Model Canvas (BMC) and Value Ring [183, 233, 180]) from the Business and Management field, become valuable.
- *Economic analysis*. To understand the context and actors involved, it is necessary an economic analysis to investigate the economic feasibility of certain measures in the short term and their sustainability in the long run, which will be monitored in the future.
- *Technology scouting*. This block concerns the scouting of the possible opportunities in term of technologies to adopt, and the most quantitative part of the approach, including simulation and optimization tools and methods.

The outcomes of these phases converge in a unique framework to support the decision process and the design of industrial and public policies. The presented framework is then

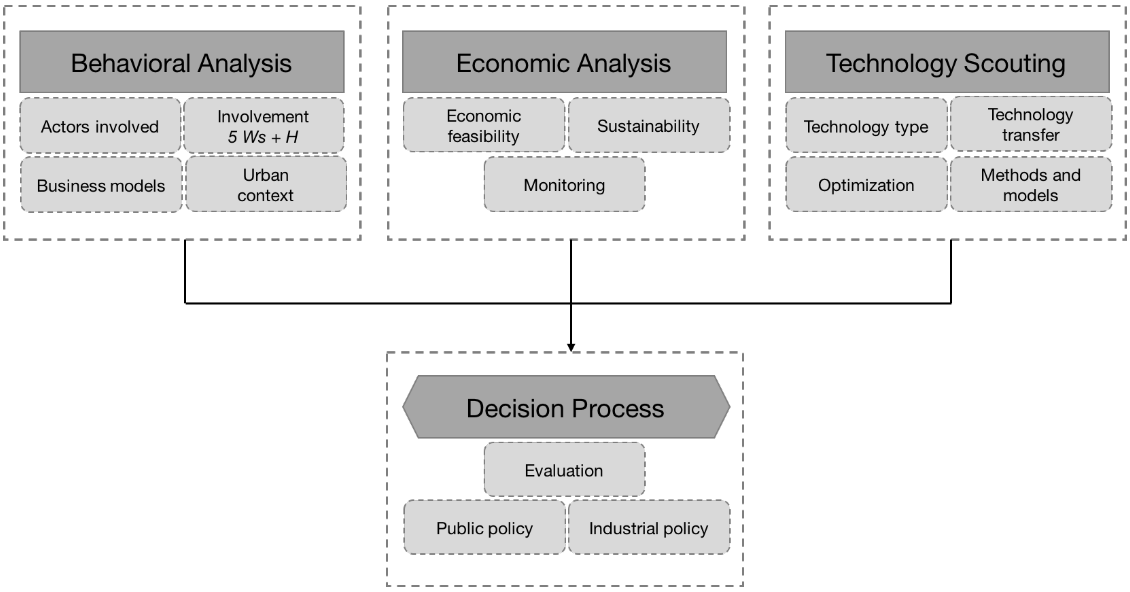

Figure 1.3: Multi-disciplinary user-centric approach for urban freight transport sustainability.

used to investigate the different challenges of urban transportation and parcel delivery system, extrapolating some useful managerial insights, industrial and public policies.

In particular, one of these challenges concerns the integration of different transportation modes and new delivery options in a unique service. It emerges from the need perceived by firms to cope with the increasing focus on maximizing service level and reduction of profitability. In this direction, the following chapter has the aim to investigate the research on the intermodal transportation to understand how intermodal systems, including intermodal and regional facilities (e.g., distribution centres and satellites) can be repurposed at a logical level, on the urban freight transportation.

Chapter 2

Intermodal transportation

The multi-level transportation systems such as those encountered in the context of urban freight transportation and City Logistics are characterized by intermediate satellite facilities, and the adoption of fossil-fuel van but also small and environment-friendly vehicles to perform the last leg of distribution operations. This phenomenal diversity of urban context as well as the adoption of multiple modes and options, require the adoption of an intermodal approach to deal with urban freight transportation issues. Indeed, intermodality is broadly acknowledged as the backbone of international trade, supporting the efficiency of the above discussed emerging operational and business models, such as City Logistics, in achieving sustainable transportation and logistics. As Catte [38] points out, intermodality is a key component of environmental policies, integrating the individual measures (e.g., congestion charges or traffic restriction) and providing viable alternatives to the traditional model.

Thus, the research on the intermodal transportation could provide valuable and interesting insights from which draw inspiration to design sustainable urban freight transportation system. This chapter aims to study the intermodal freight transportation system and simulation methods used to shape it, as proposed in the original work by Crainic, Perboli, and Rosano [46].

Intermodal freight transportation is defined as the transportation of loads from the origin to the destination of a shipment, involving at least two transportation modes and services, such that the transfer from one mode to the other is performed at an intermodal terminal.

It can be represented as a multi-actor complex system (MACSs), which involves a broad range of interacting stakeholders, decision makers, operations, and planning activities. Its complexity and the high level of interactions, make needed simulations of the system to shape and monitor the transportation activities and support the decision-making processes. On the one hand, simulation provides the instruments to validate models and algorithms and to explore their worth under various internal and external conditions. On the other hand, it is also a means to represent the behavior of a certain system and to estimate its response to various policies and changes in its environment, from the availability and quality of infrastructure to energy prices and environmental regulations. In this direction, the field of Operations Research offers a rich set of models and methods to build and manage the "best" operation plans, to select operations or manage alternatives to achieve desired levels of cost versus quality of service versus environmental and societal impacts, and to evaluate strategies and policies.

After defining the freight transportation complex system, the rich literature concerning simulation models and studies on various issues related to intermodal transportation is reviewed, through the application of a three-layer taxonomy to derive trends and patterns from the current research contributions and to propose a guide for future research analyses. This analysis included a large set of papers published in scientific journals and conferences within different disciplines, confirming the multidisciplinary nature of applications to freight transportation that involves Computer Science, Mathematics, Transportation Engineering, Management Science, and Economics. Moreover, on the contrary of the several surveys on multi and intermodal transportation issues as part of long-haul transportation or City Logistics, this taxonomy provides a global vision of the system, including the decision makers, the actors (both public and private) involved and the issues they want to address.

Several interesting insights emerge:

- Public, individuals and freight transportation are currently modeled and optimized as separate systems. There is thus the need for new models, methods and software tools able to represent the complete transportation system, including new active modes, business and organizational models. Indeed, this is not just a matter of defining a model, but to deeply understand the connection between the different actors and how and why they can cooperate, which kind of data they might share and which policies might be defined. Notice that this is an open issue at the regional level as well, where research did not really advance after the first examples of an integrated vision of the years 1990 [51, 60, 52, 130].

- The intermodal transportation systems, the rules and policies of the different actors, and the interactions among actors and subsystems are often described in an aggregated, simplified way. This approach is particularly used in network representations and multi-agent simulations, where the level of intelligence and optimization incorporated in the agents is generally quite low (e.g., simple heuristics). This simplification is affecting, in particular, the characteristics related to the geographical, organizational, behavioral and data sharing aspects. We believe that a crucial point for the relevance and utilization of simulation lies with the development of more detailed and flexible models, as well as better integration of simulation and optimization.

- The complexity of the transportation systems yields large-sized simulation models, which will grow even larger and with more details when the results of the previous items will become available. This requires significant and continuously growing computational efforts. We therefore, see a research avenue with significant benefits in increased exploration and exploitation of parallel computing, particularly for new hardware and software high-performance computing architectures, which become more and more affordable.

- New business and organizational frameworks, e.g., Hyperconnected systems (City Logistics, Physical Internet, Synchromodality) and Logistics 4.0 are viewed mainly as key concepts for the development of transportation and logistics systems [3, 18, 54]. Stakeholder cooperation and the integration, synchronization, and automation of operations are at the core of these concepts and development frameworks. Current studies of such systems are few and their representations are still quite simplified. More efforts are certainly required in this broad field, the first results with a Technology Readiness Level larger than 6 being presented currently only for a survey of the recent results in EU FP7 and H2020 projects in [193].

- Few studies address policy-making processes, and there is a need for tools supporting policy makers in designing sustainable policies appropriate for freight transportation and the continuous evolution of the society (e.g., the codesign with citizens and companies of urban policies). Overcoming this lack implies incorporating into simulation and optimization tools a managerial perspective and a representation of the business models of the various stakeholders. While such policies are currently showing their effectiveness in terms of acceptance and efficiency, the challenge for simulation development is to model, at the appropriate level for the tradeoff between detail and computation efficiency, the business models of the different actors and their interactions in terms of contracts, pricing and costing schemes and operational issues [155, 190].

  Thus, results highlight the need of a more comprehensive methodology that encourages quantitative and qualitative researchers to "speak" a common language, to support the policy-making process commonly. The first attempt took the form of the GUEST methodology used in this thesis, which is a business framework for researchers used to develop their ideas into business and managerial applications, by moving the projects to real sustainability [183, 233]. It is a lean business approach that extends the work of Osterwalder and Pigneur [179] and other lean startup movements, adapted for MACSs, such as freight transportation systems.

This chapter is organized as follows. Section 2.1 describes the intermodal freight transportation system, analyzing the stakeholders involved and their interactions. Section 2.2.1 introduces the methodology and taxonomy adopted. Finally, Section 2.3 presents the outcomes and general trends emerged.

2.1 Intermodal transportation as a complex system

Bektaş, Crainic, and van Woensel [18] define intermodal transportation as the transportation of people or freight from their origin to their destination by a sequence of at least two modes of transportation without any handling of the freight itself when changing modes. Intermodal transportation aims to reduce cargo-handling, damages, and loss, as well as to improve security and transport speed. The main characteristic of intermodal freight transportation is that the goods are moved in one loading unit or vehicle and are not handled when changing modes [89]. Although different types of packaging may be present (e.g., boxes, pallets, swap bodies, containers, etc.), going forward we will refer to the packaging simply as "containers" [89].

An intermodal transportation system is made up of several different actors interacting with each other, including shippers that generate demand for transportation, carriers that provide the transportation services, facility and physical infrastructure managers, institutional authorities that regulate the system, and customers and citizens that ask for goods.

Shippers generate the freight transportation demand, as they are generally the senders of the goods. They plan shipments to satisfy their customers and either organize or participate in the organization of how their freight should be moved. Thus, they define their logistics strategy, which may include intermodal transport.

Carriers perform the transport for the shippers. Some carriers operate dedicated services, in which a vehicle/container serves a single customer, and others operate on the basis of consolidation, in which each vehicle/container may contain different customers' freight with different origins or eventual destinations.

Freight logistics providers (FLPs), 3PLs in particular, undertake various logistics tasks within an intermodal transportation system, providing a range of value-added logistics services, such as warehousing, distribution, shipping, inventory management, co-packing, labeling, repacking, weighing, and quality control. FLPs also collaborate with shippers for both domestic and international intermodal transportation activities. Shippers may actually outsource logistics activities in order to focus on their core businesses and benefit from the expertise of the FLPs. On the other hand, 3PLs also interact with carriers to secure timely transportation capacity for their customers. In this sense, they may sometimes appear as carriers.

Facility and infrastructure managers may be public entities or private firms with public stakeholders. They do not plan, organize, or realize freight transportation services but instead deal with the management of the physical network and infrastructure, including roads and highways, the rail infrastructure in Europe, intermodal port terminals, and so on. Thus, they play a central role by providing efficient physical networks and the necessary technology and sensors layers to control and optimize the utilization of the infrastructure and facilities.

Institutional authorities (e.g., governments and public administrations) are the actors who tax, give incentives, set up policies, and regulate transport activities. Through the policies they set, these actors increasingly frequently aim to guide the transportation and logistics system towards "new", more beneficial to society, and resilient ways of operation (e.g., the usage of specific corridors or vehicle and motorization types, mode changes from road-based to water- and rail-based transportation, the reduction of externalities, the consideration of environmental impacts, etc.). We include in this class of actors local and national governments as well as transnational institutions such as the European Commission.

Finally, customers represent the receivers of the shipments. They can be the final client, retailer, distributor, or wholesaler. Customers include citizens as well, and, hence, they are mindful about emissions, safety, and viability within their local areas, and they can influence the institutional authorities through their votes.

The aforementioned actors have their own goals, make their own decisions, and are linked with the others through many interconnections, interactions, and interdependencies. All contribute to make intermodal transportation a complex system. Furthermore, these decisions and interrelations may be affected by uncertainty from many different sources, often related to demand, travel times, and handling operations [152, 187]. Hence, the efficiency and reliability of the intermodal transportation system require coordination and fast information flows among several actors, interoperability among the operational activities and modes, and behavioral aspects.

We illustrate this situation and complexity through the Social Business Network (SBN) shown in Figure 2.1. The SBN represents a complex system in a standard visual manner and is part of the GUEST methodology [183, 233]. The SBN is a graph composed of nodes and arcs. The nodes represent players grouped by type. The arcs symbolize the relationships between nodes, and their graphical representation is based on their type (i.e., commercial, normative, or stakeholdership). Figure 2.1 shows the SBN for an intermodal transportation system made up of the aforementioned actor types: shippers, carriers, customers, facility and infrastructure managers, and institutional authorities. The graph clarifies that an intermodal system has an additional level of complexity due to the correlations between the actors. Moreover, this level of complexity is just one of many that come from examining the system from various points of view, including the presence of multiple objectives (e.g., performance-based, economic, environmental, or social) and of different levels of decision making (e.g., real-time, operational, tactical, or strategic).

This brief analysis illustrates the many components, decisions, and interactions characterizing intermodal transportation and points to the many ways of approaching its study. The diversity of scope and goals of the studies reviewed in this analysis further supports these observations. A comprehensive classification of intermodal transportation simulation models and applications must reflect this diversity of means, scopes, and goals as well as identifying less-studied areas in order to provide a global picture of current research and highlight research needs and opportunities. This is the main scope of the taxonomy we introduce in this chapter, as detailed in the next sections.

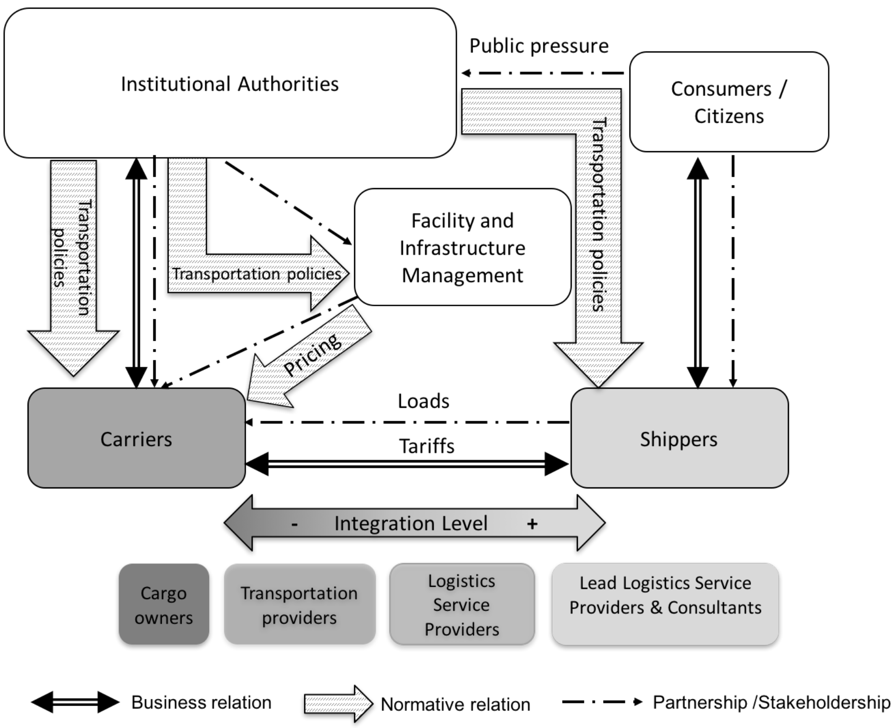

Figure 2.1: Relationships among the main actors in freight transportation systems.

2.2 The taxonomy

2.2.1 Taxonomy construction methodology

From a methodology point of view, our classification was a cluster-analysis-based taxonomy with polythetic classes [11, 12]. Thus, to build it, we followed the three-step method described by Bailey [12]. We began with an empirical analysis of a database of studies. In the second stage, we represented the cluster on paper. Finally, the third stage was envisioning a mental concept for the cluster, often by mentally generating a name or label for the cluster (such as "Network Description"). We then started to retrieve studies from refereed journals and conference proceedings to source the intermodal freight transportation simulation literature. We referred to the Scopus bibliographic database for our analysis because it contains articles from all major journals dealing with transportation. Many journals are also recognized by the ERA 2012 Journal List evaluation across eight discipline clusters [10]. The following list of keywords (and their combinations) was used to search for studies: *intermodal*, *simulation*, *freight*, *transportation*, *planning*, *network*, and *supply chain*. Only English language literature was included. Additional studies were retrieved by tracking the research cited in some studies. We also decided to include studies dated from 2007 to 2017 to consider only the most recent literature. We used the online database to find about 350 studies. We then first reduced the entire set of selected studies to a total of 150 by restricting the topic area. Thus, we did not consider studies dealing with terminal operations and management, such as the optimization of container terminal operations, the allocation and scheduling of terminal equipment, and the optimization of terminal area use. Reviews analyzing the roles of simulation and optimization in intermodal container terminals were presented by Gambardella and Rizzoli [100], Stahlbock and Voß [214], and Bierwirth and Meisel [22]. A second screening removed studies dealing with the simulation of telecommunication-related issues (e.g., connected vehicle protocols) and other similar topics, which yielded a final selection of about 89 studies.

Network Description			**Planning**			
Types	Modes	Territory	Decision Makers	Decision Objects	Objectives	Time Horizon
Unimodal	*RO*	*Urban*	*Shippers*	*Infrastructures*	*Economics*	*Strategic*
Multimodal	*RA*	*National*	*Carriers*	*Policy*	*Environment*	*Tactical*
Intermodal	*IWW*	*International*	*Inst. Authorities*	*Operations*	*Performances*	*Operational*
	M		*Facility and Infrastructure Managers*	*Cooperation*		
	A			*Technology*		

Simulation Method			**Scope**	
Numerical	Optimization	Simulation Optimization Relation	Simulated Objects	Simulation Objectives
Static-Deterministic	*Static-Deterministic*	*OSI*	*Behaviors and Interactions*	*What If*
Static-Stochastic	*Static-Stochastic*	*SOI*	*Flows*	*Forecasting*
Dynamic-Deterministic	*Dynamic-Deterministic*	*SSO*	*Static Scenario*	*Validation*
Dynamic-Stochastic	*Dynamic-Stochastic*	*ASO*	*Events*	*Enhancement*
		Simulation		

Figure 2.2: Taxonomy structure.

Figure 2.2 depicts the result of our process and is structured in three levels of detail. The taxonomy provides four axes at the first level: *Network Description*, *Planning*, *Simulation Method*, and *Scope*. The first two axes concern the problem specifications, the third axis describes how the simulation method was implemented, and the fourth investigates the role of simulation. Each axis is structured at the second level in several categories, for which more precise information is provided by subcategories at the third level. Due to the large number of factors that play important roles in defining an intermodal freight transportation system and their high correlation, we decided to consider only the axes at the root level as mutually exclusive and jointly exhaustive. Our analysis is therefore not globally exhaustive, but we believe it provides a good general overview of the literature trends in the simulation of intermodal freight transportation systems.

The rest of this section presents brief descriptions of the object and scope of each axis and its categories.

2.2.2 Network description

Intermodal freight transportation simulators may focus on the entire transportation system of the region considered or on a subset only. This axis thus identifies the network on which simulation is used, and it includes three categories: *Types*, which specify the degree of modal combination represented; *Modes*, which specify the transportation modes considered; and *Territory*, which refers to the geographical dimension of the intermodal transportation system.

Types

This category focuses on the definition of the network studied in terms of the kind of mode combination. The three main network types are:

- *Unimodal*: the term "Intermodality" is often equated in practice and in many papers to container-based transportation. Thus, for example, North American railroads created Intermodal divisions and operate many services identified as "intermodal", that is, as containers being moved by trains. This is reflected in the literature where a good number of papers focus on one particular mode as part of the intermodal chain. The unimodal-type category reflects this situation and groups the associated papers;

- *Multimodal*: involves at least two modes and one terminal for transfer;

- *Intermodal*: refers to a multimodal chain of container-transportation services [53] with no freight handling. In fact, as defined above, intermodal transportation generally implies that freight is packed into a box, a container, and is not handled from the time it is packed at the origin until the time it arrives at the point where the container is to be opened, usually at the destination. Thus, it is the container that is moved and transferred.

Modes

We describe the transportation modes according to their main transportation engineering infrastructure categories:

- *RO*: roads;

- *RA*: railways;

- *IWW*: inland waterways;

- *M*: maritime transportation and coastal navigation;

- *A*: air transportation.

When several modes are present in a study, we indicate them by a combination of single identifiers (e.g., RO/RA stands for the usage of a multimodal or intermodal system using roads and rails).

Territory

The geographic extension of the network is classified into:

- *International*: it covers from multi-country level to the continent and the entire world;
- *National*: it covers single national cases and regional cases (with multiple municipalities);
- *Urban*: it focuses on single cities and their surrounding areas.

2.2.3 Planning

This axis is concerned with the decision-making process, thereby investigating the types of decisions and actors involved according to four categories:

- *Decision makers*: refers to the actors making the decisions, thereby determining the point of view of the problem;
- *Decision objects*:states the type of planning and the object of the decision-making process on which the simulation project focuses;
- *Objectives*: gives the categories of the Key Performance Indicators (KPIs) used to measure and compare the effectiveness of alternatives;
- *Time horizon*: expresses the time perspective of the planning problem.

The last two categories are complementary in determining the objectives, formulations, and requirements of the problem and identifying scenario alternatives.

Decision makers

This category identifies the actors for which the proposed models were designed, following the main roles defined in Section 2.1.

Decision objects

This category denotes the type of problem being analyzed from the point of view of the scope of the decision process considered. We define five subcategories:

- *Infrastructure*: refers to the construction or enhancement of infrastructure, including the locations of hubs and other types of terminals and the design of the physical network;
- *Policy*: addresses the choice and evaluation of policies;
- *Operations*: is concerned with the planning of shipment and transportation activities (e.g., capacity planning, service network design, resource allocation and reallocation, storage of freight and (empty) containers, mode and route choice, vehicle routing, management of disruptions, etc.);
- *Cooperation*: is concerned with the evaluation of the strengths and synergies arising from collaborations, cooperation, and coalitions among carriers, among shippers, or between shippers and carriers, with or without participation from institutional authorities;
- *Technology*: refers to the validation of new technologies and the evaluation of their impacts on the intermodal transportation system.

Objectives

This category describes the goals of the model and the metrics used to measure and compare the effectiveness of alternatives:

- *Economics*: economic evaluation of the simulated operation, which can include several metrics besides operational costs, such as travel time, fuel consumption, vehicle-traveled distance, and charges (e.g., road pricing);
- *Environment*: evaluation of the environmental footprint of transportation networks, mainly through GHG and particle emissions and fuel consumption;
- *Performances*: metrics related to the quality of the service offered, which can be measured in terms of speed, flexibility, efficiency, reliability, and resilience.

Time horizon

As discussed in Chapter 1, planning activities can be divided into:

- *Strategic planning*: long-term planning decisions, which require the highest level of forecasting, investments, and management and which concern the physical structure of the intermodal transportation system, such as the hub and terminal location, usually identified as network design problems;
- *Tactical planning*: medium-term decisions focusing mainly on the efficient allocation and utilization of existing resources to improve the performance of the system;

- *Operational planning*: short time decisions, including real-time decisions.

2.2.4 Simulation method

This axis aims to identify the simulation method adopted in the model. It is composed of three categories: *Numerical*, which specifies numerical simulations, *Optimization*, which concerns the use of optimization approaches, and *Simulation Optimization Relation*, which describes the relationship between simulation and optimization.

Numerical

This category denotes simulations conducted numerically without using optimization methods, but simply calculating the evolution of observation parameters in the intermodal freight transportation system as a result of varying initial conditions.

Optimization

In this setting, demand is represented by one or several commodity-specific origin-destination matrices (mode choices may be included in the matrix definition as well), and the supply side of the transportation system is represented by a multimodal network with provisions for intermodal transfer. Modes are used to model services (e.g., container-based transportation), vehicles, etc. The behavior of the system under various scenarios is then simulated through an optimization network model (a nonlinear model when congestion phenomena are considered) assigning the demand to the network according to a generalized cost (combining, for example, monetary cost, time value, and energy consumption. Strategic Transportation ANalysis model (STAN) [51, 52] represents a typical example of this approach. The way both approaches work is based on the type of simulation used. The simulation commonly combines the following two categories, concerning their evolution over time and the inclusion of sources of uncertainty.

- *Static* or *Dynamic*. *Static* simulation does not represent time explicitly but rather enables the evaluation of a system behavior in a steady state. The simulation model describes the relationship between the input and output variables. Different inputs are generated from the probability distributions of a stochastic system to obtain unknown stochastic outputs. The Monte Carlo simulation is an example of a static simulation. On the contrary, *Dynamic* simulation analyzes the changes in the system state that occur over time. The simulation model describes all of the entities involved and their interactions to evaluate their impact on the entire system. Agent-based simulation is an example of this category, which can be further split into a discrete and continuous simulation.

- *Stochastic* or *Deterministic*. A *Deterministic* simulation model exactly computes the future states of the system once the input data and initial state have been defined.

On the other hand, in a *Stochastic* simulation, the behavior of the system is not precisely predicted, but it is affected by uncertainty. Thus, the model uses random inputs and produces random output variables to represent and describe the expected behavior.

Thus, the combinations of the approaches discussed above are as follows:

- Static-Stochastic;
- Static-Deterministic;
- Dynamic-Stochastic;
- Dynamic-Deterministic.

Simulation optimization relation

This category enhances the classification proposed in [95]:

- *Optimization with simulation-based iterations* (OSI): one or more complete simulation runs are performed during some iterations of an optimization procedure;
- *Simulation with optimization-based iterations* (SOI): one or more complete optimization procedures are performed during a simulation process; the simulation-by-optimization approach is a specific case of SOI in which a single iteration of the optimization model is performed;
- *Alternate simulation–optimization* (ASO): both simulation and optimization run alternately, either to the end or incompletely, with feedback loops in each iteration;
- *Sequential simulation–optimization* (SSO): simulation and optimization run sequentially, with either optimization following simulation or the opposite;
- *Simulation (SIM)*: simulation without any optimization procedure.

2.2.5 Scope

This axis classifies the role of the simulation and includes two categories: *simulated objects* and *simulation objectives*.

Simulated objects

This category defines the main objects of the simulation:

- *Behaviors and interactions*: the simulation model is used to reproduce the respective behaviors of several entities and their interactions;

- *Flow*: the object of the simulation is the estimation of traffic values, including flows of vehicles, freight, containers, etc.;
- *Scenario*: a simulation framework is created to set up the scenario to which the optimization procedure is then applied;
- *Event*: the simulation is used to reproduce a stochastic event.

Simulation objectives

This category classifies the simulation purpose according to four categories:

- *What-if analysis*: the objective is to analyze a hypothetical system under some possible/forecasted/imagined scenario as well as to compare two or more system alternatives;
- *Forecasting*: the simulation aims to study and evaluate the characteristics of an actual system as well as predict its performance under various conditions/scenarios;
- *Validation*: the focus is on the validation of a proposed solution, a new policy, a mathematical model, or a modeling approach;
- *Enhancement*: the simulation is combined with optimization to enhance the solution, which usually requires alternate simulation and optimization procedures connected through a performance feedback loop.

2.3 Analysis discussion

Figure 2.3 summarizes the number of publications from 2007 to 2017. An exponential increase in the number of published studies applying simulation models to intermodal freight transportation may be observed. The decrease observed for the years 2014 and 2017 may be explained by the fact that the volumes related to very popular conferences (e.g., City Logistics) were scheduled for publication in these years but were not yet indexed. This factor did not reflect any negative trend. On the contrary, from the rising one, more studies are expected in the near future. This confirms the fact that the simulation is a powerful tool in the decision-making process dealing with freight distribution and intermodal transportation systems.

Table 2.1 shows the list of journals where the studies used in this analysis appeared. The list is sorted according to the number of publications and listed in descending order. *Procedia - Social and Behavioral Sciences* is the most prevalent journal in this field and accounted for 25% of the total publications in the considered period. This finding can be explained by the number of referred conference proceedings published in this journal (e.g., City Logistics and EWGT). Note that some conferences changed their policy, and their

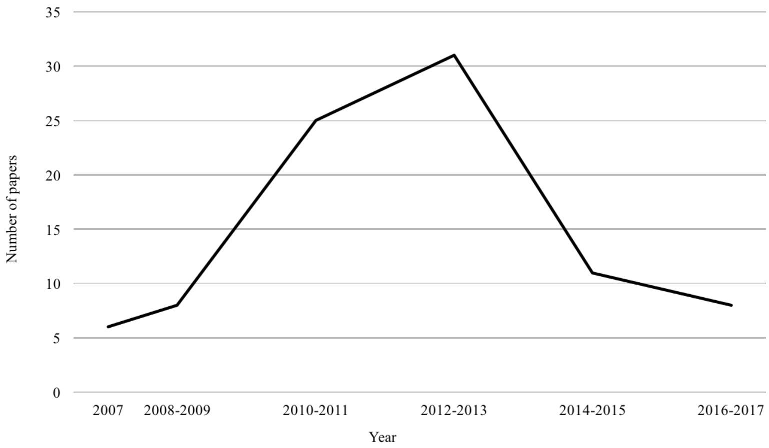

Figure 2.3: Number of studies selected from each year.

proceedings are currently part of a new journal called *Transportation Research Procedia*. The *European Journal of Operational Research* (*EJOR*), *Journal of Transport Geography*, and *Transportation Research Part B* also published several studies on the topic. These four journals accounted for 48% of total publications. On the other hand, in most journals, we found only a single contribution, underlying the extreme clustering of this topic. The journals appearing in Table 2.1 cover many areas of applications, including economics, computer science, management science, operations research, and transport engineering. This finding also shows the inter-disciplinary nature of research in the simulation of intermodal freight transportation.

We now present an analysis of the literature according to the axes and categories of the taxonomy.

2.3.1 Network description

This subsection is dedicated to an analysis of the distribution of the literature according to the different network characteristics.

Types and modes

Table 2.2 presents the studies sorted by type of network and mode. The most analyzed networks are multimodal and intermodal (54%), whereas unimodal networks account for approximately 46% of the studies. All unimodal-network studies address road transportation, as simulation models are proposed to handle emissions and congestion issues in cities. The most studied combinations of modes were road–rail and road–rail–maritime transportation. Hence, roads, studied both in unimodal and multimodal networks, appear to be the most critical mode. In particular, road transportation is the most flexible mode in terms of departure time and routing and is

Journal Name	**Count**
Procedia — Social and Behavioral Sciences	22
European Journal of Operational Research	3
Journal of Transport Geography	3
Transportation Research Part B: Methodological	4
Transportation Research Part C: Emerging Technologies	4
Transportation Research Part E: Logistics and Transportation Review	3
Winter Simulation Conference	3
Decision Support Systems	2
Transportation Research Record	2
24th European Modeling and Simulation Symposium, 8th International Conference on Service Systems and Service Management, Advanced Manufacturing and Sustainable Logistics, Applications of Evolutionary Computing, Computers and Operations Research, Control Engineering Practice, European Transport (Trasporti Europei), European Transport Research Review, EUT Edizioni Università di Trieste, Expert Systems with Applications, Flexible Services and Manufacturing Journal, ICLEM 2010: Logistics for Sustained Economic development — infrastructure, information, integration, INFORMATIK 2007 — Informatik Trifft Logistik, Beitrage der. Jahrestagung der Gesellschaft fur Informatik e.V., International Journal of Physical Distribution and Logistics Management, International Journal of Transport Economics, Journal of Computational Science, Journal of the Eastern Asia Society for Transportation Studies, Eastern Asia Society for Transportation Studies, Journal of Transportation Systems Engineering and Information Technology, Networks and Spatial Economics, Proceedings of the 2011 Summer Computer Simulation Conference, Research in Transportation Economics, Simulation Modelling Practice and Theory, Statistica Neerlandica, Supply Chain Forum: An International Journal, Open Engineering, IFAC Papers OnLine, Transport Policy, Transportation Letters: The International Journal of Transportation Research, Transportation, World Electric Vehicle Journal, WSEAS Transactions on Systems, EURO Journal on Transportation and Logistics, Winter Simulation Conference, Maritime Policy and Management, Cybernetics and Information Technologies, IEEE Transactions on Automation Science and Engineering	1 (43)
Total	**89**

Table 2.1: Journals in the intermodal freight system simulation literature.

largely involved within with the first- and last-mile activities of intermodal transportation systems [186, 184].

Mode/Combination	**Distribution**		
Modes	Unimodal (46%)	Multimodal (11%)	Intermodal (43%)
RO	100%	10%	8%
RA			3%
IWW			8%
M			3%
RO RA		40%	24%
RO/RA IWW			11%
RO/RA/M		20%	19%
RO/IWW			3%
RO/IWW M			11%
RO/M			11%
RO/RA/IWW/M		10%	11%
RO RA A		10%	
RO RA M IWW A		10%	

Table 2.2: Distribution of network modes and combinations.

	Unimodal				Multimodal/intermodal							
	RO	RA	IWW	M	RO-RA	RO-RA-IWW	RO-RA-M	RO-RA-IWW/M-A	RO-RA-A	RO-M	RO-IWW	RO-RA-IWW-M
Urban	30%	0%	0%	0%	2%	0%	2%	0%	0%	0%	0%	0%
National	5%	3%	1%	0%	4%	3%	4%	1%	0%	1%	1%	4%
International	0%	0%	0%	0%	7%	1%	3%	0%	1%	0%	0%	0%

Table 2.3: Cross analysis of modes and territory.

Geographic extension

Figure 2.4 shows the distribution of the geographic extension of the networks analyzed in the selected literature. The studies principally focused on urban networks (44%) and on Smart City and City Logistics projects in particular [21, 189] in recent years. These works introduced new freight distribution models specifically designed for urban areas and characterized by complex interactions among the considered actors in the literature [171, 229]. International and national networks made up lower percentages of the selected studies (24% and 32%, respectively).

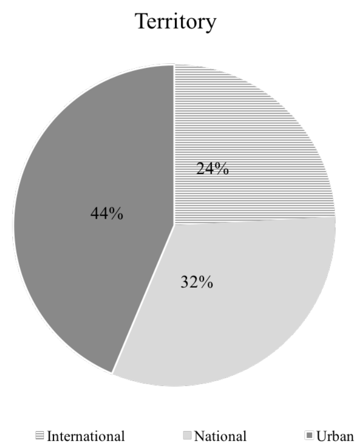

Figure 2.4: Distribution by geographical extension.

The figures in Table 2.3 confirm the previous observation regarding the strong relationship between the analyzed modes and the geographic extent of the network. The studies considering unimodal road transportation constituted 79% of the urban-network literature, which was 30% of the total set of selected studies. Hence, road transportation was the dominant mode of freight distribution studied in the literature, whereas only a few works considered mode combinations (e.g., road–rail [5, 146] and road–rail–maritime networks [200]).

The studies at the national level usually considered multimodal or intermodal networks (75%) rather than unimodal networks (25%). The most studied networks were composed of the road–rail–maritime [72, 75, 91, 143], road–rail–inland waterways–maritime [207,

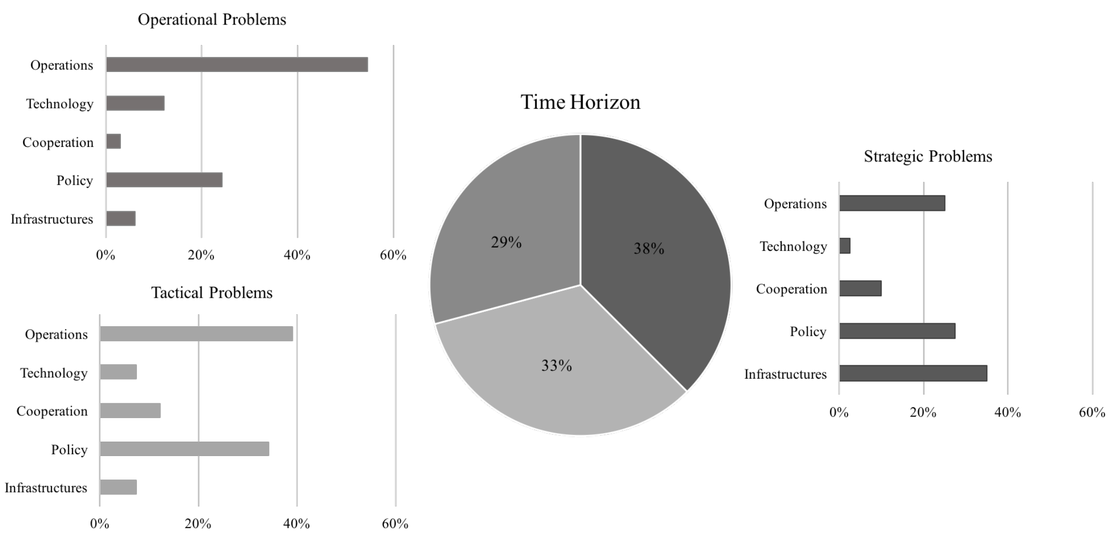

Figure 2.5: Distribution of decision objects according to the time horizon.

141], and road–rail–inland waterways [30, 151, 150] modes, with a few studies considering a unimodal road network [9, 68, 129, 8]. The road–rail mode was the most analyzed network at the international level [27, 127, 211, 213, 256, 115], followed by the road–rail–maritime [124, 162] and road–maritime [170, 248, 194] modes.

2.3.2 Planning objectives

This subsection analyzes the literature from the point of view of the objective of the planning process.

Time horizons and decision objects

Figure 2.5 shows the distribution of the research efforts dedicated to simulating transportation systems according to the time horizon and decision object. Most papers addressed strategic planning (38%), whereas the remaining ones were split between tactical and operational problems (33% and 29%, respectively).

Considering the decision objects, studies addressing the planning of operations accounted for approximately 37% of the total, whereas those investigating policy and infrastructure measures covered approximately 30% and 17% of the total, respectively. Cooperation and technology were less frequently studied decision objects (approximately 10% and 7% of the total, respectively).

Operation planning problems were principally studied at the tactical and operational levels. The papers within this category addressed the following problem classes:

- Freight demand and freight flow forecasting [40, 129, 174, 205, 256];

- Evaluation of costs and performance associated with different transportation networks and alternative routing [27, 70, 159, 211, 255, 81];
- Dynamic resource allocation for intermodal freight transportation [247];
- Improvement of service level and enhancement of operational efficiency [8, 212, 77];
- Representation of actors and their logistics decisions [26, 91, 181, 200, 209];
- Measurement and maximization of network resilience [30, 162];
- Vehicle routing and variants [58, 62, 115, 135, 196]; and
- Optimization of empty container allocation [136].

The papers comparing different policies, mostly at the tactical or strategic levels, dealt with:

- Evaluation of new forms of e-grocery services and City Logistics measures in e-commerce [79, 231];
- Assessment of alternative urban freight initiatives and policies [111, 126, 217, 224, 232, 78];
- Analysis of route choice strategies and routing policies [178, 235, 236];
- Assessment of policy strategies to develop intermodal services [6, 13, 33, 124, 143]; and
- Assessment of consolidation strategies and cooperation policies [6, 34, 146].

Infrastructure studies were mainly undertaken at the strategic level. They included the stochastic location-routing problem [120], network design [27, 72, 122], intermodal hub-and-spoke networks [254], hub locations in urban multimodal networks [5, 127, 213, 69, 242, 249], terminal locations [151, 150], and the effect of land bridges [248].

A small set of papers investigated cooperation and collaboration. Horizontal cooperation was studied by Dahl and Derigs [68], Gonzalez-Feliu et al. [112], Gonzalez-Feliu and Salanova [110], and Liu et al. [145], and Naima [170], whereas vertical collaboration between trading partners and carriers was analyzed by Chan and Zhang [39] and Puettmann and Stadtler [194]. Caris, Macharis, and Janssens [34] analyzed the cooperation between inland terminals, and Wisetjindawat et al. [252] investigated the cooperation between government agencies and logistics companies in disaster relief operations.

The effect of technology was mainly studied at the tactical and operational levels. The technologies most frequently involved were mobile communication and in-roadway sensors [182], tracking technologies [9], information and communication technologies [75, 116, 228, 74], and electric commercial vehicle fleets [26, 93].

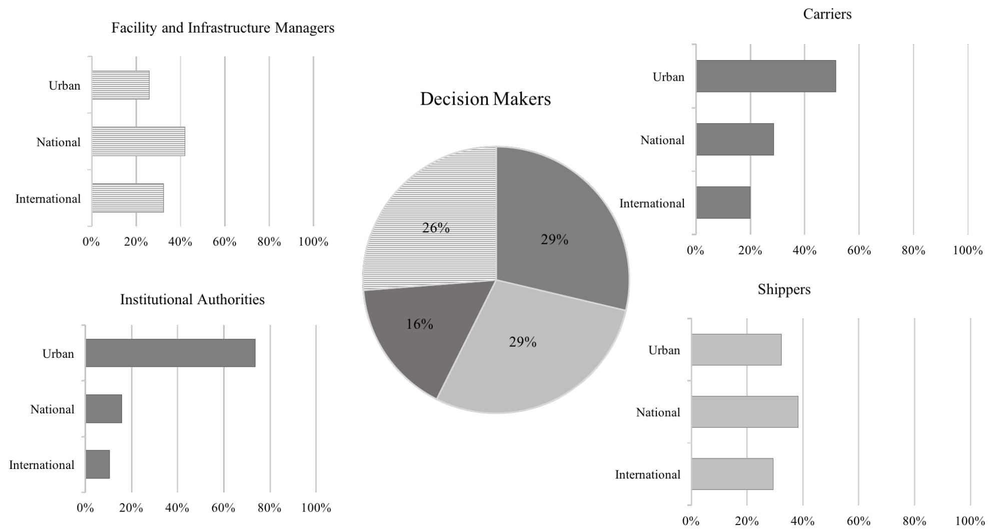

Figure 2.6: Distribution of papers according to decision makers and geographical extension.

Decision makers

Figure 2.6 shows the distribution of papers according to the different decision makers considered. Clearly, the institutional authorities' perspective, combined with the facility and infrastructure managers' perspective, was the most analyzed (42%), with the remaining 58% being equally split between carriers and shippers.

The predominance of institutional authorities may be traced to their increasing involvement in addressing environmental and city-related issues. With respect to the former, note that following the ratification of the Kyoto Protocol, institutional authorities have introduced numerous projects since 2005 to promote more environmentally responsible freight transportation, supporting intermodal and collaborative transportation systems. Regarding the latter, a key role is played by the local governments within City Logistics and Smart Cities concepts and projects aiming to reduce negative transportation impacts and improve security and quality of life [144]. This finding was evidenced by the prominence given to urban transport in studies funded under major EU framework programs, such as the comprehensive policy framework on urban transport presented in the Green Paper [42], the Action Plan on Urban Mobility [41], and the Roadmap to a Single European Transport Area in the White Paper [73]. Papers addressing institutional authority efforts strongly focused on the freight distribution within urban areas (about 74%). They studied the introduction of new policies (approximately 48%), the interactions within the freight transportation system, and the estimation of freight flow (approximately 24%).

Papers addressing the facility and infrastructure managers' perspectives were mainly concerned with the infrastructure and policy fields (23% and 38%) in a national context (42%). The carrier perspective was principally considered within an urban context (57%) and principally dealt with operations planning (39%) and technology (18%) issues. Finally, shippers were considered as decision makers in all three network subcategories, with the problems addressed focusing on the operations planning subcategory (35%).

Objectives

With respect to the simulation objectives, 49% of the papers addressed the reduction of operating costs, 23% addressed emission reductions, and 28% addressed the improvement of service performance. Focusing on emission reductions, the evolution in the number of studies considering the topic is interesting, as illustrated in Figure 2.7, which shows a significant increase in 2012-2013. After this peak, the number of papers explicitly dealing with the emissions reduction goes back to the same levels of the the period 2007-2010. This behavior, in our opinion, is not a sign of a less focus on emissions reduction, but is related to the introduction of a more global vision of sustainability in transportation mixing economic, social and environmental aspects. Table 2.4 shows that emission reductions were considered when addressing urban areas (67%) and road transportation (70%). Institutional authorities and carriers appeared most often as decision makers in papers aimed at the environmental impacts of freight transportation (22% and 44%, respectively). The institutional authorities were particularly concerned with new policies (33%) and operations planning (37%) at the strategic and tactical levels. The environment impact of freight transportation was considered in a multitude of different ways. A set of papers indirectly evaluated this impact by measuring, for example, traffic reduction [5], road usage, traveled kilometers, the fill rate of trucks, or the number of trucks needed [9, 79, 159, 174, 167]. Other papers directly estimated GHG emissions; Gonzalez-Feliu and Salanova [110] and Hrušovský et al. [125] considered emissions in CO2 equivalent units, Hillbrand and Schmid [122] and Holmgren et al. [124], and Sihn et al. [211] measured CO2 emissions in tons, and Tamagawa, Taniguchi, and Yamada [224] and Teo, Taniguchi, and Qureshi [231, 232], and Duin et al. [78] focused on NOx emissions.

Emissions metrics were usually mixed with other metrics. For example, Crainic et al. [62] proposed an optimization model for the Two-Echelon Vehicle Routing Problem (2E-VRP), whose objective function aimed at reducing generalized travel costs, composed of fixed, operational, and environmental costs. In Teo, Taniguchi, and Qureshi [231] and Teo, Taniguchi, and Qureshi [232], the authors considered different performance measurements to evaluate the short-term effect of distance-based road pricing, including carrier and shipper costs; the number of trucks; the distance traveled; the number of complaints; and SPM, CO2, and NOx emissions. Similarly, Tamagawa, Taniguchi, and Yamada [224] presented a methodology for evaluating City Logistics measures considering both economic aspects (e.g., toll revenues, transport profits of freight carriers, and transport costs of shippers) and environmental aspects (e.g., total NOx emissions and the number of zones in which NOx emissions exceeded the environmental limit).

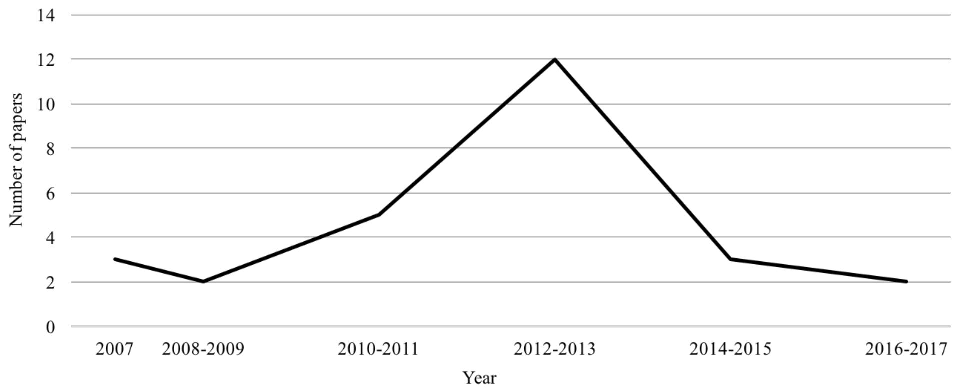

Figure 2.7: Trends in studies considering emission reductions as final objective.

Geographic extension	**International**	**National**	**Urban**		
	15%	19%	67%		
Modes	**RO**	**RA**	**IWW**	**MA**	
	70%	19%	4%	7%	
Time horizons	**Strategic**	**Tactical**	**Operational**		
	44%	30%	26%		
Decision makers	**Carrier**	**Shipper**	**Inst. Authorities**	**FI Managers**	
	44%	19%	22%	15%	
Decision objects	**Infrastructure**	**Policy**	**Cooperation**	**Technology**	**Operations**
	19%	33%	4%	7%	37%

Table 2.4: Emission reductions in relation to the other categories.

2.3.3 Simulation method

This subsection focuses on the different aspects of the simulation methodology used, providing insights about the simulation types adopted in the literature and how the simulation process is mixed with optimization models.

Numeric or optimization

Figure 2.8 presents the distribution of the studies according to the methods that they applied.

Simulation combined with optimization was most frequently applied (69%), and numerical simulation accounted for the remaining 31% of the papers. *Dynamic simulation* was proposed in approximately 66% of the papers. Among these, 43% focused on urban areas, 41% on national areas, and 16% on international networks.

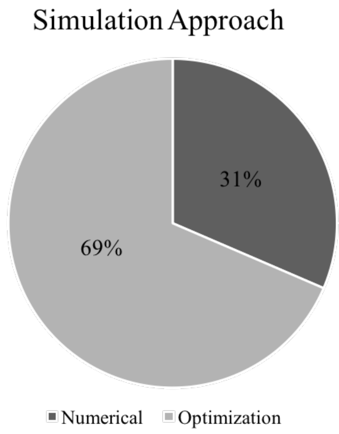

Figure 2.8: Distribution of the simulation methods.

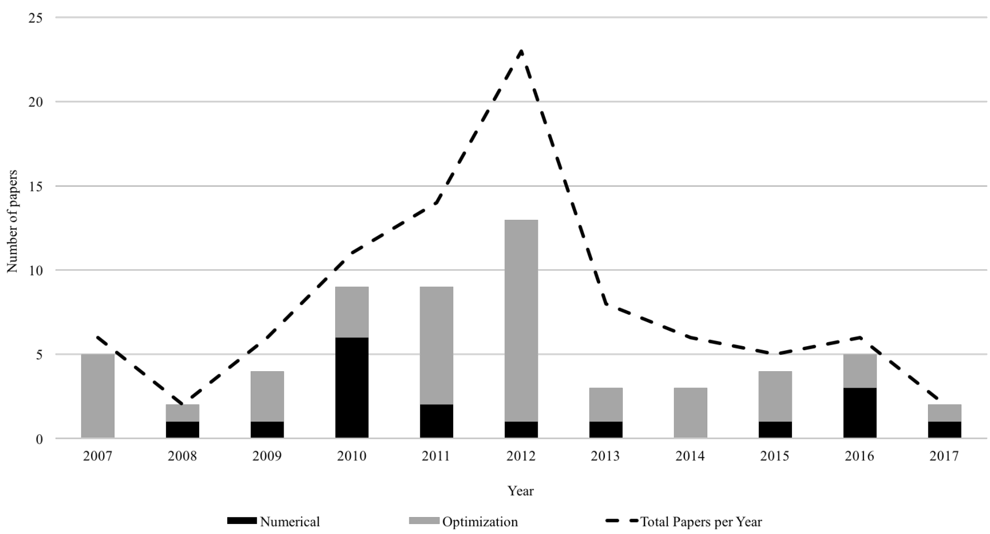

Figure 2.9: Composition of studies with dynamic simulation by year.

Figure 2.9 shows the number of papers that applied dynamic simulation to intermodal freight transportation from 2007 to 2017. Confirming the previous result, a large portion of the total published papers studies that applied simulation to the topic of interest (dotted line) adopted dynamic simulation models (bars). Among these papers and along the considered time period (with the exception of the years 2010 and 2016), we observe more use of dynamic simulations combined with optimization models than of numerical simulations.

Deterministic simulation is still very present (slightly less than 50% of the studies). Yet, as illustrated in Figure 2.10, this presence is currently diminishing, stochastic approaches appearing more often. Notice that the peak of 2012 corresponds to a flurry of studies

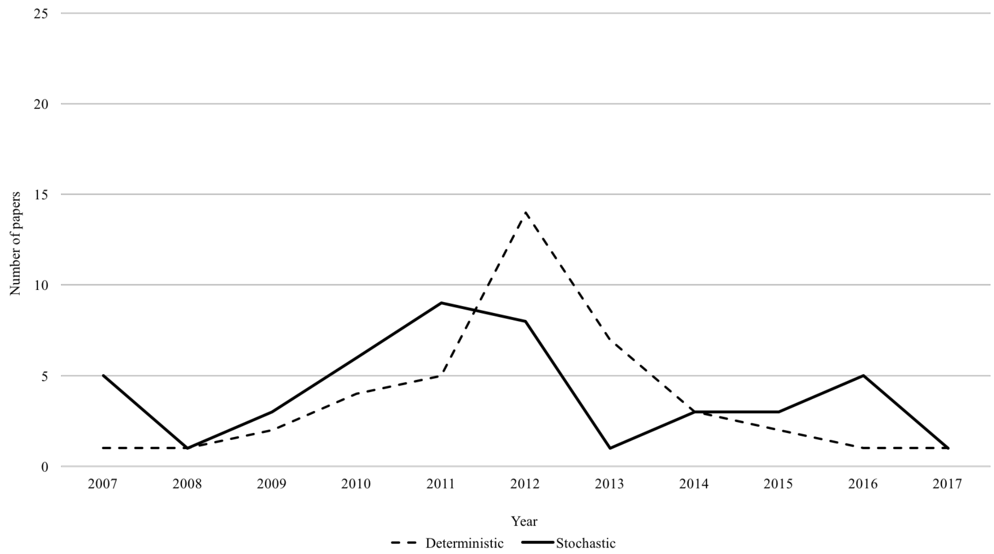

Figure 2.10: Number of papers with stochastic/deterministic simulations per year.

targeting issues in urban last mile and City Logistics.

We complete the analysis of the simulation methods applied to intermodal freight transportation systems according to a more global vision. Table 2.5 presents the distribution of the literature for each simulation method resulting from the combination of the Numerical/Optimization, Static/Dynamic, and Deterministic/Stochastic approaches.

Optimization / Numerical	**Deterministic**	**Stochastic**
Static	12% / 9%	10% / 1%
Dynamic	17% / 10%	30% / 9%

Table 2.5: Distribution of the simulation methods.

The main outcome highlighted that a subset of papers (30%) adopted stochastic and dynamic simulations combined with optimization methods, whereas numerical simulations were mainly dynamic and deterministic (10%). Furthermore, the results that referred to static simulation pointed out that it was mainly applied as an experimental tool for validating new optimization models or procedures, either by reproducing a stochastic phenomenon or by generating hypothetical scenarios. For the latter, each generated scenario represented a static system because, once determined, it did not change during the execution of the procedure. Hence, the main role of the static simulation was to produce several combinations of the input data for testing the procedure under study. However, the low values indicate that very few models were validated by means of simulations, limiting their validity in some cases.

Static simulation usually created scenarios by randomly generating values either from a specific distribution, which was supposed to fit the real data, or by applying a Monte Carlo simulation. For example, Andersen, Crainic, and Christiansen [6] applied simulation during the experimental phase to observe the behavior of the proposed model and to analyze the impact of possible modifications in external and internal policies. In addition, starting from statistical data, the authors introduced a random number generator based on a uniform distribution to study the uncertainty about future demand that arises throughout the planning horizon. Another example comes from Yang, Low, and Tang [255], where simulation was used to represent the variability of the transit time of an intermodal route in experimental tests. Authors assumed that transit times follow a Beta distribution, which is a popular choice for modeling time distributions thanks to its versatility in defining the shape of the time distribution. Several other papers applied static simulations in similar contexts (e.g., [8, 58, 115, 127, 135]).

Several papers used a Monte Carlo simulation as their main tool. Tadei, Perboli, and Perfetti [219] proposed a deterministic approximation to the multi-path traveling salesman problem with stochastic travel costs and applied the Monte Carlo method for the validation of their approximation. The Monte Carlo simulation used random sampling and statistical modeling to estimate the distribution of travel times in the city of Turin. Similarly, Wang and Meng [248] proposed a mathematical model to estimate the market share of Asian ports from a network level, considering the intermodal route choices of intermodal operators. They applied Monte Carlo simulations to estimate the port market share estimation model because of the stochastic nature of the route choice. Miller-Hooks, Zhang, and Faturechi [162] dealt with the measurement and maximization of network resilience when forecasting possible future disruptions. The authors applied a Monte Carlo simulation for the generation of disaster realizations based on assumed probability distribution functions for event occurrences and consequences. Wanitwattanakosol et al. [249] proposed a multiple criteria decision-making model based on a combination of a fuzzy stochastic analytic hierarchy process (AHP) and data mining techniques to select a suitable freight logistics hub. The authors employed Monte Carlo simulation to handle the uncertainty in the global AHP weights and to allow the investigation of whether the differences among the decision alternatives were statistically significant. This type of analysis provided more information for decision makers to make more precise discrimination among the competing alternatives. Finally, Martínez-López, Munín-Doce, and García-Alonso [157] presented a multi-criteria decision method to identify the most suitable motorways of the sea, with specific attention paid to the freight flows between France and Spain. Through a Monte Carlo simulation, the authors conducted a sensitivity analysis to evaluate the influence on the results of the forecast assumed, and they constructed a multi-criteria decision matrix.

A subset of static simulation papers applied game theory to understand the interplay among multiple actors. Engevall and Dahlberg [83] applied cooperative game theory for the analysis of the cost impact on different actors (municipality and shippers) in a city distribution center system under different scenarios. Liu et al. [145] focused on behavior analysis of the competition between separate carriers in the duopoly intermodal freight transport market. A two-stage dynamic game model with complete information on cooperative investment and price competition strategies was formulated based on game theory. Naima [170] applied a two-stage game to find the best form of cooperation that allowed a win-win situation for all of the actors involved. The authors considered three freight forwarders: two truck-operating freight forwarders and one freight forwarder with its own ship. The resulting best form of cooperation was that between a large truck-operating company and the ship-operating company. According to the simulation results, this cooperation should generate larger payoffs in the form of profits not only to the members of the coalition but also to the freight forwarders.

Finally, a static simulation was applied by Macharis and Pekin [150] to show the effects of different policy measures for the stimulation of intermodal transport in Belgium by applying a location analysis model based on a geographic information system (GIS). After the creation of a GIS network connecting the port of Antwerp, intermodal terminals, and end-consumer locations using the road, rail, and inland waterways modes, the model compared the price of intermodal transport with that of unimodal road transport.

A large subset of simulation by optimization papers considered demand models for urban freight transportation. Traditionally, demand models were developed to estimate the number of trips undertaken by people, usually back and forth between their residences and workplaces during rush hour in a city, and were based on the so-called four-step approach: 1) trip generation to determine the number of origin and destination trips in each zone; 2) trip distribution to determine the number of trips between origin-destination pairs; 3) mode choice to compute the proportion of trips between origin-destination pairs by transportation mode; and 4) the assignment step, which simulated the behavior of the system by assigning the demand for origin-destination trips, eventually by mode, to the network representation, yielding the flow traffic on the network. Applied to freight, such models involved significantly more complex modal network representations as well as the definition of commodities groups [51, 60, 117].

There is, however, a rather widespread consensus in the scientific community that, for people and, even more so, for freight, the traditional models do not suitably account for the actual decision processes generating the demand for travel. More disaggregated models are therefore proposed, which is reflected in the simulation literature. Thus, Gentile and Vigo [102] claim that traditional approaches to estimate freight demand models seem to be more suitable for regional and national planning than for the urban context due to, among other things, the somewhat arbitrary aggregation of many different economic activities into a few broad categories. The authors proposed new generation and distribution models of freight movements in urban areas disaggregated by commodity type (e.g., fresh food, dry, frozen, and hanging garments). Comi and Nuzzolo [40] underscored the importance of considering end-consumer choices because, according to the authors, such choices undoubtedly affect freight distribution flows. Hence, they presented a modeling system to simulate urban freight flows with combined shopping and restocking demand models. The set of models involved the simulation of end-consumer choices and restocking processes related to the type of retail activities. A similar observation was made by Russo and Comi [205]. They argued that goods arrive in a city to satisfy end consumer demands (pull movements), whereas, at the regional scale, the producer seeks to anticipate consumer demand, and the freight arrives on the market before it is required (push movements). Hence, the authors developed a framework for the simulation of goods movements at the urban scale to analyze the relationships between end consumers and other concerned decision makers (e.g., producers, wholesalers, and retailers). Gonzalez-Feliu et al. [111] also developed a simulation framework using an interactive trip substitution module to model end consumer movements, the links between these movements and inter-establishment movements, and the integration of these flows. In a similar vein, Nuzzolo and Comi [174] argued that the existing models of urban freight demand forecasting were mainly developed to simulate only some aspects of urban freight transport and, thus, are unable to forecast all of the numerous effects of implementing urban traffic and transportation measures. Therefore, they presented a modeling approach that focused on the relationships among city logistics measures, actors, and choice dimensions in the form of a multi-stage model considering a discrete choice approach for each decision level. Durand and Gonzalez-Feliu [79] focused on e-grocery and applied a simulation-by-optimization approach to three scenarios related to e-grocery distribution developments to identify and analyze the effects of new forms of proximity delivery on household shopping trips.

The papers mentioned above focused on demand, estimating urban goods movements in an aggregated manner. However, there are several examples of micro-simulation models of urban goods movements representing explicit tours and individual shipments [126, 142, 129, 251]. Hunt and Stefan [126] proposed a tour-based micro-simulation of individual vehicle movements combined with a network equilibrium, which considered the congestion on links. We will further discuss Liedtke [142] and Joubert, Fourie, and Axhausen [129], and Wisetjindawat, Yamamoto, and Marchal [251] in the next section because they modeled freight systems using multi-agent approaches.

A subset of papers proposed models for more extended geographical areas. Liedtke and Carillo Murillo [143] developed a logistics and transport market equilibrium model that, combined with a hierarchical choice model mapping the decisions of shippers forwarders, covered the interactions between the demand for freight transport and the infrastructure supply, including potential investors in the intermodal infrastructure. The model was used to analyze the welfare effects of two policies that could promote intermodal services, that is, investment grants for terminal operators and the internalization of external costs. Zhang et al. [256] developed a dynamic intermodal multi-product freight network simulation-assignment equilibrium model applied to a large-scale intermodal rail network. In their model, shipper decisions were disaggregated at the individual shipment level using a dynamic micro-assignment methodology in which a joint mode, path, service, and carrier choice was made. Puettmann and Stadtler [194] tested the idea that collaboration reduces operational costs on a chain with one multimodal operator and two carriers in charge of pre-haul and end-haul drayage. In the explored collaboration scheme, the three parties did not exchange any information and planned their own operations. However, they iteratively exchanged proposals, and the resulting costs were compared to those in the solution without coordination. The authors included stochastic demand in their scheme, which called for the adaptation of plans, because of the time lag between the departure and the arrival of orders. Vidović et al. [242] addressed the problem of optimally locating intermodal freight terminals in Serbia. They combined a multiple-assignment p-hub-network design with simulation, which was used as a tool to estimate the intermodal transport flow volumes caused by the unreliability and unavailability of specific statistical data. The simulation was also used as a method to analyze, in quantitative terms, the time, economic, and environmental effects of different scenarios concerning the intermodal terminal development.

As discussed above, dynamic simulation was proposed in a relevant proportion of papers. Several studies applied multi-agent simulation (MAS) to urban areas. Suksri and Raicu [217], Tamagawa, Taniguchi, and Yamada [224], Taniguchi, Tadashi, and Masayuki [228], Teo, Taniguchi, and Qureshi [231], Teo, Taniguchi, and Qureshi [232], and Roorda et al. [200] presented different methodologies to evaluate City Logistics measures combining multi-agent approaches and learning models to simulate the dynamic behavior of urban stakeholders. All of them simulated the dynamic behavior of freight carriers, retailers or shippers, residents, transport planners, and local authorities. Hence, citizens and local authorities were considered as actors and decision makers who react to carriers and shippers' decisions. The citizens complained to the local authorities if the negative impact of freight transportation exceeded their tolerance limits, and the local authorities were accountable for the wellbeing of the residents. Their aim was to minimize the level of the residents' dissatisfaction as well as to decide whether they should implement new urban freight distribution measures in the areas. However, there are some examples of MAS applied to urban areas that did not consider these two types of decision makers. Schroeder et al. [209] applied micro-simulation and agent-based approaches for transport policy analysis, but they considered only two actors, transport service providers, and carriers, under different traffic conditions and policy measures. Other MAS applications to urban areas were presented by Duin et al. [78] and Page, Knaak, and Kruse [181]. Duin et al. [78] evaluated the dynamic usage of UDCs, and Page, Knaak, and Kruse [181] modeled city courier services to study alternative logistic structures from ecological, economic, and social points of view. Boussier et al. [26] and Patier et al. [182] applied MAS to model the management process of delivery area booking while also considering car drivers. Finally, Bakhtadze et al. [14] introduced a systematic approach to MAS supply chain dynamic organization and the management of motor vehicle traffic in the case of a swap body for urban and interurban transportation.

Only one paper applied discrete event simulation to reproduce urban freight transportation, Ambrosino and Sciomachen [5]. In this study, the authors developed an algorithm to solve the problem of locating hubs for freight mobility in urban and suburban areas, and a discrete event simulation model implemented in Witness 2008 was applied to validate the solution under different operational scenarios. Finally, Uchiyama and Taniguchi [235] and Uchiyama and Taniguchi [236] proposed an evolutionary game theory approach. The approach considered a route choice model considering travel time reliability and traffic impediments, including traffic accidents.

MAS models applied at the national and international levels were proposed by Baindur and Viegas [13], Burgholzer et al. [30], Holmgren et al. [124], Joubert, Fourie, and Axhausen [129], Liedtke [142], and Samimi, Mohammadian, and Kawamura [207], and Sirikijpanichkul et al. [213]. These models investigated different issues from the previous set of MAS models. Public policy evaluations were performed by Baindur and Viegas [13] and Holmgren et al. [124]. Baindur and Viegas [13] presented an agent-based simulation model to understand the impacts of different policy interventions proposed by the European Commission and business strategies by intermodal operators to encourage modal shifts from road to maritime-based intermodal services on a given trade corridor. Holmgren et al. [124] developed TAPAS, a model composed of two connected layers. One layer simulated physical activities and passive entities (e.g., vehicles, production facilities, and transportation infrastructure). The other layer simulated the decision making and interactions between the actors (e.g., the transport-chain coordinator, product buyer, transport buyer, transport planner, production planner, and customer). Similarly, Liedtke [142] developed a commodity transport model for a multi-national context consisting of a micro-behavior simulation with an agent-based approach assessing the effects of behavior-oriented transport policy measures while considering complex logistics reaction patterns. Burgholzer et al. [30] analyzed the impact of disruptions in intermodal transport networks by developing a micro-simulation-based model. Samimi, Mohammadian, and Kawamura [207] proposed an activity-based framework of freight demand modeling in which an individual firm or a group of firms with similar characteristics is the main actor. Finally, Joubert, Fourie, and Axhausen [129] used an agent-based approach to generate commercial activity chains to understand the effect that the inclusion of commercial vehicles has on private cars.

More DES models were proposed for national and international settings than for cities, in particular, by Arnäs, Holmström, and Kalantari [9], Caris, Macharis, and Janssens [33, 34], Dekker et al. [70], Dotoli et al. [75], Fanti et al. [91], Hillbrand and Schmid [122], Lam, Lee, and Tang [136], Macharis et al. [151], McLean and Biles [159], Meng and Wang [160], Sihn et al. [211], and Sinha and Ganesan [212], and Febbraro, Sacco, and Saeednia [92]. The simulations in these papers aimed to reproduce a process and the movements of orders through the physical network rather than the dynamic behavior of the decision makers. Thus, Arnäs, Holmström, and Kalantari [9] reproduced the shipment process to analyze how in-transit services offered to customers may constitute a platform for hybrid shipment control. Caris, Macharis, and Janssens [33] introduced a DES model, named SIMBA, aimed to support decision making in intermodal barge waterway transport, and they used the model to analyze the behavior of the system under various network configurations. Applications of SIMBA were reported by Caris, Macharis, and Janssens [34] for the evaluation of the potential of cooperation mechanisms previously selected by a service network design model in a corridor network as well as by Macharis et al. [151] for the analysis of the impact of a new intermodal barge terminal on the Belgian waterways network. McLean and Biles [159] presented a DES model of a container liner (maritime) shipping network considering multiple service routes and schedules. Reproducing shipping activities, container ship operations, and intermodal container movements, the model aimed to evaluate the operational costs and performance associated with liner shipping as well as the effect of the individual service schedules on the overall system. Focusing on the same segment of the industry, Meng and Wang [160] proposed a DES model to assist in decision making for container carriers and port operators in a competitive context. Implemented in ARENA, the model yields predicted container shipment demand for each carrier and throughput for each port. Dotoli et al. [75] focused on motor carriers and presented the timed Petri net modeling technique to describe their operations and the movements of trucks within an intermodal transportation system. The model structure was modular with a top-down approach. Each module reproduced a subsystem of the network: truck terminals, highways, railways, ports, and ships. The model was applied to evaluate the effect of the introducing a new Information and Communication Technology (ICT).

Dekker et al. [70] simulated a company's supply chain with a DES model from the (stochastic) order generation process to the production and distribution processes to test the use of temporary storage offered by intermodal transshipment points for the positioning of stocks of fast-moving consumer goods. Additionally, taking a logistics-network perspective, Hillbrand and Schmid [122] and Sihn et al. [211] designed a DES simulation and evaluation model to evaluate multimodal logistics concepts (e.g., point-to-point transportation, consolidation terminals, and milk runs) by combining individual logistics building blocks (e.g., a factory, a transshipment center, etc.). Luan [146] presented a system-dynamic and continuous simulation model to analyze the advantages of freight consolidation. The analysis showed that freight consolidation tended to increase the capacity utilization of a single vehicle, the vehicle loading ratio, and the freight profit. Note that this study included the only example of a model based on the system-dynamic approach.

DES models were also proposed as components of more comprehensive solution methods. Thus, Lam, Lee, and Tang [136] proposed a linear approximation method under the temporal difference learning framework to address a stochastic model for a simple two-ports two-voyages system. The algorithm required a discrete event simulation model for updating the predicted parameters and average cost. Herazo-Padilla et al. [121] presented a similar approach considering the stochastic version of the location-routing problem. A hybrid solution procedure based on ant colony optimization and a discrete-event simulation was proposed. Fanti et al. [91] inserted a DES model in a DSS for tactical and operational decision making within intermodal transportation networks. The DES model mimed the system and applied the optimization strategies proposed by the optimization module. The model also provided performance measures. Similarly, Sinha and Ganesan [212] considered a typical container business operation problem and deployed a simulation optimization technique to analyze several opportunities to improve the overall system performance. The DES model therein measured the performance of the optimization technique based on different KPIs, including fleet size, unmet demand, service level, and utilization.

Simulation-optimization relationship

Simulation with optimization-based iterations (*SOI*) was the approach used by the largest (40%) group of studies considered in this analysis. Recall that, in the SOI approach, the optimization procedures run within a simulation framework. Accordingly, Macharis et al. [151] evaluated different policy measures to stimulate intermodal transport in Belgium with a GIS-based simulation model, which applied Dijkstra's algorithm to compute the shortest paths and associated transport costs from the port of Antwerp to Belgian municipalities via intermodal terminals. Wisetjindawat et al. [252] developed an evaluation model for relief operations in response to the three most likely earthquake scenarios to affect the Aichi prefecture. The framework included four steps: initial assumptions, estimation of the level of damage, estimation of the number of victims, and delivery of relief supplies. A Vehicle Routing Problem (VRP) was applied within the last step to estimate the optimal level of resources (e.g., the number of drivers, number of trucks, and expected fuel consumption) to dedicate to the operation. Another example was proposed by Teo, Taniguchi, and Qureshi [232], in which an agent-based model included an exact solution method to solve the vehicle routing problem of the carriers' delivery jobs. The model was used to evaluate the short-term effect of distance-based road pricing on the major stakeholders, including carriers, shippers, administrators, and customers. Approximately 50% of the SOI approaches were applied within a multi-agent framework to simulate the actors' behavior [13, 30, 142, 181, 182, 200, 207, 209, 217, 228, 231, 232, 78].

The *sequential simulation-optimization* approach was considered in 22% of the papers[5, 8, 34, 58, 93, 115, 120, 127, 135, 151, 162, 196, 219, 242, 249, 255, 256, 125]. Ambrosino and Sciomachen [5] illustrates this class of approaches. The authors considered the problem of locating hubs for freight mobility in urban and suburban areas, with an application to the freight multimodal network of the city of Genoa. The solution was validated using a discrete event simulation model. The model analyzed the freight flows in the city under different operational scenarios with and without the selected platforms. A second illustration is the work of Miller-Hooks, Zhang, and Faturechi [162], which formulated the problem of measuring the network resilience level and determining the optimal set of preparedness and recovery actions by developing a two-stage stochastic program. Monte Carlo simulation was employed to generate the disaster realizations. The integer L-shaped method was then applied.

A set of papers adopted *alternate simulation-optimization* techniques to analyze several opportunities and improve overall system performance [91, 116, 178, 212, 224, 136, 213]. These approaches, also identified as hybrid approaches because of the complementarity of the two models, integrate a feedback loop between the optimization and simulation models, the former selecting a set of candidate variables based on the output of the latter. For example, Fanti et al. [91] described an optimization model connected by a web service to a simulation module (implemented in ARENA). The mechanism was as follows: the optimization algorithms proposed solutions that were sent to the simulation module, which applied the proposed solutions, matching them to the current state of the system. The simulation outputs thus evaluated the effects of the proposed solutions on the system, and they were then sent back to the optimization model. Finally, the optimization model evaluated the system performance and provided a new set of candidate variables to the simulation model until the simulation outputs led to a satisfactory system performance. The set of candidate variables was selected at this point. This approach is highly interesting because it allows an automatic re-planning of values proposed by the optimization model. Furthermore, the simulation model here has two important objectives: the forecasting of system performance and the improvement of the optimization model solution. A similar approach was proposed by Sinha and Ganesan [212]. The model in this study aimed to manage container business operations with heterogeneous customer demand and service priorities under an uncertain environment. The problem was based on an optimization model where the objective function was estimated using a function of the stochastic simulation output. The optimization engine selected a set of values that were used as inputs to the simulation model. The optimization model selected the next trial solution based on the KPIs computed by the simulation until the predefined satisfaction criteria were achieved or the desired level of improved output was obtained. As in the previous case, this simulation model was based on a discrete-event simulation technique to evaluate the system performance in terms of increased profit and demand fulfillment rate under various scenarios. Sirikijpanichkul et al. [213] developed a model for the evaluation of road-rail intermodal freight hub location decisions. The modeling process began with an analysis of potential hub location sites using a set-covering problem. The result was a set of scenarios of the candidate hub locations. The screened options were then transmitted to the land-use allocation and transport network model as input data. Next, the hub and network outputs of each option were calculated. These output data were then fed into individual stakeholders' objective functions in the multi-objective evaluation model. The model determined if the solution was mutually satisfactory for every player by considering the results of every individual objective function. If so, the location choices became the outcome; otherwise, feedback was provided to re-select a new set of screened hub location options. The process was iteratively repeated until the final solution was achieved.

Finally, 30% of the papers applied *simulation* without any optimization procedure [9, 26, 27, 33, 39, 40, 75, 79, 102, 111, 122, 124, 126, 129, 146, 159, 173, 174, 170, 211, 248, 251]. One-third of these papers dealt with freight demand models for estimating urban freight transport flows. They applied *simulation by optimization* to estimate the different O–D matrices (e.g., shopping mobility O–D matrices, restocking quantity O–D matrices, delivery O–D matrices, and restocking vehicle O–D matrices). The remaining

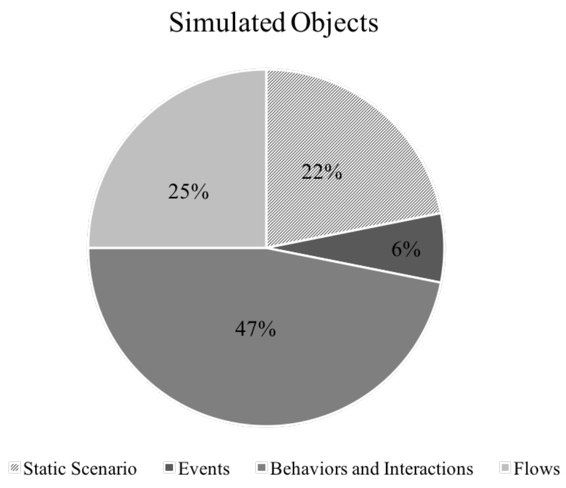

Figure 2.11: Distribution of papers according to the objects simulated.

two-thirds proposed simulation models to evaluate the effects of policy measures on the performance of the transport network (34%), compare several logistics organizations and service schedules (40%), evaluate the effects of new technologies (13%), and compare different network designs (13%). These papers applied DES in 46% of the cases and *simulation by optimization* in 34%.

2.3.4 Scope

We complete the literature analysis with the simulation object and objectives.

Simulated object

Figure 2.11 presents the objects simulated in the selected literature and the corresponding distribution of papers. Simulation is usually applied to reproduce the *behaviors and interactions* between actors (47%). Approximately 22% of the studies used simulation to forecast *flows* and 25% to reproduce *scenarios*. Only 6% of the studies applied simulation to represent an *event*.

Behaviors and interactions were mainly simulated by *dynamic simulation* (84%) applying MAS (47%), DES (28%), and game theory (6%). Furthermore, behaviors and interactions were modeled by applying optimization with the assumption that each actor was rational and acted according to his objective. Hence, the majority of these papers (50%) applied an SOI combination where the optimization methods were included in the simulation frameworks.

From the geographic extension point of view, 48% of the studies in this group was concerned with urban areas, whereas the remaining 52% was split between national and international geographic coverage (33% and 20%, respectively). Focusing on the decision makers, institutional authorities were those that principally studied behaviors and interactions (44%), followed by carriers (31%) and shippers (25%). Finally, behaviors and interactions were principally considered when evaluating policies (47%), logistics services (30%), the building of infrastructure (19%), and cooperation mechanisms (19%).

Flows were usually estimated by *simulation by optimization* (72%), whereas DES was used in only 28% of papers. Simulation was also usually applied alone to forecast the flows. All user equilibrium models are included in this category. From the geographic extension point of view, 61% of the papers estimating flows were concerned with urban areas, 33% considered the national level, and 6% had an international geographic range. Focusing on decision makers, institutional authorities were the most interested in flow forecasting (68%), followed by carriers (28%) and shippers (11%). Finally, flows were principally forecasted when evaluating logistics services (40%), policies (20%), and infrastructure building (18%).

With respect to the simulation of a static scenario, the simulation represented the framework of optimization methods when various policies were applied. Hence, the optimization procedure was run once the scenario was set up. This was a typical SSO combination, which occurred in 50% of the papers simulating static scenarios. The SOI approach was applied in 17% of the cases.

Only a few papers applied simulation to reproduce complex micro-events. For example, Andersen, Crainic, and Christiansen [6] used it to represent more accidental demand, and Orozco and Barceló [178] randomly generated different events (e.g., new customer calls) during the simulation. Qureshi, Taniguchi, and Yamada [196] presented a micro-simulation-based evaluation of an exact solution approach for the vehicle routing problem. The simulation reproduced the traffic network under normal conditions and conditions in which a stochastic traffic incident event occurs, thereby changing the travel times. A stochastic event was considered when simulating freight distribution services (80%), and it was reproduced applying a DES and distribution approach.

2.3.5 Simulation objectives

Figure 2.12 shows that most studies used simulation to compare two or more alternatives. Furthermore, 42% of the papers proposing *what-if analysis* investigated the behavior and interactions between several actors in the system. The what-if analysis was performed using the SOI (48%) and SIM (43%) approaches. In addition, 28% of the studies applied simulation to *validate* an optimization model, an approach, or a solution. This validation was generally performed with the SSO approach (about 53%). The simulation reproduced the scenarios, evaluating alternatives to demonstrate the efficiency and applicability of the proposed optimization model. Approximately 19% of the studies applied simulation to *forecast* the future behavior of an existing system. This category

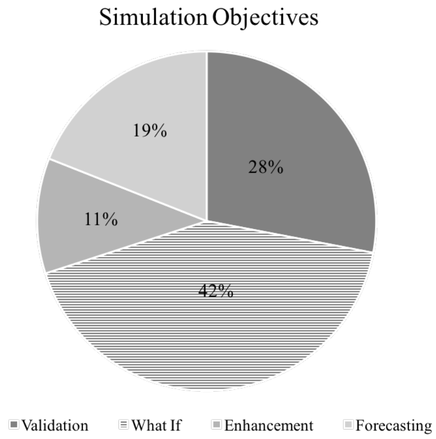

Figure 2.12: Distribution of the simulation objectives.

included all freight demand models. Finally, approximately 11% of the studies applied simulation to *enhance* a solution proposed by optimization models. The approach used to improve the solutions was the ASO approach. The feedback loop between the two models allowed the improvement of the solutions according to the simulation outputs.

Researchers have increasingly studied the urban context as well as the environment, with most analyses having the reduction of GHG emissions as final objective. Environmental aspects were mainly considered in urban areas , either directly or indirectly by means of generalized costs, e.g., measuring traffic reduction, road occupancy, and traveled kilometers in CO_2 equivalent units. Only a few papers directly estimated GHG emissions by measuring CO_2 or NO_x emissions in tons. Furthermore, very few papers proposing a multi-criteria approach considered different metrics for the comparison of potential alternatives. It would be interesting to integrate simulation and multi-criteria analysis because of the multi-criteria nature of the urban intermodal transportation system. Almost all papers proposing new policies and solutions for freight distribution within cities considered trucks or trucks and electric vans only. Hence, while intermodality appears very successful for interurban, national, and international networks, urban freight distribution seems currently to be analyzed from an unimodal, road transportation, with few, if any, interactions with the surrounding intermodal transportation. An interesting result is the role of institutional authorities as decision makers. They appear to be very active and interested in the improvement of freight distribution within urban areas, particularly by reducing the environmental impact. This finding may be a consequence of the direct involvement of the public sector in smart city and city logistics projects. On the other hand, the studies insist on an operational perspective, while just a few evaluate the policy impacts on the overall system over a long time horizon. Moreover, no significant presence of public authorities as decision makers was observed in the national context. From a modeling point of view, *dynamic simulation* is the most frequently applied. This type of simulation is particularly used to reproduce both the behavior of several entities and the dynamism and interaction between them. An increasing number of studies have proposed multi-agent simulations, even if, as highlighted in the future directions, they are still lacking in terms of accuracy of behavior representation.

Chapter 3

Mixing traditional and green business models for urban parcel delivery

The analysis in the previous chapter highlighted the lack of appropriate and efficient tools that incorporate into simulation and optimization methods the managerial perspective, supporting decision makers in designing sustainable policies. This lack is relevant both in urban freight transportation and people mobility. Indeed, the work by Francesco et al. [97] and Perboli et al. [190], concerning the business of car-sharing mobility service, already proved the absence of studies linking the business models of the stakeholders operating the system, their business development, and the operational models.

An analysis of such a complex and hyper-connected system requires a holistic vision of the context, adopting different methodological approaches in order to gain full insights and to understand the extent of the challenge posed. Such tools imply facing the issues of the urban freight transportation system through a multi-disciplinary approach described in the introduction, incorporating qualitative and quantitative methods and models. In fact, they have to be able to incorporate different sources of information, including socio-demographic and managerial data, city and traffic information. This approach provides the managers of transportation companies and local administrations with a tool able to quantify and certify the service costs, to compare the commercial behavior of different transportation companies subcontractor and to perform *what-if* analyses of a specific City Logistics measure, assessing its real impact on a specific city.

The next chapters propose the application of this multi-disciplinary methodology to deal with different aspects of the urban freight. One of these issues is associated with the introduction of new delivery options among emerging technologies, including drop boxes [71], cargo bikes [184], electric vehicles [223], autonomous vehicles [101], and drones [169], to increase the efficiency of delivery activities, mitigating the effects of decreasing marginal revenues. In particular, this chapter focuses on the integration of one of the most popular new business models (e.g., green delivery operated by cargo bikes) with those of traditional methods (i.e., vans). Many contributions in the literature investigate the adoption of green transportation modes, but without considering integrating them with traditional systems, in terms of operations management, cost and revenue structures, and policies. This study, published in [185] represents the first attempt to fill this gap. Unfortunately, the integration of different delivery options is not straightforward, owing to the interactions and conflicts among actors, their business models, and the technologies themselves [220]. Thus, to assess and harmonize the different business and operational models, we propose an unconventional approach, starting with qualitative research from a business perspective of parcel delivery systems, using qualitative business management tools (i.e., BMC, SBN, and SWOT analysis). Then, we investigate the operations of such system thought a context-aware integration of business and operational models, and finally, we present a strategic discussion based on a quantitative analysis of the options and policies available. In particular, this quantitative analysis of strategic actions and their execution in operations is implemented by means of a simulator.

The key innovative research investigations can be summarized as follows:

- we investigate the integration of modes (traditional and green), supported by a detailed cost and revenue analysis based on the business model, which is an area that is under-researched. In fact, although a few studies have investigated the costs associated with the last mile [105], our is the first to consider a cost structure for delivering goods in urban areas, which includes economic and environmental costs. In particular, we consider the emissions and costs of the overall last-mile chain, according to the latest regulation, the ISO/TS 14067:2013 "Greenhouse gases - Carbon footprint of product - Requirements and guidelines for quantification and communication", which is not present in the literature.

- We provide the first analysis of business models that characterize the new practices and technologies of urban parcel delivery by couriers. Thus, our approach does not focus strictly on operations but proposes a holistic vision, including interactions between international couriers and external firms or subsidiaries managing activities in the last-mile segment.

- We show how mixing qualitative and quantitative analyses enabled us to derive better results than when using quantitative analyses alone.

This chapter is organized as follows. Section 3.1 introduces how the proposed multidisciplinary methodology has been implemented in this study. Section 3.2 goes into the details of the MACS presented in the previous chapter (Figure 2.1) analyzing the context of the urban parcel delivery and presenting the business models of the actors involved. These actors' operational models are discussed in Section 3.3 in terms of the times, distances, and costs (both operating and environmental) associated with various types of vehicles. In Section 3.4, we introduce our Monte Carlo-based simulation-optimization framework, while in Section 3.5 the results are used to highlight synergies between operators in the last-mile segment and to extrapolate mixed-feet policies.

3.1 Methodological framework

The main innovative feature of this study is the proposal of a holistic vision of a complex parcel delivery system, including both business and operational perspectives. The multi-disciplinary approach presented in this thesis is implemented through the key five steps of the GUEST methodology that mix qualitative analyses, particularly in first stages to understand the complex system, with quantitative analyses to extrapolate mixed-fleet policies, useful for the industrial decision-makers involved. In particular, the phases are the following:

- Go. This phase investigates the stakeholders in the last mile segment of the supply chain. Here, we focus on the city of Turin, in particular, and Europe, in general, as well as an international courier delivery service operating in Italy. The aim of this preliminary analysis is to gather information and provide a full description of the stakeholders' profiles in terms of their needs and cost structures.

- Uniform (see Section 3.2). The knowledge of the system must be assessed in a standard way in order to obtain a shared vision of a MACS. In doing so, in this phase we represent the system by means of the SBN that depicts the relationships and interconnections between actors. Then, we explicitly describe the governance and business models of each operator deriving the BMC [179] and finally, opportunities and threats in such system are identified using a SWOT analysis.

- Evaluate (see Section 3.3). Given the gap in the research concerning the link between business and operational models, we overcome this lack by proposing a deep analysis and comparison, identifying the key factors of the business and operational models. On the one hand, the full structure of the costs and revenues is described explicitly for each transportation option. On the other hand, the integration of business and operational models is supported by a performance analysis of the traditional and green delivery options, based on the main variables that affect the last-mile logistics in urban areas (e.g., distance, delivery time).

- Solve (see Section 3.4). Given the outcomes from the previous phase, a Monte Carlo simulation is conducted to obtain a comprehensive vision of the overall complex system, rather than focusing on the central area, as in the previous step.

- Test (see Section 3.5). The findings of the Monte Carlo simulation are tested and analyzed in order to extrapolate mixed-fleet policies.

These analyses are conducted using three streams of data related to the business models, the cost structures, and the operations. These data are the result of primary research on parcel delivery systems in Europe, focusing on the city of Turin, along with information provided by a major international parcel delivery company operating on all continents and involved in the URBan Electronic LOGistics (URBeLOG) project

[240, 155] and the stakeholders involved in the Synchro-NET H2020 project [218, 193]. With regard to the business models, the data were gathered from interviews with the Chief Executive Officer (CEO) and Chief Operating Officer (COO) of this company. The simulation analyses are based on the customer distribution and daily volumes of deliveries in Turin, and registered by the international parcel delivery company during the final three weeks of 2014 and the beginning of 2015. Finally, the data on costs are taken from financial statements and the interviews with the COOs and marketing directors of the stakeholders in order to obtain specific feedback on the financial and operational dynamics.

3.2 Parcel delivery business model analysis

As discussed in the previous chapter, transportation and CEP industry can be represented as a multi-actor system owing to the number of players involved and their high level of interconnection. Focusing on the urban area, the aim of this section is to conduct a comprehensive study of this industry, the operators, and their interactions, by adopting a business-development oriented approach, which has received little attention in the literature. The results of this section represent the starting point and the knowledge base needed for the quantitative analysis conducted in this study.

Figure 3.1 represents a declension of the global SBN illustrated in the Figure 2.1, with emphasis on the commercial relationships between transportation and logistics companies at the urban level. Then, for each actor, we define a business model using the BMC tool proposed by Osterwalder and Pigneur [179]. The purpose of this analysis is to identify, for each of the nine building blocks of the BMC, similarities, conflicts, and possible synergies between the various strategies adopted by the companies and, in general, to evaluate their coexistence, especially given the complexities typical of the last-mile segment. Besides, adding a further level of detail, a SWOT analysis is conducted to identify relevant strengths, weakness, opportunities, and threats in each case, and to investigate how these models might achieve a strategic fit.

We identify three main actors in the urban transportation and parcel delivery systems, as shown in Figure 3.1. For the sake of simplicity and clarity of exposition, we provide a brief overview of the actors and their roles, while Sections 3.2.1 to 3.2.3 give details about their business models:

- International courier delivery services (hereinafter, international courier). This is a parent company that operates international and national long-haul shipments (e.g., TNT, FedEx, UPS, etc.).
- Manager of a traditional fleet. In general, this actor is responsible for the management of parcel delivery in the last-mile segment and, depending on the geographical area, may take different configurations. For example, in North America, this is an internal department of the international courier, but with

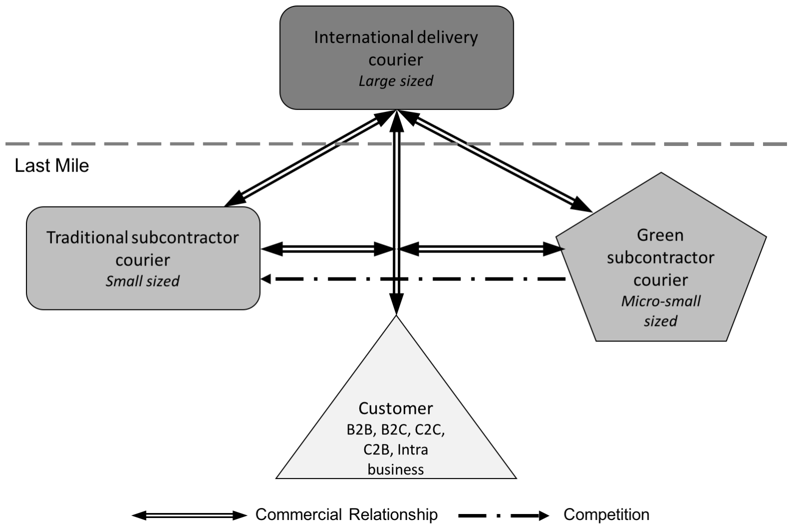

Figure 3.1: Relationships among the main actors in the urban transportation and parcel delivery systems.

autonomy in the management of the area and in the procurement of external capacity in the market. In contrast, in European countries, it is common practice to outsource the operations in the last-mile segments to traditional courier delivery services (hereinafter, traditional subcontractors). These are typically small or medium-sized firms, generally organized as a legal form of cooperatives with limited financial capacity, but capable of managing parcel deliveries locally. From an operational standpoint, the activities are not affected by the different structures. However, in the second case, the flexibility increases because costs can be reduced if demand decreases, and it is necessary to guarantee profit margins for both companies.

- Manager of a green fleet. The increasing awareness of environmental problems related to transportation and the drive toward sustainability has led to the development of new business models for more conscious and optimized management of parcel deliveries in the last-mile segment. In fact, new firms known as green subcontractor courier delivery services (hereinafter, green subcontractors) now operate in several European cities (e.g., Turin, Milan, Paris, Berlin, London, Copenhagen). Their business models are similar to those of traditional couriers, except they also consider the environmental impact of their activities, often using green vehicles such as bikes and cargo bikes. As mentioned earlier, we focus on the European parcel delivery system and, thus, we consider external firms responsible for the management of traditional and green fleets. However, owing to the decision-making and economic autonomy of the single departments in North American companies, the results of this study are still valid when these firms decide to internalize all operations.

- Customers. Customers are the final users of logistics and transportation activities, and include the business-to-business (B2B), business-to-consumer (B2C), consumer-to-consumer (C2B), consumer-to-consumer (C2C), and intra-business segments.

3.2.1 Business model of international courier

Figure 3.2 depicts the BMC related to the international courier. Its main customers are differentiated in the following segments, each with their own behaviors and needs that must be satisfied. The B2B segment consists of firms that use couriers as a means to move products output from their logistic chain, which represent the inputs to other customer firms. The B2B segment also includes e-commerce, involving goods flows between e-retailers and between e-retailers and producers. The B2C segment consists of firms that sell goods directly to final consumers, bypassing distribution chains. Examples include e-stores and website service providers. Then, the C2B segment is strictly related to reverse logistics. This represents the process of returning products, which retrace the supply chain, for different reasons, such as the disposal of waste, processing scraps or packaging, end-user guarantees, dismantling or recycling end-of-life products, customer rejections, or order mismatches for new products. Individuals who require transportation of goods or documents for private needs and online auction websites (e.g., eBay) are parts of the C2C segment. Finally, intra-business consists of firms that use courier services to link plants and warehouses. The value proposition that the international courier offers is mainly represented by "time sensitive" or "time critical" transportation of products. For their features of speed and reliability, these services are also called "express and overnight deliveries," because they must be performed in a shorter time window. For this reason, couriers provide more than a transportation service, and include a specific time, called a "transit time" [37]. Another component of the value proposition is a superior customer experience, owing to the high added value of express deliveries. In fact, customers obtain benefits deriving from the shipment efficiency, speed, reliability, and security (e.g., through "tracking & tracing") of the services received. Other important benefits are customized pickup and delivery activities in the last mile, and solutions based on product types to be transported (e.g., fragile or perishable products). For small and medium-sized business customers, the international courier offers two other types of value, namely cost optimization and sales market extension. First, firms using express deliveries are capable of realizing Just-In-Time (JIT) manufacturing, with the resulting reduction in inventory levels and optimized production process and costs. The last component of the value proposition is strictly related to the customer strategy. In fact, time-sensitive transport, together with internationalization, increase catchment areas and create new business opportunities for firms. The main channels used to reach customers and to communicate with them to deliver this value proposition can be classified as direct and indirect channels. Website and mobile applications represent the first contact points with customers to raise the awareness of the services offered and to help them to evaluate several propositions. Retail stores are physical structures located throughout a territory in order to increase customer proximity. Another type of channel related to marketing strategy is brand identity, realized through personalized vehicles showing the brand of the courier. These channels are generally owned by the company, and allow an immediate awareness, without intermediaries. The indirect channels are mainly partner-owned websites used in e-commerce. Customer relationships are maintained through the availability of retail stores, websites, help desks, and call centers. These provide customers, both businesses and consumers, with direct support and assistance in all phases of the shipment process, offering a high level of customer retention and loyalty. Lockers and, in general, delivery machines located in urban areas allow an indirect relationship with customers and provide them with a self-service option, available 24 hours a day, throughout the year. Moreover, in order to increase the strength of customer relationships, the international courier interacts with its customers through social initiatives and the creation of a community (e.g., the "UPS Foundation" [239]). The revenue streams that the international courier obtains derive from selling time-sensitive delivery services to each customer segment, through identified channels. The key resources required to make the business model work are the physical assets, such as vehicle fleets and point-of-sale systems, intangible assets, such as software and other tools used to optimally allocate trips, licenses and partnerships, and, finally, the human resources, including drivers. According to the analysis of value chain conducted by LUISS Business School and Associazione Italiana Corrieri Aerei Internazionali (AICAI) [37], the main activities that represent the core business of the international couriers are process and operations management and customer care. The first consists of ordinary activities, such as route planning, intermodal transportation, customs clearance, pickups and deliveries, and monitoring the overall process. The second refers to activities for customer relationship management, and are strictly related to the steps in the transportation process: pre- and after-sales support, tracking and tracing of parcels, and proof of delivery. To support its business model, the international courier creates partnerships and alliances with high strategic value. The key partners are suppliers, subcontractors for outsourcing activities in the last mile, cargo operators and handling agents, logistics, and commercial joint ventures, all aimed at making the business more efficient and developing new models. Finally, another relevant partnership is created with local administrations in order to meet government regulations and to ensure the sustainability of parcel delivery in urban areas (e.g., the URBeLOG project [240]). To operate the business model, the main costs the international courier incurs are related to the key resources, as well as materials (e.g., fuel costs, packaging, consumables, etc.), personnel costs, handling fees, acquisition and maintenance of vehicles, equipment, structures and ICT systems, operation costs, such as government and auditors fees, and subcontractor fees when outsourcing activities. Other costs include marketing and advertising expenditure, and those related to risk management.

3.2.2 Business model of traditional subcontractor

As mentioned previously, international couriers outsource pickups, deliveries, and transportation activities in the last-mile segment to subcontractor couriers (see Figure 3.3 for the BMC), representing the main customer segment to whom they offer a value proposition, consisting of last-mile parcel deliveries. Outsourcing generates value for customers through several benefits in terms of more efficiency and flexibility, owing to better management of activities in urban areas with respect to peak demand and qualitative and temporal constraints imposed by time-sensitive deliveries. Other advantages for the international courier are the wide geographical coverage, cost reductions, the possibility of focusing on its core activities (e.g., multimodal and intermodal transport or customer care), access to specialized resources and expertise (e.g., about territorial knowledge), and benefits from learning economies. The traditional subcontractor firms reach customers through commercial agreements and tenders, which represent their best practice. Thus, subcontractors establish a relationship with the customer segment, maintained by a constant information exchange along all transportation activities (e.g., tracking services and feedback), permitting the co-creation of value for the final user. The main revenue stream for traditional subcontractors consists of the income they receive from customers for last-mile parcel delivery services. The key resources required to make their business models work are the physical assets, such as vehicles (mainly vans, often customized with the customer brand), warehouses, and human resources, such as drivers and the employees responsible of parcel handling and warehouse management. The key activities included in the core business of traditional subcontractors are the optimal management of transportation services and the planning of trips and dispatchers in order to achieve high service levels in terms of parcel delivery, fulfilling their timeline constraints. After receiving parcels at the hub, the traditional subcontractor checks on the accuracy and integrity of packages, as well as the related information and bar codes, along conveyors called “sorters”. Then, parcels are assigned to a driver according to zoning criteria, and are ready for shipment [184]. An important key activity is also the management of anomalies, such as returns for data errors or residuals when receivers are not at home. These days, there is a considerable impact of deliveries that fail at the first attempt (approximately 12% of all deliveries) [246]. Another key activity is related to its coordination with international courier customers. The interplay between these two actors is important to the success of multimodality and to the correct fulfillment of parcel deliveries, along with the subsequent satisfaction of final users. A key partnership is established with suppliers of strategic assets, particularly with vehicle dealers and leasing companies, but also with drivers. The cost structure consists of expenses related to acquisitions, maintaining and fueling vehicles, equipment and materials, warehouses, personnel costs, and penalties, which may be incurred as a result of breaching contractual terms.

3.2.3 Business model of the green subcontractor

The increasing awareness of environmental problems related to transportation and the intent to make the industry more sustainable have led to the development of new business models for more conscious and optimized management of parcel deliveries in the last-mile segment. Examples are new firms that use business models similar to those of traditional subcontractors, but that also consider the environmental impact of their activities, often using green vehicles such as bikes and cargo bikes. Figure 3.4 depicts the BMC related to the green subcontractor. The customer segments are identifiable principally as those where international couriers outsource last-mile operations, but also include the B2B and B2C segments for intercity and intracity postal services. The value proposition offered by green subcontractors consists of cycle-logistics services capable of overcoming the complexities of parcel deliveries in urban areas. For example, these include mobility restrictions (e.g., LTZ areas), and inadequate or insufficient infrastructure (e.g., limited usability of loading and unloading zones). Furthermore, their value proposition penalizes the competitiveness of traditional subcontractors. Cycle-logistics provide customers with several sources of gain creators and pain relievers, including speed, punctuality, and flexible service, because of the better performance of bikes in city traffic, the interoperability between traditional road vehicles and bikes, and cost reductions, but without compromising quality of service. This last factor is another important component of the value proposition. In fact, better management of parcel delivery in the last mile, and the decreases in expenditure (e.g., fuel, insurance, parking fine, etc.) lead to cost optimization. Green subcontractors offer their customer segments the possibility of delivering small-sized parcels, between 0 to 3 kg, or up to 6 kg. Finally, another value proposition for customer segments is provided by the green image and green credentials required to create a sustainable supply chain. Green subcontractors reach their customers through websites, which are the first channel through which they can increase awareness and knowledge of their services. Other channels include media and interviews published in magazines that specialize in transportation and environmental issues. As was the case with traditional subcontractors, green subcontractors establish relationships with customer segments that are maintained by constant information exchange along all transportation activities (e.g., tracking services, feedback, and information about CO2 savings). The main revenue stream for green subcontractors consists of the income they receive from customers for the sale of last-mile parcel delivery services and cycle logistics, revenue from CO2 savings and the carbon credit trading, and fees and royalties from affiliates. The key resources required to make the business model work are the physical assets, such as vehicles with a low environmental impact (bikes and cargo bikes), warehouses, and fit human resources (bikers), whose performance determines the service quality and punctuality. Owing to the simplicity of this business model, it is affected by high repeatability. Thus, important key resources include intangible assets such as partnerships, but also the ICT tools and software required to optimize operations management [184]. The key activities underlying the business model are the same as those of the traditional subcontractors. In fact, green subcontractors are generally start-ups and, thus, fundraising is an important activity, necessary for the future development of their business models. Key partnerships are established with technical partners, investors, and sponsors, who are all important in terms of providing support and improving the business model. Other key partners are the bikers and, importantly, local administrations. In order to operate their business models, the main costs to green subcontractors are related to their key resources, as well as to vehicles, equipment (e.g., bags customized for parcel transportation), consumables, information technologies, personnel, warehouses, and marketing and advertising.

<table>
<tr>
<td rowspan="2">Key Partners
• Suppliers
• Subcontractors
• Cargo operator and handling agent
• Joint Venture
• Local administration</td>
<td>Key Activities
• Process and operations management
• Customer care</td>
<td rowspan="2">Value Propositions
• Time-sensitive transportation services
Express deliveries
• Superior customer experience
• Costs optimization
• Sales market extension</td>
<td>Customer Relationships
• Retail stores
• Web site
• Help desk
• Call center
• Locker
• Community</td>
<td rowspan="2">Customer Segments
• Business-to-Business (B2B)
• Business-to-Consumer (B2C)
• Consumer-to-Business (C2B)
• Consumer-to Consumer (C2C)
• Intra-Business</td>
</tr>
<tr>
<td>Key Resources
• Physical assets
Vehicle fleets
Warehouses and retail stores
• Intangible assets
ICT
Licenses
Partnerships
• Human resources</td>
<td>Channels
• Direct channels
Web site and mobile apps
Retail stores
Brand identity
• Indirect channels
Partner web sites</td>
</tr>
<tr>
<td colspan="3">Cost Structure
• Costs of materials (e.g., fuel costs, packaging, consumables)
• Personnel costs
• Assets costs (e.g., vehicles, equipment, structure and warehouses, software)
• Handling fees
• Subcontractors fees
• Marketing & advertising
• Risk management
• Other operative costs (auditor and governmental)</td>
<td colspan="2">Revenue Streams
• Revenues from time-sensitive delivery services</td>
</tr>
</table>

Figure 3.2: Business Model Canvas of an international courier.

<table>
<tr>
<td rowspan="2">Key Partners
• Suppliers of strategic assets (vehicles)
• Drivers</td>
<td>Key Activities
• Operations and dispatchers management (ground operations)
• Anomalies management
• Coordination with international express courier</td>
<td rowspan="2" colspan="2">Value Propositions
• Last mile parcel deliveries
• Efficiency and flexibility
• Geographical coverage
• Costs reduction
• Focus on core business activities
• Access to specialized resources and know-how</td>
<td>Customer Relationships
• Information exchange process (tracking and feedback)</td>
<td rowspan="2">Customer Segments
• International courier</td>
</tr>
<tr>
<td>Key Resources
• Physical assets
Vehicle fleets (van)
Warehouses
• Human resources</td>
<td>Channels
• Commercial agreements and tenders
• Web site</td>
</tr>
<tr>
<td colspan="3">Cost Structure
• Costs of materials (e.g., fuel costs, consumables)
• Personnel costs
• Assets costs (e.g., vehicles, equipment, structure and warehouses)
• Penalties</td>
<td colspan="3">Revenue Streams
• Revenues from last mile parcel delivery services</td>
</tr>
</table>

Figure 3.3: Business Model Canvas of a traditional subcontractor.

<table>
<tr>
<td rowspan="2">Key Partners
• Technological partners
• Investors
• Partner
• Bikers
• Local administration</td>
<td>Key Activities
• Operations and dispatchers management
• Anomalies management
• Fund raising</td>
<td rowspan="2" colspan="2">Value Propositions
• Cycle-logistics services
• Costs optimization
• Small sized parcel delivery (0-3 kg and 3-6 kg)
• Green image and green credentials</td>
<td>Customer Relationships
• Information exchange process (tracking, feedback, CO2 savings)</td>
<td rowspan="2">Customer Segments
• International courier
• B2B and B2C for intercity and intracity postal services</td>
</tr>
<tr>
<td>Key Resources
• Physical assets
Vehicle fleets (bikes and cargo bikes)
Warehouses
• Human resources (bikers)
• Intangibles assets
Partnership
ICT</td>
<td>Channels
• Web site
• Media and interviews</td>
</tr>
<tr>
<td colspan="3">Cost Structure
• Costs of materials (e.g., consumables, bags)
• Personnel costs
• Assets costs (e.g., vehicles, equipment, structure and warehouses, ICT tools)
• Marketing & advertising</td>
<td colspan="3">Revenue Streams
• Revenues from last mile parcel delivery services
• Revenues from CO2 savings and carbon credits trading</td>
</tr>
</table>

Figure 3.4: Business Model Canvas of a green subcontractor.

Analyzing the BMCs, all operators offer their customer segments a value proposition consisting of time-sensitive transportation services and express delivery. However, the SBN highlights how the dynamics within the urban transportation and parcel delivery system become more complex with the diffusion of subcontracting and the partial autonomy of fleet managers. In particular, major international couriers in the industry do not manage the entire process. Indeed, to serve their customer segments, they focus on long-haul shipments, while outsourcing the deliveries in the last-mile segment to subcontractors, both traditional and green. This process allows better operational performance and economic efficiency in terms of road transportation in urban areas, as well as capillarity and strategic diffusion in territory, leading to customer proximity.

The SWOT analysis (Figures 3.5 and 3.6) and the BMCs show that, for traditional subcontractors, the main sources of weaknesses and threats are their impact on the environment and the critical issues affecting European regions, as traffic and congestion, Low-Traffic zones (LTZ), and the absence of loading and unloading zones. These factors compromise the management of deliveries, inducing disadvantageous conditions for couriers with traditional vehicles. In contrast, these same points represent strengths for green subcontractors. The latter group uses low-emission vehicles with a low environmental impact, such as bikes, in last-mile parcel deliveries, allowing them to earn additional income from CO2 savings and carbon credit trading, as highlighted in the revenue streams block of the BMCs (Figure 3.4). However, the operational model of green subcontractors has a limitation in that the reduced capacity of bikes limits the sizes of parcels they can deliver. This constraint is partially overcome using next-generation cargo bikes, which have a maximum payload of about 100–150 kg per bike, according to estimates provided by [198] based on Europe.

For all operators, vehicles represent a main item of the cost structure, both in terms of operational costs and social costs related to externalities. Owing to the relevancy of these costs, a further quantitative analysis is provided in Section 3.3.2. Finally, the SBN shows how the international courier can guide subcontractors using a financial lever. On the other hand, the competition arcs between traditional and green subcontractors represents a threat, as confirmed by the SWOT. In fact, if subcontractors begin competing on operational costs, customers of the international courier may perceive a reduction of in service quality. Such a price war might be caused by the coexistence of traditional and green subcontractors in the same geographical area, or by the similarities in their business models, in terms of their cost and revenue structures, which reduce the margins of differentiation. A similar situation might occur when a fleet is owned internally by the international courier. In fact, the partial organizational independence of local depot fleet managers and their strategic objectives in terms of cost reductions might have similar effects to those of a price war between traditional and green subcontractors.

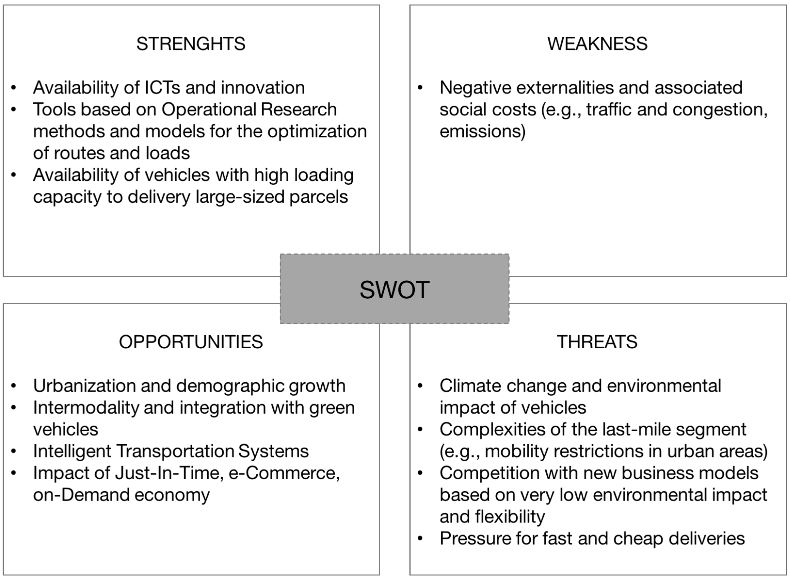

Figure 3.5: SWOT analysis referred to the traditional subcontractor.

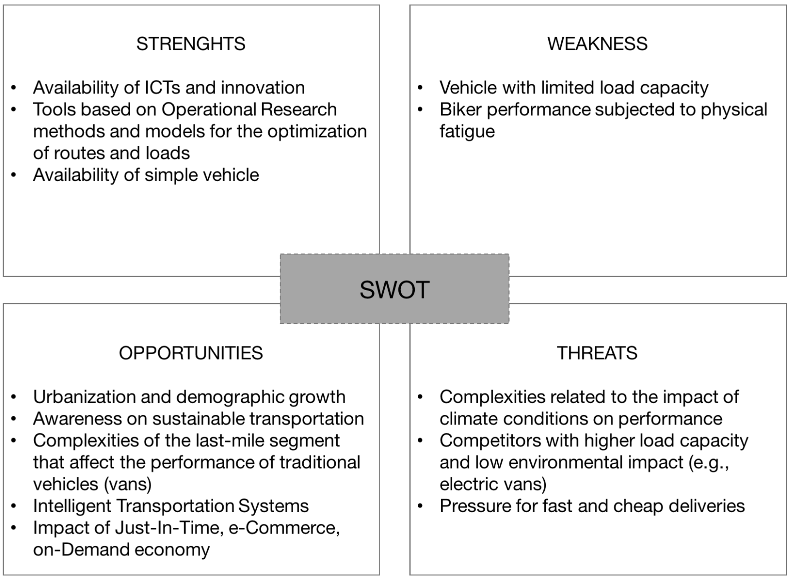

Figure 3.6: SWOT analysis referred to the green subcontractor.

3.3 Parcel delivery operational model analysis

The analysis of the BMCs shows how combining traditional and green subcontractors might determine benefits in terms of efficient last-mile supply chain management but, at the same time, may hide the threat of a price war, reducing the service quality. Thus, there is a need to better understand the costs and the performance structure of the system. More specifically, we analyze two issues that have received scant attention in the literature:

- the break-even points for vehicles and cargo bikes, in terms of the distance between two consecutive stops, in order to determine the portion of a city where they can coexist (Section 3.3.1);
- the operational costs per kilometer of the different classes of vehicles (Section 3.3.2). In this case, partial data can be found in the literature, but no detailed cost analyses have been conducted previously for the parcel delivery sector.

The following analyses are conducted using real data from the customer distribution and daily volumes of deliveries in Turin for the last three weeks of 2014 and the beginning of 2015. The primary data are provided by an international parcel delivery company that operates in Italy and is involved in the URBeLOG project [240].

3.3.1 Break-even distance between vehicles and bikes

The methodology adopted is based on the main aspects that affect the last-mile logistic system: destination features (e.g., number, localization, delivery frequency, and lead time), parcel features (e.g., quantity, weight, and volume), and the performance of the respective vehicles. Referring to these variables, the following sections analyze the locations of deliveries within the city and the break-even distances between them.

Delivery locations and parcel sizes According to [103], reaching the critical mass is one of the major problems associated to the last-mile. Thus, to evaluate the presence of a critical mass for the value proposition of green subcontractors, we studied the distribution of the destinations in the urban areas and, in particular, in the city center. In these areas, the benefits related to the use of environment-friendly vehicles are more relevant because of the presence of mobility restrictions (e.g., LTZ areas) and the various aspects related to the quality of life of the public. Therefore, we have designed an ideal area composed of quadrilaterals (see Figure 3.7, where the coordinates of the vertices are highlighted) that includes the center of Turin, as well as the surrounding neighborhoods directly reachable by bikes.

First, we filtered the deliveries in this area by the weight of parcels. As defined in the Green Paper proposed by the European Commission [86], the term “parcel” refers to a box with a weight less than 30 kg, and manageable by a single person. Thus, we classify parcels as follows: “mailer” (0–3 kg), “small parcels” (3–6 kg), and “large deliveries” (more than 6 kg). We observed that the mailers are the predominant parcels and with the small parcels account about the 80% of the total flow of parcels, and the remaining part is represented by the large deliveries. This trend highlights the increasing role of e-commerce that implies frequent deliveries of limited sizes. Despite the 77.49% of deliveries falling outside the city center, the mailers still represent the more profitable category for both subcontractors. They are easy to handle for green couriers using bikes, who can avoid traffic and other urban restrictions. Thus, the distribution of these parcels represents the critical mass to make the business model of green subcontractors sustainable.

Figure 3.7: Ideal area of direct coverage by green subcontractors using bikes.

Distance analysis and definition of the break-even distance In this step, we analyze the total time per vehicle stop for traditional vehicles and bikes. Here, we aim to determine the break-even distance, expressed in kilometers, where the performance of traditional subcontractors is equal to that of green subcontractors. Note that the term "stop" refers to the time when the vehicle stops to do one or more deliveries. The term "time per stop" refers to the "travel time" plus the "delivery time", expressed in minutes. The first is the time required to reach the destination point of the delivery from the origin point (e.g., hub, subcontractor location, or a previous destination). The second is the time required for parking and performing the delivery (e.g., customer contact, pick up the parcel in the vehicle, and collect the proof of delivery). The time per stop is strictly related to the distance traveled by the courier. Thus, we calculate the distance from the hub of a green subcontractor operating in Turin to each destination point, referred to as the customer location [240]. We measure it using the Manhattan distance, which is the distance measured along axes at right angles. This can be computed by adding, as an ideal point, an intermediate point with the latitude of point A and the longitude of point B. This approach considers the topography of the grid of Turin, according to Roman town planning. We extract a representative sample with mean μ=0.58 km and variance σ^2=0.05 km^2. Then, we conduct an analysis based on the total time per stop, using different speed profiles and delivery times for the traditional and green subcontractors. These parameters are assumed as follows:

- for traditional subcontractors, the average speed in the town center is 25 km/h, 35 km/h, and 40 km/h, with a delivery time between 4 and 5 minutes, considering the complexities related to parking;

- for green subcontractors, the average speed is 15 km/h, 20 km/h, and 30 km/h, with delivery times between 2 and 2.5 minutes.

This analysis is based on several scenarios related to speed and delivery times for both types of couriers, and on the location of the final customers destinations. The findings confirm those of the previous qualitative SWOT and BMC analyses. Thus, although traditional subcontractors can travel faster, the analysis highlights the benefits of cargo bikes. In fact, given the delivery time of traditional subcontractors, when urban congestion reduces the speed (e.g., from 40 km/h to 25 km/h) the total time per stop increases from about 5.40 to 6 min, increasing the benefit of using bikes. Therefore, we analyze the break-even distance between the two options (see Table 3.1). The average break-even distance is about 1.89 km. By varying the values of speed and time, we deduce the following. The break-even distance increases when the driver speed increases or the delivery time decreases. Similarly, the break-even distance increases when the condition $v_B < v_D^o$ is true and the bike speed increases or its delivery time decreases. The combination of the speed of the vehicle at 25 km/h and the bike at 30 km/h gives a constant advantage to the bike. This setting is similar to the values measured in congested city centers, showing the advantage of using cargo bikes in urban delivery operations.

Table 3.1: Break even distances.

$v_D[km/h] / t_D[min]$	4	4.5	5	4	4.5	5	
		2			2.5		$t_B[min] / v_B[km/h]$
25	1.25	1.56	1.88	0.94	1.25	1.56	
35	0.88	1.09	1.31	0.66	0.88	1.09	15
40	0.80	1.00	1.20	0.60	0.80	1.00	
25	3.33	4.17	5.00	2.50	3.33	4.17	
35	1.56	1.94	2.33	1.17	1.56	1.94	20
40	1.33	1.67	2.00	1.00	1.33	1.67	
25	Bike	Bike	Bike	Bike	Bike	Bike	
35	7.00	8.75	10.50	5.25	7.00	8.75	30
40	4.00	5.00	6.00	3.00	4.00	5.00	

3.3.2 Cost efficiency analysis of vehicular and cargo bike delivery

Operating cost analysis In recent years, several companies have been faced with a trade-off between a reduced environmental impact of their activities and the reduced economic efficiency as a result of the consequent additional costs. However, they have also recognized the benefits for competitiveness, in terms of value proposition and brand reputation, of having a greener image. According to this new perspective, they have adopted measures in the city logistics domain when renewing vehicles in their fleets, eliminating those lower than the Euro 4 class and experimenting with green vehicles. The first type of vehicle uses innovative propulsion systems (e.g., electric, hybrid, or methane vans). We also consider alternative vehicles, such as bikes and cargo bikes, and traditional and electric pedal cycles. An actual case is represented by the partnership between Nissan Motor Co. Ltd. and DHL Express in their *"GoGreen"* program. They introduced fully electric vehicles ("e-NV200") in their courier fleet, first testing them in Tokyo's urban area, and then adopting this option in several Italian branches [172]. Each type of vehicle has different impacts, both environmental and economic. Here, couriers need to consider the financial requirements and investment, as well as the outsourcing strategies and the costs related to fleet management and maintenance. The operating cost analysis (see Table 3.2) compares the different vehicles in terms of cost efficiency and environmental impact. The selection of the benchmark vehicles in our study reflects the transition occurring in the industry. In particular, we consider traditional vehicles (gasoline or diesel), fully electric vehicles, and cargo bikes. These vehicles cover a large part of couriers' fleets.

In the proposed methodology, we estimate and compare the total cost per kilometer (TCK) [31] for each vehicle. According to [31], the TCK includes both operating costs (OPC), represented by variable costs (e.g., gasoline) and the cost of ownership OWC, which includes fixed monthly costs. Moreover, the latter costs are not related to the distance traveled, which means the courier incurs these costs regardless of usage (e.g., purchase costs, personnel costs). The sum of these two costs is then expressed in euros per kilometer for the last-mile segment [€/km], which the company incurs when using the vehicle for a year of its technical life cycle. The TCK [31] function is:

$$TCK = (OPC + OWC)/TK = ((v + tx + i + p) + (f + t + mr))/TK, \tag{3.1}$$

where:

- OWC is the cost of ownership, including all annual fixed costs (i.e., purchase cost of vehicles, taxes, and personnel costs). In particular, concerning the purchase cost of vehicles, we consider the interests based on fixed rate paid by the company according to the financial plan and we imputed a fixed depreciation rate (20% annual) due to usage and obsolescence of the vehicle, allocating the the cost of vehicle over its useful life. For simplicity, we did not considered neither value discounts due to inflation, nor opportunity costs being the considered assets essential for the core business of the parcel delivery company and the investment in these physical assets in line with the current practice;
- OPC is the total annual variable (operating) cost (i.e., fuel and tire costs);
- TK is the total kilometers traveled annually.

The values for each item, described in detail below, were estimated from the primary data with regard to the commercial practices and costs. These data were obtained from financial statements and from the interviews with the COOs and the marketing directors of the international courier, its service providers and suppliers, as well as the partners and the Advisory Board members of the Synchro-NET project. A number of further assumptions are made with regard to the operational aspects of the company in our study, considering actual conditions:

- total annual usage, in terms of kilometers traveled in the last mile segment, of about 25000 km/year;
- total annual usage, in terms of hours required to reach each destination and to deliver the parcels, of about 2000 h/year;
- the speed of commercial vehicles in urban areas is about 35 km/h;
- each driver must make about 80 deliveries per day, with an average time of 4.5 minutes per delivery to perform all operations, from parking the vehicle to the collecting the proof of delivery;
- each cost component refers to the technical life cycle of the vehicle, estimated to be five years.

The components of fixed and variable costs are the following:

- **Purchase cost of vehicle** (v): based on estimates realized by several car dealers, and based on a leasing agreement of five years. During this period, the company operating in the transportation and parcel delivery market in the last mile provides a depreciation and amortization schedule of this asset.
- **Vehicle taxes** (tx): refers to the expenditure and taxes related to the vehicles, according to current regulations, such as ownership tax.
- **Insurance** (i): the cost of the truck liability insurance, based on the capacity of the vehicle and the third-party cargo insurance. This excludes theft and fire insurances, which is included in the leasing agreement. Owing to the liberalization process in the insurance industry in 2014 in various countries, including Italy, the cost of the policy refers to an average price offered by several insurance companies, based on secondary research.
- **Personnel costs** (p): the total remuneration payable to a driver, including taxes and employees' social security contributions, according to the National Collective Labor Agreement prescribed for the category to which they belong.
- **Fuel** (f): the costs related to the fuel supply (gasoline and diesel) and to the power supply, depending on the propulsion system of the vehicle. These values are estimated from the consumption figures in the technical specifications provided by the manufacturers. For gasoline and diesel, prices are the average monthly domestic

prices, taken from statistical data provided by the Italian Ministry of Economic Development for 2015. The electricity price is an average cost, based on the prices charged to business customers by major suppliers operating in the energy industry.

- **Tire costs** (t): based on the list prices charged by the leading manufacturers, discounted by a corrective factor of 15% for the purchase of high quantities for the whole fleet. Furthermore, the average usage is estimated to be 50000 km/year (data given by fleet managers).

- **Maintenance and repair costs** (mr): estimated from the data provided by the Automobile Club Italia (ACI) [1], and related to the expenditure for activities required to maintain the effectiveness of the vehicle performance during its life cycle, given the distance traveled. These activities are classified in terms of time or condition-based maintenance, which prevent negative events and maintain normal conditions of use. Otherwise, this is the breakdown maintenance or repair cost after a failure has occurred.

Environmental costs According to the technical specification ISO/TS 14067:2013 "Greenhouse gases – Carbon footprint of product - Requirements and guidelines for quantification and communication", the carbon footprint is defined as the total amount of GHG emitted directly or indirectly by an activity, a product, a company, or an individual. As such, we quantify the amount of emissions for the last-mile delivery process. In particular, we consider the GHG emissions derived directly from fuel combustion, the indirect emissions emitted during the production process of the fossil fuel, and the consumption of energy related to the charging of batteries. However, because we focus on the last-mile segment, we omit the GHG emissions from the long-haul shipment that connects the first and the last mile, and those of the production and disposal process of vehicles. We also consider other pollutants involved in the process, such as nitrogen oxides (NO_x), which are included in the conversion to CO2, using an appropriate factor of 4.7 kg per liter of fuel consumed [133]. To evaluate how the environmental impact affects the cost efficiency of the courier, we express the carbon footprint in economic terms by applying the Pigouvian tax, known as the carbon tax, based on the price paid for CO2 emissions in the atmosphere (see Table 3.2). This price mechanism does not limit the quantity of emissions, but reduces them by making it cost-effective to switch to innovative technologies with a lower environmental impact. In particular, we conduct a scenario analysis imposing different values of the carbon tax, based on the tariffs applied in several counties, for example, 17 €/t in France, and 150 €/t in Sweden [82, 128].

As shown in the BMCs, all operators incur costs related to vehicles used, including the operational and social costs. As illustrated in the above analysis, this cost is higher for the traditional subcontractors using fossil-fuel vehicles than it is for green subcontractors. In particular, while diesel vans are preferred to petrol engines, few of which are used because of the high running costs, electric vehicles permit greater cost savings because

Table 3.2: Cost analysis results.

Costs	Tariffs Carbon Tax [€/tons]	Fossil fuel vehicle [€]	Diesel fuel vehicle [€]	Electric vehicle [€]	Bike [€]
TCK [€/km]					
Annual kilometer cost		2.70	2.68	2.66	1.50
Environmental costs [€]					
Direct CO2 Emissions [tons]		4.15	3.38		
Indirect CO2 Emissions [tons]		4.15	3.38		
Equivalent CO2 Emissions [tons]		8.46	5.52		
Total Emissions [tons]		16.76	12.28		
Carbon Tax [€]	17.00	284.92	208.63		
	30.00	502.80	368.18		
	90.00	1508.40	1104.53		
	150.00	2514.00	1840.88		
Electric Battery Emissions [tons]				3.08	
Carbon Tax [€]	17.00			52.31	
	30.00			92.31	
	90.00			276.94	
	150.00			461.56	
Direct CO2 Emissions [tons]					0.00

of the lower insurance tariff and the exemption from the ownership tax payment. Bike couriers obtain an economic efficiency derived from lower vehicle management costs, as well as from lower personnel costs related to the skills of riders (e.g., they do require a driving license, lower job time). Moreover, they benefit from the additional revenue earned from CO2 savings and carbon credit trading. In fact, assuming that carbon credit prices are 30% lower than the carbon tax tariffs, using bike subcontractors might earn an average revenue of about 0.02 € per stop [185], as compared with traditional vehicles (petrol and diesel). This estimate assumes greater relevance when we consider the high volumes of parcels delivered in urban areas.

3.4 Simulation

As stated in Section 3.2, in order to avoid the service quality reduction due to competition among traditional and green subcontractors, the international courier should identify strategic policies able to harmonize the two. The complexity of the overall system suggests adopting a tool that considers the interconnection between the actors, while explicitly considering their operations and optimization. Thus, we develop a DSS for managing and deploying mixed-fleet policies in a specified urban area. The overall system is based on the simulation-optimization approach presented in [191] for the air transportation market, while the economic and operational data are the same as those used in Section 3.3.2.

3.4.1 The DSS

The diagram of the DSS is shown in Figure 3.8. According to Crainic, Perboli, and Rosano [46], the DSS applies a sequential simulation-optimization, where the simulations are numerical. It is based on a Monte Carlo simulation, a last-mile optimization meta-heuristic, and a data aggregation and analytic module. The first block is a high-level generator of realizations. These are the inputs to the meta-heuristic that optimizes the day-to-day operations of the various fleets. The solutions to each realization are then analyzed in terms of the KPIs. Finally, the data aggregation block computes the average KPIs from the Monte Carlo simulation, which is performed to evaluate the impact of the combination of traditional and green subcontractors. For this simulation, we focus only on couriers using bikes and cargo bikes. Future studies will also consider other green vehicles, such as fully electric and hybrid vans.

The simulator implements a Monte Carlo method, a module for geo-referencing the data, and a post optimization software to compute the KPIs. It requires a logical graph of the city including a set of depots and customers, an instance that describes the deliveries to be performed, and the operational scenarios needing to be evaluated. These inputs include also information concerning the customer density, specificities of the vehicles adopted in a certain operational scenario, as well as their travel times and costs matrices. Moreover, time dependence and sources of uncertainty in the travel times, classes of parcels and service times can be also taken into account in the simulation. The overall simulation process for a given demand situation is described as follows:

- Consider an instance defining the number of parcels and, for each parcel, the volume and the parcel types (mailer, standard, etc.).
- Create a set of 30 realizations **R**, one for each day of a month, with the same number of parcels and characteristics, but different destinations. Each of them represents the realization of all the random variables and thus, corresponds to a operational working day. The process is the following:
  - Identify the set of destinations located in central and semi-central areas;
  - For each parcel, find the node of the logical graph nearest to its actual GIS position, and assign the parcel to the node. The distance between the GIS position of the parcel destination and a logical node is computed by means of the Manhattan distance.
- For each realization $r \in \mathbf{R}$, build a vehicle routing problem. Then, evaluate the resulting problem for each operational scenario. To evaluate the scenarios, the simulator integrates an optimization algorithm that minimizes the costs of deliveries and computes the routes for the fleet of the vehicles. Our algorithm is inspired by the method based by Ropke and Pisinger [201], which is one of the most successful approach for different Vehicle Routing problems, including the Vehicle Routing

with Time Windows (VRPTW), and it implements the ruin and recreate paradigm with an adaptive selection of its destruction and reparation operation. The existing time slots make this problem a VRPTW, and the number of trip settings made it necessary to have an underlying flexible algorithm capable of handling multiple configurations. Additional constraints are related to technical restrictions due to the usage of the bikes, the possibility to fix the number of routes, and balancing of the routes in terms of workload. In fact, the algorithm can be run in two different ways: minimization of the fleet or fleet with fix dimension and load balancing among the vehicles. In the first, the costs are minimized reducing the number of vehicles to use. While in the second, the fleet is given and the algorithm split the deliveries among the vehicles, balancing the load. After building an initial solution using a best insertion algorithm, the heuristic iteratively chooses a removal heuristic $\mathscr{R}$, removes q customers from the routes in the current solution by applying $\mathscr{R}$, and reinserts the previously removed customers in the existing routes. If the new solution is better than the best one found so far, the new solution is accepted as both the new best and the new current solution. On the contrary, if it is not better, the new solution becomes the current solution according to the greedy acceptance concept defined in the work by Schrimpf et al. [208]. We use three removal heuristics:

– random removal: q customers are chosen randomly;
– radial ruin: given a customer c^* , a percentage chosen at random on the total number of customers equal to $\alpha = 0.5$ is removed. The customers are the ones nearest to c^* according to the distance matrix;
– small radial ruin: similar to radial ruin, but with $\alpha = 0.3$.

The removal heuristics are chosen by a roulette wheel algorithm, where the probability of each heuristic is set to 0.2, 0.4, and 0.6, respectively. The insertion heuristic implies a standard regret insertion. In order to increase its portability in cloud-based environments, the algorithm was implemented using Jsprit, a Java based, open source toolkit for solving rich traveling salesman and vehicle routing problems [114].

• Given the solutions and the KPIs, the data aggregation module geo-references the routes using the Google Maps API, attaches their respective KPIs, computes the fleet KPIs, and presents the performances of the traditional and the green subcontractors. Then, in order to obtain more accurate values of the KPIs, each route duration is evaluated using the empirical distribution of the travel times over the day, as presented in the work by Maggioni, Perboli, and Tadei [152].

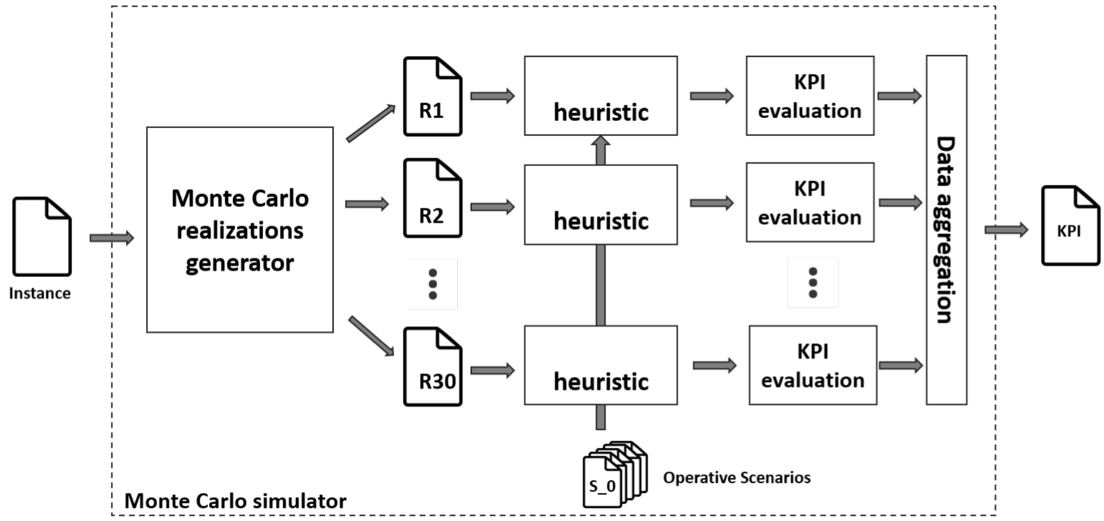

Figure 3.8: Monte Carlo simulator diagram.

3.4.2 Test instances and KPIs

This section briefly describes the test instances used for the numerical experiments. We performed our experiment using data from actual missions observed during the URBeLOG project [240]. More specifically, we consider three typical settings, named I1, I2, and I3, ranging from 1000 to 4000 parcels. The settings were generated from real data gathered during the three weeks at the end of 2014 and the beginning of 2015 in a medium-sized city (e.g., Turin, Italy). For each setting, 30 instances were considered. Each parcel is characterized by a destination point (e.g., latitude and longitude), a weight, a volume, and a time window within the delivery must be made. We also consider that parcels are available at the depot of the (traditional or green) subcontractor at the beginning of the working day. Each instance includes more than 50% "mailer" parcels, distributed mainly in the central area. "Large" parcels comprise, on average, 20% of all parcels, but their destinations are located in semi-central or suburban areas, where the green courier cannot operate. The courier operates from a central depot outside the city for the vehicles, while a secondary depot is located nearby the city center for the cargo bikes. All parcels are considered to be destined for urban areas only. For the sake of simplicity, we suppose there are no availability issues for vehicles and cargo bikes. The TCK are those computed in the Section 3.3.2.

The traditional and green subcontractors are characterized by the classes of parcels they can handle, their average speed in central and semi-central areas, service time, and maximum capacity. The values use in this study are taken from interviews with the CEO and the COO of the international courier company.

- **Classes**. The traditional subcontractor can handle any class of parcels, while the green subcontractor one only handle "mailer" and "small" parcels.

- **Speed**. In the meta-heuristic, the cost function considers travel times. The vans of traditional subcontractors have an average speed of 20 km/h in city center, which is usually affected by traffic congestion, and 35 km/h in a semi-central area. The speed of green subcontractors is 20 km/h, on average, in both areas.

- **Service Time**. The service time is about four minutes when operators handle large deliveries, and three minutes for smaller parcels. On the other hand, green subcontractors can easily stop their bikes (e.g., on the sidewalk), so the average service time is about two minutes.

- **Capacity**. Vans have a maximum capacity of 700 kg. The green subcontractor uses messenger bags, with a capacity of 20 kg, and cargo bikes that have a box that can contain up to 50 kg. When necessary, green subcontractors combine a cargo bike and a messenger bag.

All data come from the URBeLOG project [240].

For each instance, we define five operational scenarios combining the two areas to be served by the green subcontractor and the three classes of parcels that each subcontractor can handle. Note that for the simulation, we defined the "small" parcel class as those parcels with a weight of up to 5 kg. The scenarios are as follows:

- **Scenario S_0**. Only the traditional subcontractor operates in this area.

- **Scenario S_3_C**. The green subcontractor delivers "mailer" parcels (up to 3 kg) in the central area. The traditional subcontractor delivers all remaining parcels.

- **Scenario S_3_S**. The green subcontractor delivers "mailer" parcels (up to 3 kg) in both the central and semi-central areas. The traditional subcontractor delivers all remaining parcels.

- **Scenario S_5_C**. The green subcontractor delivers "mailer" and "small" parcels (up to 5 kg) in the central area. The traditional subcontractor delivers all remaining parcels.

- **Scenario S_5_S**. The green subcontractor delivers "mailer" and "small" parcels (up to 5 kg) in both the central and semi-central area. The traditional subcontractor delivers all remaining parcels.

To evaluate the efficiency of combining traditional and green subcontractors in each scenario, we measure three KPIs:

- **Equivalent vehicle (Veh Eq)**. The number of equivalent vehicles used by the subcontractors. Note that to compare traditional and green subcontractors, we implement a conversion from bikes to vans. The conversion considers a full-time work shift of a traditional subcontractor, which, based on European regulations, is six-and-a-half hours. More specifically, we compute the number of equivalent vehicles as the sum of the working time of each biker, divided by the hours in a work shift of a traditional subcontractor.

- **Number of parcels per hour (nD/h)**. It is common practice to define the efficiency of a courier in terms of the number of parcels per hour. This KPI considers only the speed and the service type of the courier.

- **CO2 savings**. CO2 savings measures the kilograms of CO2 not emitted in the case of green subcontractors and their environment-friendly vehicles.

3.5 Computational results

The simulation highlights how the emergence of green subcontractors changes the dynamics of urban freight distribution systems in the last-mile segment. Figure 3.9 and Figure 3.10 summarize the efficiency of the traditional subcontractor and green subcontractor, respectively. These are measured in terms of equivalent vehicles and number of parcels per hour, when the green subcontractor delivers “mailer” and “small” parcels. Note that KPIs are expressed in percentages with respect to the benchmark scenario S_0. The detailed results obtained from the Monte Carlo simulation are shown in Table 3.3. The values reported in the table are the mean values of the 30 replications. We do not report the detailed measures of the variance or the confidence level, because they are relatively low. In particular, the intervals of the variances of the values of equivalent vehicles and parcels per hour are less than 1%, while for CO2, they are less than 3%. This proves the significance of the discussion in terms of a combination of traditional and green vehicles. With regard to the performance of the traditional subcontractor, the simulation highlights three main results:

- the number of equivalent vehicles is reduced by half;

- there is a loss of efficiency;

- the capacity of vans is saturated.

By outsourcing “mailer” and “small” parcels, the traditional subcontractor manages only large parcels (over 5 kg), which are usually difficult to handle, with a consequent increase in the service time needed to execute the delivery operations. The latter causes a rapid saturation of the vans’ capacity and, thus, a reduction in the number of parcels in a single round and in the duration of each route. Consequently, the traditional subcontractor needs double the number of rounds and loses efficiency, here measured as the number of deliveries per hour. Figure 3.9 shows that the traditional subcontractor loses more than 15% efficiency when “mailer” parcels are delivered by the green subcontractor, and more than 30% when “small” parcels are outsourced as well.

Finally, it is interesting that the choice of the city area where the green subcontractor operates does not affect the KPIs of the traditional subcontractor, owing to the distribution of the parcels. In contrast, Figure 3.10 shows that, for the green subcontractor, the area of service is relevant for its efficiency. In fact, when it manages "mailers" and "small" parcels, extending the service from the central area to the semi-central area decreases the efficiency of the green subcontractor, in terms of the number of deliveries.

However, to maintain an equilibrium condition in the system after the transition to low-emission vehicles, it is necessary to improve quality of service, which, based on the value proposition of the green subcontractor's business model, must at least compensate for the loss of efficiency the traditional subcontractor incurs. In fact, the results of the simulation highlight that when the green subcontractor manages parcels up to 5 kg in size, the benefits are negligible compared with the consequent inefficiency incurred by the traditional operator. However, particularly when the green subcontractor operates in the central and semi-central areas, the benefits in terms of costs savings (operational and environmental) are, on average, 29% and, thus, are lower than the reduction in efficiency of about 34%. This negative variance discourages the traditional courier from outsourcing this segment, while it is more inclined to outsource parcels up to 5 kg in the central area.

Moreover, it is important to extend this analysis to the case in which the fleet of vehicles is owned by the international courier (internal fleet) as opposed to being owned and managed by another firm (external fleet). In the latter case, the green subcontractor incurs costs related to the vehicles, general costs, those related to the structure, and a percentage of its margin. Thus, according to this classification, the above-mentioned values refer to the case of an internal fleet.

In contrast, when the fleet is external, the dynamics change. First, we have to move from a cost per kilometer to a cost per stop, owing to the typical contract scheme. This can be done by considering an average distance between two vehicle stops of about 700 m and a minimum requirement of 80 deliveries per day [240]. Then, the results of the analysis show that a loss of efficiency of 30% for the traditional subcontractor, as illustrated in Figure 3.9, must be overturned by an increase in the performance of the green subcontractor of about 70%, without guaranteeing its desired fee of a 15% margin. This percentage, related to the increase in the performance, translates to 130 deliveries per day, which is difficult to achieve for the green subcontractor. Moreover, for the external fleet, the cost savings connected to parcels between 3 and 5 kg in the semi-central area are, on average, 36%, compared with the loss of efficiency of the 34%. Therefore, the consequences of this inefficiency do not justify outsourcing the deliveries. More specifically, the contractual schemes imply revenue based on the number of deliveries and penalties should a minimum number not be fulfilled. Thus, the loss of efficiency owing to the smaller number of deliveries of the traditional subcontractor, resulting from the outsourcing to the green subcontractor, and the higher distance of the remaining deliveries might have a negative impact on the service quality of the traditional subcontractor, forcing a renegotiation of the agreement conditions. The new contract should consider increasing the number of deliveries required for the green subcontractor in order to balance the loss of efficiency for the traditional subcontractor, without altering the equilibrium state of the service level in the system. Specifically, the green subcontractor should decrease its costs per stop to a value of about 1.90 €/stop and have a critical margin of the 10%, which is nearly identical to the gross contribution margin. Moreover, the outsourcing of all parcels leads to complexity in the management of a high number of agreements with different contractual clauses, based on the class of parcels. This could imply strategic risks, owing to reduced control over the process, entrusting activities that could be strategic levers, and increasing the bargaining power of green subcontractors.

With regard to environmental issues, we compute the CO_2 savings from outsourcing “mailer” and “small” deliveries. Table 3.4 shows the CO_2 savings in each scenario as the difference between the total emissions generated in scenario S_0 and those generated in the other scenarios by traditional vans. Outsourcing both “mailer” and “small” parcels (scenarios S_5_C and S_5_S) to the green subcontractor can lead the highest reduction of emissions, close to 14 tons of CO_2 per year. The area served by the green subcontractor has a strong impact on the number of kilometers traveled and, thus, on emissions. Reducing the need to access the central and semi-central areas, the length of the routes traveled by the traditional subcontractor reduce by about 25%. Consequently, the CO_2 savings are more than 40%.

Thus, it is possible to derive policies that guide the behavior of the various operators and stakeholders in the urban freight transportation system. In particular, the main actions to consider in order to guarantee a balanced mix of traditional and green transportation and, thus, the efficient performance of the system are as follows:

- In the case of an internal fleet (i.e., the fleet is owned by the international courier), the green subcontractor must manage the “mailers” in the central and semi-central areas. In fact, as shown in the analysis described in Section 3.3.1, this is the most profitable segment for this courier, because it permits it to maintain the high quality level imposed by the international courier customers. Moreover, the green subcontractor must manage the small parcels in the center of the city, where traffic conditions and mobility restrictions increase its benefits and reduce the costs for the traditional subcontractor. In contrast, outsourcing the management of deliveries of parcels greater than 5 kg in the rest of the city not only affects the quality level perceived by the final customer, but also decreases the efficiency, reducing the margins for the traditional subcontractor.

- In the case of an external fleet (i.e., the fleet is owned by a series of subcontractors), the green subcontractor must manage the “mailers” in the central and semi-central areas. The outsourcing of parcels between 3 kg and 5 kg requires a change in the contractual scheme, decreasing the margins of the green subcontractor, which must increase its role in the selling of energy and environmental credits. Thus, the results show that the goal required by the green subcontractor in terms of increases in deliveries, and the reduction in the efficiency of the traditional subcontractor means the model is neither feasible nor sustainable. For the traditional subcontractor, a

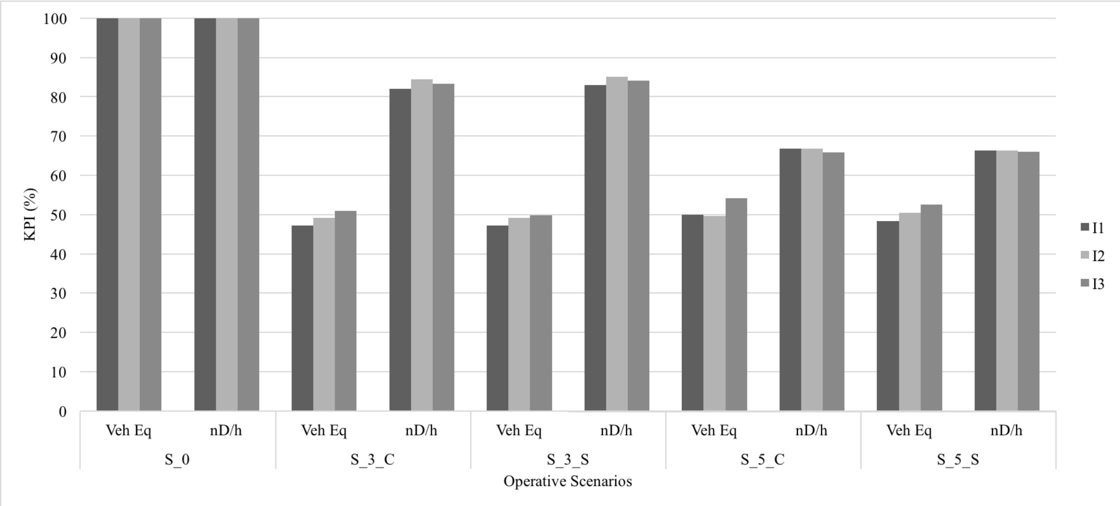

Figure 3.9: Traditional subcontractor efficiency in terms of equivalent vehicles (Veh Eq) and parcels delivered per hour (nD/h).

better solution is to internalize the green fleet, which it will use to manage parcels up to 3 kg in the central area.

- However, the green aspects of the problem are currently important topics. The introduction of business models based on a low environmental impact leads to a reduction in emissions in a medium-sized city, such as Turin, which means efficient management and control of the system are needed. In fact, focusing only on a reduction of emissions could lead to a cannibalization between the two types of business models. As such, the operational processes of the two couriers need to be optimized and monitored.

3.5.1 Sensitivity analysis

The main sources of uncertainty in our study that have been the subject of our assumptions are related to the service times, classes of parcels and travel times. While the service times are monitored by the companies and the travel times depend mainly to the speed of vehicles, heavily affected by traffic and congestion, the composition of the demand is the most relevant parameter whose uncertainty will affect in the near future the congestion and the development of urban areas [108]. Moreover, according to the annual report by Amazon [4], the parcels weighing up to 5 kg represents about 85% of e-commerce parcels in Italy. Thus, we now turn to the sensitivity of the problem, analyzing how the sustainability performance indicators vary when e-commerce conditions change significantly resulting in higher (e-commerce market growth) or lower (e-commerce market downturn) demands of mailers and small parcels. In doing so, we created a second

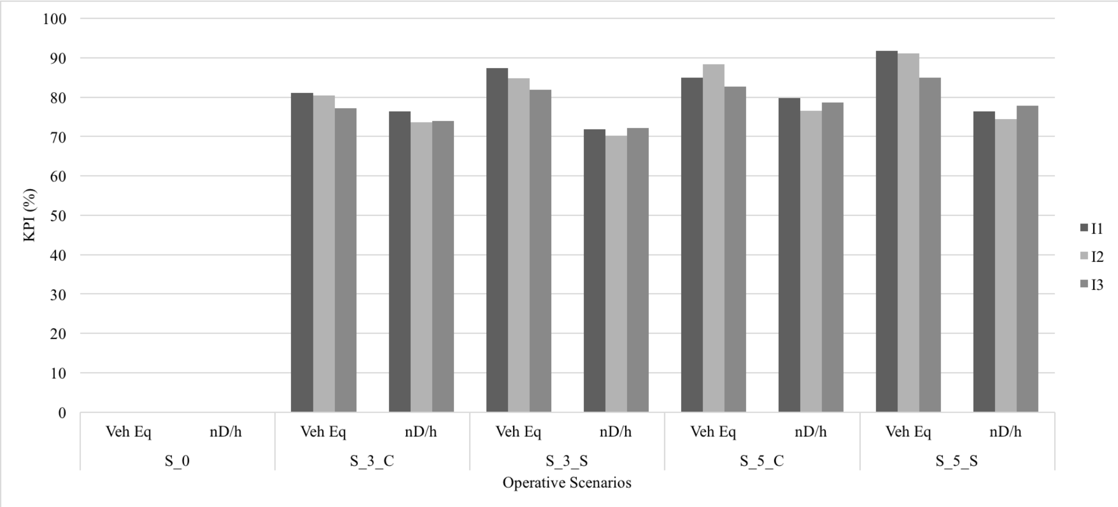

Figure 3.10: Green subcontractor efficiency in terms of equivalent vehicles (Veh Eq) and parcels delivered per hour (nD/h). Notice that S_0 has no value because the green subcontractor is not used in this scenario.

Table 3.3: Results of Monte Carlo simulation. Note that the green subcontractor has no value in S_0 because it is not included in this scenario.

Instances	**nD/h**					**Veh Eq**				
	Traditional subcontractor									
	S_0	S_3_C	S_3_S	S_5_C	S_5_S	S_0	S_3_C	S_3_S	S_5_C	S_5_S
I1	15.65	12.82	12.98	10.44	10.38	7.49	2.16	3.53	2.28	3.62
I2	16.18	13.79	13.77	10.92	10.73	9.89	3.03	4.86	3.07	4.98
I3	15.47	13.29	13.01	10.50	10.21	8.40	2.54	4.18	2.70	4.41
	Green subcontractor									
	S_0	S_3_C	S_3_S	S_5_C	S_5_S	S_0	S_3_C	S_3_S	S_5_C	S_5_S
I1	NA	11.94	11.24	12.47	11.94	NA	3.70	6.55	3.88	6.88
I2	NA	12.03	11.36	12.51	12.06	NA	4.96	8.39	5.45	9.02
I3	NA	11.82	11.16	12.56	12.04	NA	3.85	6.89	4.12	7.14

set of instances with up to 500 customers, varying the composition of the demand in terms of classes of parcels, as follows:

- current situation: 55% of mailers, 25% of small parcels and 20% of large parcels;
- e-commerce market downturn: 50% of mailers, 20% of small parcels and 30% of large parcels;
- e-commerce market growth: 60% of mailers, 30% of small parcels and 10% of large parcels.

Table 3.4: CO2 savings per day with respect to scenario S_0.

Instances	CO2 savings			
	S_3_C	S_3_S	S_5_C	S_5_S
I1	22%	34%	27%	45%
I2	16%	34%	26%	44%
I3	16%	41%	20%	48%

Table 3.5 reports the average results of the sensitivity analysis, assuming that the best policy suggested in the previous section has been designed. In particular, we show the changes in the solutions with respect to the cost of the vehicle used (Column 3), CO2 savings (Column 4) and nD/h (Column 5). Notice that the CO2 savings are not reported in the scenario S_0, which refers to the adoption of vans only.

We observe that the e-commerce market downturn, and the relative reduction of the number of parcels up to 5 kg, take benefit in terms of reduction of vehicle costs. On the contrary, nD/h are more sensitive to this market condition. Indeed, the downturn increases the number of parcels with more than 5 kg and penalizes the number of deliveries, causing a decrease of the operative efficiency of the traditional courier (-22% and -23%, in the scenario without and with green subcontractors, respectively).

The e-commerce market growth increases the number of vehicles needed to cope with the higher flows of mailers and small parcels, with a consequent increase in the operative cost (25% in S_0), while the effect of this condition in the vehicles cost is limited in the scenarios in which the cargo bikes are adopted (12%). Despite the nD/h increase, the results confirm the outcomes above, highlighting that in the scenarios with the subcontracting to green operators, the traditional subcontractor incurs in a potential deterioration of its operative performance. The increasing number of mailers and small parcels typical of e-commerce growth allows obtaining the highest CO2 savings (28%), due to the possibility to outsource these classes of parcels to the green subcontractor. On the contrary, in case of a market downturn, the higher number of large parcels may cause the saturation of vehicles and the increase of traveled distances, penalizing the environmental sustainability (3% of CO2 savings compared to 28%), as discussed in the computational results.

Based on our analysis and simulation results, the outsourcing of deliveries to green subcontractors could result in benefits in terms of CO2 emissions and on the quality level required by time-sensitive services, owing to the reduction of delivery times.

However, the switch to vehicles with a low environmental impact could cause a loss of efficiency for traditional subcontractors. For this reason, to maintain an equilibrium in the system, it is important that this inefficiency is contained and balanced by an increase in service quality when using green vehicles, without compromising the profitability already undermined by the dynamics in the CEP industry. This requires two measures of action. First, redefining contractual schemes between traditional and green subcontractors or

Scenario	**Market condition**	**VehEq costs [€]**	**CO2 savings [kg]**	**nD/h [n.]**
S_0	Downturn (-15%)	- 18%		-22%
S_3,5_C,S	Downturn (-15%)	- 21%	3%	-23%
	μ	998,55	-1.16	0.99
	σ^2	535041.03	333.29	0.014
S_0	Growth (+15%)	25%		20%
S_3,5_C,S	Growth (+15%)	12%	28%	14%
	μ	-1197.93	-55.56	-0.81
	σ^2	1620417.72	278.45	0.39

Table 3.5: Sensitivity analysis.

integrating the green fleet into the international Courier company. Second, a continuous process of optimizing activities by implementing a DSS is needed to assess in advance the consequences of mixed fleet policies and to achieve reasonable levels of efficiency.

In this direction, Chapter 4 extends this study analyzing the integration of vans, cargo bikes and self-service pick-up and delivery points named lockers, by introducing a new simulation-optimization framework that generalizes many types of routing problems encountered in urban areas, for building instances and assessing operational settings in realistic urban scenarios.

Chapter 4

A simulation-optimization framework for intermodal last-mile delivery

This chapter introduces a simulation–optimization framework for building instances and assessing operational setting. This framework, originally applied in the work by Perboli et al. [192], is used to evaluate the integration of traditional transportation modes and new intermodal delivery options (e.g., lockers) to cope with ever-increasing volumes of freight generated by e-commerce. In particular, it extends the study presented in the previous Chapter 3, discussing the integration of different transportation modes and delivery options, i.e., vans, cargo bikes, and lockers. This simulation-optimization framework arises from the awareness emerged in Chapter 3 about the need of DSSs for a continuous process of optimization to achieve reasonable levels of efficiency in urban freight transportation. According to the multi-disciplinary approach presented in this thesis, the simulation-optimization framework generalizes to many types of routing problems encountered in urban areas and allows to describe and combine requirements coming from various stakeholders, mixing data and information gathered from different sources (e.g., behavioral and socio-economic data, city network). Moreover, this DSS generates new instance sets which are realistic (i.e, they include all the characteristics of the original datasets) making the results and validation of models directly comparable with real or realistic settings. Thus, it mitigates the issues of current solutions based on artificial data, concerning their limited exploratory capacity and thus, the technology transfer to the CEP industry.

The framework has the innovative feature of describing an (urban) operational context by combining different sources of data, which to our vision are needed to contextualize the problem and to validate different scenarios or policies in the urban context.

To illustrate the usefulness of that framework, we apply it to address the dynamic and stochastic VRP with time windows (DS-VRPTWs) problem under the context of the online urban freight distribution in the city of Turin (Italy). We analyze how the solution quality in realistic urban scenarios is sensible to various stakeholder parameters such as customers' geographical distribution, the available types of vehicles and their limitations and the use of lockers for delivering part of the demand.

Our experimental plan leads to a broad variety of realistic benchmarks, each of these being specialized in a particular operational context in the online urban collection of parcels. This portfolio of benchmarks is made available to the community under a simple common format, to reuse them in different case studies.

This chapter is organized as follows. Section 4.1 review the literature for vehicle routing case studies and applications in realistic urban areas. In Section 4.2, we describe the simulation-optimization framework proposed to analyze realistic urban freight distribution problems. Section 4.3 shows how the framework can be exploited to realize a concrete case study in a realistic urban context.

4.1 Literature review

The research community has been recently devoting significant efforts to propose efficient and innovative approaches to address many types of urban freight distribution problems. However, a standard framework for simulating and studying the impact of optimization in City Logistics is currently missing, limiting the possibility to validate in real settings the technology transfer to industry. In particular, as highlighted by Kim et al. [132] there is an obvious lack of available realistic benchmark dataset for the city VRP. Indeed, while different contributions on VRPs in urban areas are present in the literature, real-world based applications represent a small portion of it. For this reason, we focus our review on realistic VRP related case studies one can find in the literature up to these days, identifying the scope of the city VRP applications already addressed by the scientific community, and the benchmarks that are still currently available in that field. This review is initially based on the excellent work by Kim et al. [132], which we restrain in order to focus on real case studies, in particular, those for which the benchmarks are still available. Vigo [244] considers a real-world problem of distributing pharmaceutical products in downtown Bologna (Italy), modeled as an asymmetric Capacitated Vehicle Routing Problem (CVRP). The test instances, involving up to 70 customers, are still available on the author's web page. Variability in vehicle travel times has been studied from several aspects. In particular, in [134] the authors worked on shortest paths under dynamic travel times in a downtown area in Shanghai. The raw data based on 1 month of taxi Global Positioning System (GPS) data and 3 months of bus GPS data in Shanghai during the year 2007 are still currently available on demand to the authors.

Multi-level vehicle routing problems, such as the Two-Echelon VRP (2E-VRP) introduced by Perboli, Tadei, and Vigo [188], have also received recent interest in urban context. In [85], the authors present a real-world case study involving a time-dependent VRPTW in Zaragoza (Spain), in which customers can be either directly delivered from the classical depot or by mean of green vehicles by using intermediate urban depots.

Environmental-friendly decision systems in the context of (City) VRPs are increasingly studied nowadays under various names: Green Vehicle Routing Problem

(GVRP), Pollution-Routing Problem (PRP), Emissions Vehicle Routing Problem (EVRP), etc. Alternative fuel vehicles are considered in [84] by means of the GVRP. The objective is to minimize the total routing cost given limited refueling stations. Numerical experiments are conducted based on data from a medical textile supply company in Virginia. These data are still available under demand.

In [19], a realistically generated benchmark is used in order to illustrate the PRP over a set of cities in United Kingdoms. The benchmark is still available.

A number of similar studies have been conducted on artificially generated benchmarks, many of them based on Solomon's instances. More recently, Maggioni, Perboli, and Tadei [152] provided a realistic benchmark for the Multi-path travelling salesman problem (TSP) with stochastic travel costs [219] applied to electric and hybrid vehicles in freight distribution. In particular, Maggioni, Perboli, and Tadei [152] propose a first example of instance generator. However, it was in a prototype form and strictly dependent on the application, lacking a global vision.

Our literature review highlights that the City VRP contributions contain very few real-world based applications and the results are normally based on academic (and unrealistic) datasets. The instances in the literature are based on the generalization of classical instances, often not created for urban applications, or on artificial data, i.e., data not coming from any historical or empirical datasets. The validation of models and methods becomes more difficult, being the results not directly compared with real or realistic settings. Up to our knowledge, among those studies that are based on realistic data, the corresponding benchmarks are still currently available for only 6 papers [19, 84, 134, 152, 163, 244]. Even when real data become available as in these application, some other issues come from the lack of a global vision, the availability of a finite dataset, the necessity to anonymize them or to mix real data with empirical distributions. Furthermore, the different categories of stakeholders playing an important role in urban applications are rarely considered all together, leading the search to some local optimum [132].

These issues are linked to the following current limitations that make the solutions generated by the applications, scarcely repeatable in a different context:

1. unavailability of full data: given an urban area, gathering the real data associated with all four stakeholders usually requires to much time and/or expertise to be actually implemented;

2. difficulty of combining/reusing existing data: whereas existing studies may provide realistic data involving one or more stakeholders, there is still no trivial way to combine such data from different sources.

Thus, in the next section, we introduce the simulation-optimization framework, proposed to overcome these issues. Recently, the DATA2MOVE initiative started to collect data from different sources for Logistics and Supply Chain applications, but the project is still at an early stage [241]. A lack emerging from the literature is the identification of the main source types, how to mix and how to interface them with one or more simulation and optimization module in order to give flexible solutions to the stakeholders and the users.

4.2 Simulation-optimization framework

The simulation-optimization framework is depicted in Figure 4.1. According to Crainic, Perboli, and Rosano [46], this framework applies a sequential simulation-optimization, where the simulations are numerical and based on the Monte Carlo method. The simulation is implemented in Python, while the optimization modules can be defined directly in Python by the Pyomo modelling tool, including the PySP library for Stochastic Programming problems [118, 250] or can be integrated as external modules. Thus, the framework is composed of the following modules:

1. **Data fusion and operational context description**. The first phase of the framework consists in describing both the problem studied and the operational context, which may consider different types of data sources. We define the operational context using the following five sources of information: city network graph, vehicles and travel times, behavioural data (e.g., users choice preferences), socio-demographical data and city constraints (e.g., limited traffic zones, specific restrictions for certain vehicles, etc.) and problem objectives and constraints. Some data may be stochastic, i.e., they can be described by random variables, whenever some component of the operational context is uncertain (e.g., service or travel times, customer demand or presence, etc.). The problem is then fully defined by the problem objectives and constraints data type.

   The framework requires as input a problem (or operational context) description consisting of five types of data:

   - *City network graph and maps*. They are represented by complete directed graphs over a set of depots and customers. Ideally, vertices should be associated geographical coordinates so that to be visualized on real maps. The city network graph is usually obtained using raw data from cartography and the companies, including maps and empirical distributions of customers and depots. Amongst the four main stakeholders identified by Kim et al. [132] (residents, carriers, shippers and local administrators), the city network graph explains the baseline geographical attributes and means of the residents (customer locations), the shippers (the location of the depots) and the carriers (the available road network).
   - *Vehicle fleet and travel times*. They include the specificities of the vehicle types, as capacity, speed, fuel consumption, etc., as well as their respective travel times and costs matrices. Vehicle fleet and travel times capture the means supplied by the shippers. In practice, these are provided by the company and

possibly combined with data from external sources (such as sensors spread over the city network). Time dependence and/or uncertainty in the travel times/costs, if any, may also be described here together with other uncertainties (e.g., vehicle breakdown probability distributions).

- *Behavioural and socio-demographic data*. They include information concerning the density and the purchasing behaviours of final customers for a specific market. Thus, they clearly describe the residents stakeholders in all of their possible attributes. In a static context, these capture the customers' constraints (e.g., time windows, demands, origin-destination matrices, etc.). In dynamic applications, any stochastic knowledge about the customer habits can be described here (e.g., demand or service time probability distributions, etc.).
- *City constraints*. Regulations imposed by the local administrators, such as access time windows (e.g., forbidding trucks during rush hours), vehicle weight restrictions (e.g., no heavy truck in the city centre). City constraints clearly represent the administrators in all the regulations that could be imposed on the other stakeholders (e.g., the carriers).
- *Problem objectives and constraints*. Describe the problem itself in terms of constraints, preferences, as well as the objective function to be optimized. They can be defined by declaring the specific optimization module including its interface with the scenarios or using a MIP solver by the Pyomo modelling tool.

This partitioning of the data into five distinct types allows to easily study the impact of modifying a specific aspect of the operational context. Furthermore, it provides the possibility of combining/reusing data from existing case studies, hence alleviating the above mentioned issue. For instance, provided a real-world case study on a classical CVRP, modifying only the last two components (i.e., *City constraints* and *Problem objectives and constraints*) of the problem allows to study the impact on the total carbon emissions of restricting the access of the city centre to green vehicles. Furthermore, filling component *Behavioural and socio-demographic data* with customer demand probability distributions permits to study Stochastic VRPs, whereas updating component *Vehicle fleet and travel times* could allow studying the impact of taking travel time variability into account, as well as to use empirical distributions coming from other studies, letting to anonymize industrial data.

2. **Scenario generation and simulation**. Once both the problem and the operational context are well defined, a broad set of scenarios is generated by using a high-level scenario generator, which allows the researchers to develop specific scenarios for different frameworks. Each scenario represents a particular realization of all the random variables involved in the problem data. In other words, each scenario

is the description of a particular operational day. If the problem and operational day description contain no uncertain data, the scenario becomes the description itself. Otherwise, a set of instances are generated using Monte Carlo sampling. The framework let the user define deterministic operational scenarios or stochastic ones with associated a scenario tree to each simulation scenario.

The present version of the simulator implements a Monte Carlo method, a module for georeferencing the data and a post-optimization software. In more detail, the method works as follows:

- The Monte Carlo simulation module repeats the following process for a given number $|I|$ of iterations.
  - Given the different data of the operational context as well as eventual distributions of the data themselves, the simulator generates a series of city scenarios.
  - The chosen optimization module is executed in each scenario.
  - A first statistical analysis on the aggregate results of the scenario-based optimization of a single iteration of the Monte Carlo simulation is performed. These data are used in order to check if one or more unrealistic or extreme situations have been introduced in the simulation itself.
  - In order to make a more accurate definition of travel times and cost matrices, the georeference module is used. The georeference feature is implemented by means of Google Earth APIs and it is also used to graphically represent the results of the simulation itself.
- The distribution of the simulation-based optimization solutions is computed and a series of statistical data are collected.
- A post-optimization software module is devoted to computing additional KPIs (e.g., CO2 and NOx emissions, stop per working hour, service and travel times).

3. **Optimization**. During this phase, each scenario is solved using a dedicated optimization algorithm that we consider here as a black box. Provided that the solver outputs the KPIs required by the case study into consideration, the post-optimization analysis is conducted. In order to cope with different contexts in urban areas, this simulation-optimization framework is composed of different building elements addressing the following problems:

   - Mathematical model generated by the Pyomo modeling tool;
   - VRPTW combined with the load balancing;
   - Stochastic TSP;

- Dynamic Stochastic VRPTW (DS-VRPTW) solved by the optimization algorithm proposed by Saint-Guillain, Deville, and Solnon [206].

4. **Context modification**. During this phase, some properties of the description are modified, leading to a new operational context to be analyzed by reiterating through phases 2 to 4.

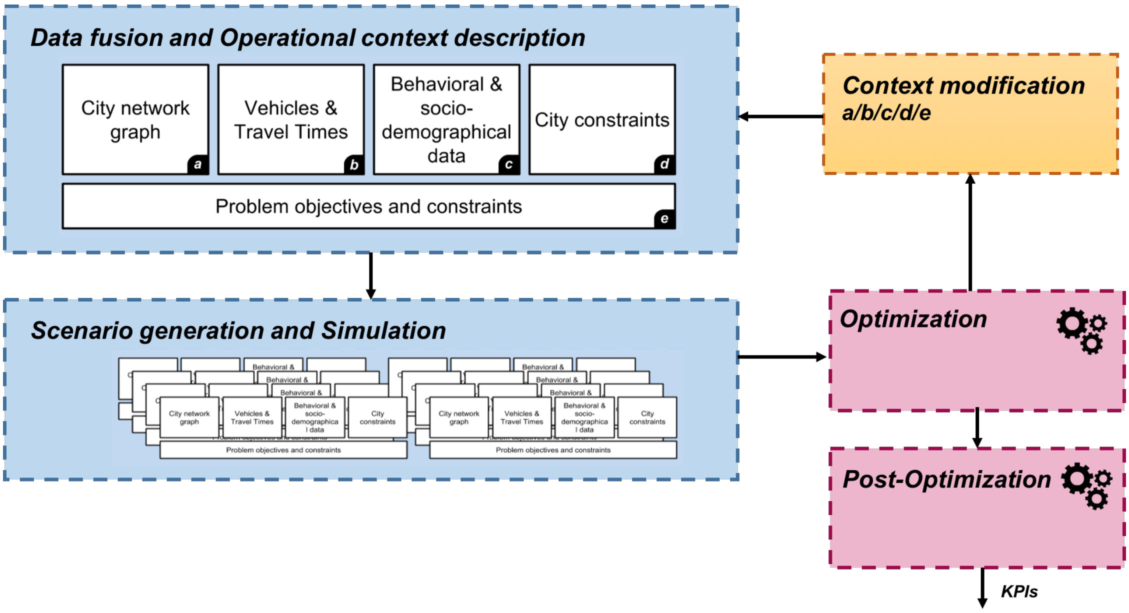

Figure 4.1: The simulation-optimization framework.

4.3 Case study: last-mile delivery in Turin (Italy)

In order to demonstrate the potentialities of the proposed simulation-optimization framework, we adopt it in the case study of the city of Turin (Italy). Our aim is twofold:

- analyze the impact of multimodal delivery options to face the demand generated by the e-commerce, extending the study presented in the previous chapter.
- highlight the importance of considering real benchmark data set for DS-VRPTW coming from different sources and stakeholders.

4.3.1 Operational contexts and benchmark generation

Online shopping is rapidly increasing the freight flows which transit into the urban areas. According to Cardenas et al. [32], Copenhagen Economics [43], and FTI Consulting

[99], while the B2C segment of e-commerce represents around 30% of the e-commerce turnover, they generate 56% of all e-commerce shipments. Moreover, e-commerce involves individually fragmented and time-sensitive orders of generally small-sized items, leading to more traffic in urban areas and negative externalities on the environment [226]. These are challenging factors for urban freight transportation and City Logistics applications, which are more and more focused on the integration of different delivery options (e.g., cargo bikes, drones, lockers, etc.). In this direction, the study extends the previous study in Chapter 3, considering the following four benchmarks:

- **Benchmark 1 (B1)**. Only traditional vehicles (i.e., fossil-fueled vans) are used to manage the parcel delivery in urban areas.
- **Benchmark 2 (B2)**. We consider that a green subcontractor delivers the parcels up to 6 kg in the central and semi-central areas of Turin. On the contrary, the traditional carrier manages all remaining parcels.
- **Benchmark 3 (B3)**. We consider the adoption of delivery lockers. They represent self-service delivery location, in which the customer can pick up or return its parcel, according to the best and convenient time for him. In practice, these can be seen as special “super-customers” that aggregate the daily demands of a subsets of the actual customers.
- **Benchmark 4 (B4)**. In this benchmark, we consider the integration of the vans with both cargo bikes and lockers.

These specific benchmarks derive from the combination of three parameters defined *a priori*: the size of the traditional vehicles’ fleet, the size of the green vehicles’ fleet and the number of lockers. These data are provided by an international parcel delivery companies and an international e-commerce operator, which acting in Turin. Other input data considered in the DS-VRPTW are:

- City network graph and maps. We consider a 2.805 x 2.447 km area in Turin, which includes the center of the city and a semi-central area as in Section 3.3.1 (see Figure 4.2). Moreover, the list of the depots, the locations of lockers and of the potential customers inside the selected area are considered. Concerning the depots, we contemplate a distribution center located on the outskirts of the urban zone and a mobile depot in the city center. The former supplies the traditional carrier, while the second represents a satellite facility for the green carrier. In addition, the list of all the roads inside the city area is also required. Such list is arranged as a network of road-segments, each road-segment is defined as a sequence of two connected points, i.e., the crossroads. The information concerning the roads was extracted from the shape-files made available by the local public authority in Turin. For each road-segment, the average daily speed is measured by speed-sensors. Each element of the mentioned lists is defined with a unique identification number and its real GPS coordinates.

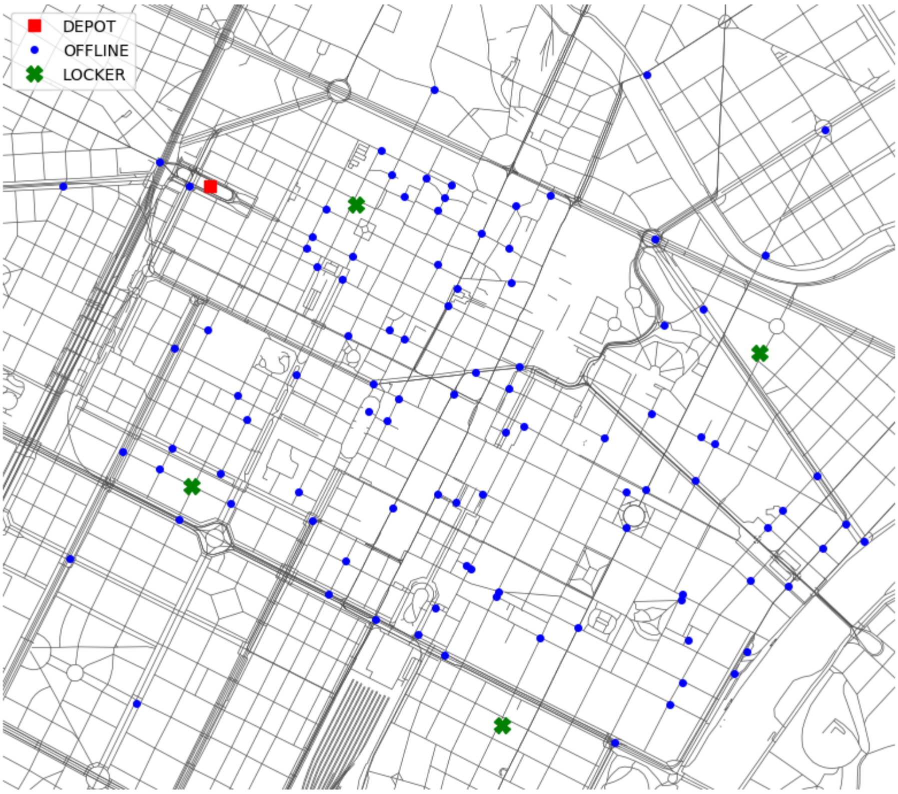

Figure 4.2: Area considered in the case study. Note that in the figure the mobile depot (square) and a set of offline customers (circles) and lockers (crosses) are represented.

- Vehicle fleet and travel times. As mentioned above, we consider two type of vehicle fleets: vans and cargo bikes. The parcel delivery company interviewed provides the characteristics of vehicle fleets (e.g., capacity, service time, speed). The service-time is a vector containing the information for each type of parcel handled, for the upload from the depot and for the unload into the locker. We consider the same three classes of parcels and the expected number of parcels for each class (expressed as a percentage of the total number of parcels delivered) of the above: mailers (i.e., parcel with a weight up to 3 kg) small parcels (i.e., parcel with a weight between 3 and 6 kg) and large deliveries (i.e., parcel with weight over 6 kg).

- Behavioural and socio-demographic data. The horizon size is given here. We consider an 8-hours working day, from 9:00 to 17:00. The time-unit considered is 1 minute and the time-horizon is split into four time-buckets with the same length. For each potential customer, the demand expressed as parcel's volume is provided, together with the time-window for the service. The time-windows are assigned considering the percentage of prime members (i.e., those whose requests are prioritized restricting the time-window to the first two time-buckets). Then, the expected behaviour of each potential customer of the DS-VRPTW is described.

It gives the probability that, for each customer location i and each time-unit t of the time-horizon, an online request (i.e., picking up a parcel) appears at time t for location i.

- City constraints. We do not consider any specific city constraint.
- Problem objectives and constraints. The objective is first to maximize the (expected) number of online requests satisfied by the end of the horizon, and second minimize the total distance traveled by the vehicles.

The operational context defines the number of potential customers in the city map, the number of offline customers selected among the potential ones and the percentage of prime members. In this simulation, we generate three different-sized operational contexts with respectively 500, 250 and 100 potential customers. Each context contains 70% of offline customers and 25% of prime members. These potential customers are randomly picked from the pool of potential customers listed in the input data and then anonymized for confidentiality matters, by offsetting the Cartesian coordinate system. Once the potential customers are defined, it is possible to compute the matrix of the mutual distances among the customers and the depots on the map. Such distances are computed applying the Dijkstra's shortest path to the network of road-segments specified in the input data. The high level of detail in the network, coupled with the haversine formula used to estimate the distance between each pair of points that compose a road-segment, provide us an outcome, which is much more accurate than a simple application of the Manhattan distance.

The obtained results are in line with the once provided by the most common web-mapping service Google Maps. From the distance matrix is then possible to compute the travel-times between pairs of locations, by using the measured road-segments' speeds available in the input data. The set of online requests appearing during the daily time-horizon is defined by considering three different degrees of dynamism: 15%, 30% and 45%. Three sub-contexts are thus defined for each operational context, according to the degree of dynamism assignation. For each sub-context, a set of n instances is sampled by generating n Poisson Random Variates (PRVs) with parameter λ dependent on the degree of dynamism considered. Each PRV i represents the effective number of online requests that appear in the Instance i. The accorded set of online customers is finally randomly selected from the list of potential ones, allowing multiple requests for the same customers, but provided that they appear at different moments (i.e., time units). Each scenario, which in the case of DS-VRPTW corresponds to a sequence of revealed online requests along the day together with their specific reveal times and locations, is then independently solved by the optimizer.

All the instances are generated and classified in classes (i.e., the benchmarks presented above), depending on the operational context, as described in Section 4.2.

The benchmarks are available on the git repository available at the address `https://bitbucket.org/orogroup/city-logistics.git`.

Table 4.1: Input data.

Classes of parcel			
Class	*Weight range*	*% on total parcels*	
Mailer	0-3 kg	57%	
Small delivery	3-6 kg	13%	
Large delivery	> 6 kg	30%	
Capacity			
Vehicle	*Parcel size max*	*Capacity*	*Coverage*
Locker	6 kg	$20^{*}parcels$	1 km
Van	70 kg	700 kg	NA
Cargo bike	6 kg	70 kg	NA
Speed in urban area		**Setup time**	
Vehicle	*Speed*	Load locker	15 min
Van	40 km/h	Load bikes at mobile depot	15 min
Cargo bike	20 km/h		
Service time to deliver each class of parcels			
Vehicle	*Mailer*	*Small delivery*	*Large delivery*
Van	4 min	4 min	5 min
Cargo bike	2 min	2 min	NA

* max number of parcel per day. Note that part of the locker is actually filled with the parcels of the previous three days

Table 4.1 resumes the values of the input data considered in our analysis. This information derive from interviews with CEO, COO and logistic director of an international parcel delivery company and of an e-commerce company operating in Turin. For further information about these data, the interested reader could refer to the Chapter 3. Moreover, the tests are conducted using real data concerning the customer distribution and daily volumes of deliveries in Turin between 2014 and 2015, provided by the international parcel delivery company that operates in Italy and is involved in the URBeLOG project [240].

4.3.2 Specific optimization problem definition

In this section, we define the DS-VRPTW problem that we address using the proposed simulation-optimization framework. Given a discrete horizon of length h, a depot location and a set of n customer locations, we define the set $R = \{1, \dots, n\} \times \{1, \dots, h\}$ of potential requests, that is, one potential request at each time unit for each customer location. We assume the probability of each potential request to appear to be known, together with its own demand, service time and time window in case it actually appears. Whenever it happens and by the end of the current time unit, the request must be either *accepted* or *rejected*. In case it is accepted, the request must be guaranteed to be satisfied according to its time window and the vehicles capacity constraints. A function $c : R \to \mathbb{R}_+$ defines the penalty cost inquired whenever a request $r \in R$ is rejected. Provided a finite set of capacitated vehicles, the asymmetric travel times matrix between all pairs of locations and the set of potential requests, the goal (at each time unit) is to operate the fleet of vehicles such that the expected total penalty cost is minimized by the end of the horizon.

Generally speaking, VRPs aims at modelling and solving a real-life common operational problem, in which a known set of geographically distributed customer (pickup) demands must be satisfied using a fleet of capacitated vehicles. The VRPTW introduces a time dimension by restricting each customer visit in a predefined interval. The objective is to find an optimal feasible solution, where optimality is classically defined in terms of travel costs. In urban applications, some additional characteristics must be taken into account: the *dynamic of the customers*, i.e., the customer requests are not known in advance, but are instead revealed as the operations go, and the *stochastic nature of some parameters*, i.e., some attributes are random variables. For the aforementioned reasons, we incorporate as optimization model the Dynamic Stochastic VRP with Time windows (DS-VRPTW) solved by the algorithm described in the work by Saint-Guillain, Deville, and Solnon [206]. Based on Monte Carlo sampling, the main idea of the Global Stochastic Assessment (GSA) algorithm aims at maintaining a unique feasible current solution being continuously optimized with respect to a restricted pool of sampled scenarios, while preserving nonanticipativity constraints in the evaluation function. A classical local search approach is used, exploiting well-known VRP neighbourhood operators such as relocate, swap, inverted 2-opt and cross-exchange to construct neighbouring solutions. A diversification mechanism is provided by regularly renewing the scenario pool, hence modifying the shape of the evaluation function, making needless the use of any other meta-heuristic. Note that the algorithm implements a relocation strategy, allowing the vehicles to anticipatively travel and possibly wait at promising strategical (customer) locations, even when these do not require a service (yet, if any).

4.3.3 Numerical analysis

In this section, we discuss the computational tests of the simulation-optimization framework on the DS-VRPTW. The experimental plan is composed of a set of randomly generated test problems. For each benchmark and each operational context, we perform 10 independent runs, obtaining totally 360 instances, which are independently solved by the optimizer.

To evaluate the results we measured the KPIs defined in Chapter 3 that reflect the sustainability according to the following standpoints:

- Economic Sustainability. As mentioned above, the carrier incurs in operating costs related to fleet management and maintenance, and personnel costs. These costs are increased by a margin equal to 15% when the fleet is managed by an external firm subcontractor [185]. Moreover, typical contract scheme in the parcel delivery industry imposes the conversion from a cost per kilometre to a cost per stops. Thus, the KPIs measured are:
  - Cost per stop (internal fleet), in the case in which the fleet of vehicles is owned by the carrier (CpsI).
  - Cost per stop (external fleet) in the case in which the fleet of vehicles is owned by the subcontractor (CpsE).
- Environmental Sustainability. In order to evaluate the impact of the adoption of green delivery means on the environment, we computed the CO2 savings (CO2EMsav) as the kilograms of CO2 not emitted in the B2, B3, and B4. Moreover, as the externalities have a social cost that impacts on the economic efficiency of the logistics operator, we express the emissions saved (compared with the B1) in monetary terms by applying the carbon tax, based on the average price paid for CO2 emissions [185]. This KPI is the environmental costs saving (CO2CSsav). Note that according to the regulation ISO/TS 14067:2013 we consider the total amount and costs of GHG emitted directly or indirectly by the overall parcel delivery chain, as in the Chapter 3.
- Operational Sustainability. It is referred to the operational performance and efficiency of each operator involved in the urban parcel distribution. Generally, it is expressed in terms of number of parcels delivered per hour (nD/h)
- Social Sustainability. It is strictly related to the operational sustainability, as the fulfillment of the increasing demand of time-sensitive and online deliveries and the high service quality required by the final customers affect the working conditions of the drivers.

To provide the reader an easier understanding of the results, we computed the percentage of each KPI compared with the reference benchmark B1, as shown in Figure 4.3. Thus, Figure 4.3 depicts the performance of the traditional courier in the B2, B3, and B4. The values are computed as percentage variation of each KPI with respect to the value of the same KPI in the Benchmark $B1$. In particular, the ΔOperating costs and ΔEnvironmental costs show the percentages of costs savings, both operating and environmental, that the traditional carrier obtains when the parcels up to 6 kg are outsourced to the green carrier or delivered by means of the lockers. While, the item ΔEfficiency represents the loss of efficiency that affects the traditional carrier due to the reduced number of deliveries and the high saturation of vans, particularly in B2.

Figure 4.3 highlights improvement of both economic and environmental sustainability when green delivery options (cargo bikes and lockers) are introduced. In particular, in

B2 the adoption of cargo bikes and the optimization of routes lead to a reduction of the vans used of about 32% and of the kilometers traveled, with consequent benefits in terms of reduction of operating costs (-37%). At the same time a reduction of the CO2 emission on average of 303 kg, is registered, which correspond to a decrease of 40% in the environmental costs.

Figure 4.4 reports the number of deliveries per hour of traditional vans and green vehicles in the different operational contexts, segmenting the results according to the number of customers in the scenarios and the degree of dynamism. For the operational context $B1$ the green carrier has no bar because it is not present in it. Thus, the number of deliveries per hour (nD/h) are given for the traditional vans only. They are reported in order to provide a reference value while comparing the results in the operational contexts $B2$ and $B4$. The values of $B3$ are not given because no green vehicle is usable in this operation context. As figured out in Chapter 3, the outsourcing of the small parcels (mailers and small deliveries) to the green carrier, the traditional one incurs in a reduction of efficiency of 80% at maximum. This means, for example, a reduction of the number of deliveries per hour from 126 to 25 in 10 working days when there are 100 customers locations and 30% of dynamism. Figure 4.4 shows how the green carrier reaches the highest number of parcels delivered when the degree of dynamism is equal to 45%. Similarly, when the deliveries are managed by means of lockers, there is an improvement of the economic and environmental sustainability. However, here the reduction of the costs, both operative (-25%) and environmental (-21%), is lower than B2. The reason is that, although there is a reduction in the kilometers traveled by the vans to serve the home deliveries directly to the customers, these vehicles are still adopted to reach and supply the lockers. When the number of customers to serve and the degree of dynamism are both to a low level, the adoption of lockers leads the highest decrease of the number of deliveries managed by the traditional carrier (-38%). This impact on the efficiency corresponds to costs savings of the same order. On the contrary, although the presence of the lockers, when the degree of dynamism is high and, i.e., the online requests increase, they are served by the traditional carrier. In fact, when the class of customers locations and the degree of dynamism are of respectively 500 and 45%, the loss of efficiency for the traditional carrier reaches the minimum value (-12%). A significant finding is that, combining all the delivery options (B4), the highest reduction of emissions and operating costs is reached. In particular, this reduction becomes more evident when there is a low number of customers. Thus, they are served by environmental-friendly delivery modes, while a very few number of parcels is delivered by the traditional carrier. On the contrary, when we consider 500 customers, the performance of the traditional and the green carriers in terms of efficiency are similar to those achieved in the B2. This means that in case of high demand the lockers saturate quickly. Thus, bikes and vans (particularly) are used to cope the most considerable part of the deliveries, as more flexible.

The results obtained figured out that we can minimize the number of rejected requests by adopting the optimization solver. In fact, only 1, 2 and 9 requests are rejected respectively in B2, B3, and B4. This rejection happens when the classes of customer locations and/or the degree of dynamism are medium-high. On the contrary, in the other instances all the online requests are fulfilled.

As mentioned above, the operational sustainability is strictly related to the social sustainability. The integration of traditional delivery mode with the two new options (i.e., bikes and lockers) could have a positive impact on the social sustainability. In fact, at present, the drivers are hard-pressed to face the high demand of home-deliveries, respecting the time windows. Moreover, their working conditions are affected by a broad range of issues, as traffic and congestion, unavailability of loading/unloading zone, as well as second-time deliveries because the customer is not at home. All these problems make difficult in a regular working shift the achievement of the 80 deliveries per day imposed by the common practice in the industry [185]. Thus, considering the revenues based on the number of deliveries and the penalties in case of not fulfillment, these problems impose pressure on the drivers of the traditional carrier company. On the contrary, the reduction of the number of parcels that the traditional carrier have to deliver, combined with the optimization of the routes and the reduction of vehicles on road, lead to a less and more balanced workload and the improvement of the working conditions. However, a necessary fundamental condition is that this integration must be made in a reasonable manner. In fact, as stated above, the loss of efficiency for the traditional carrier must be contained and balanced by an increase in service quality led by the bikes and lockers and by a continuous process of optimization and monitoring of the activities in the overall last-mile chain [185].

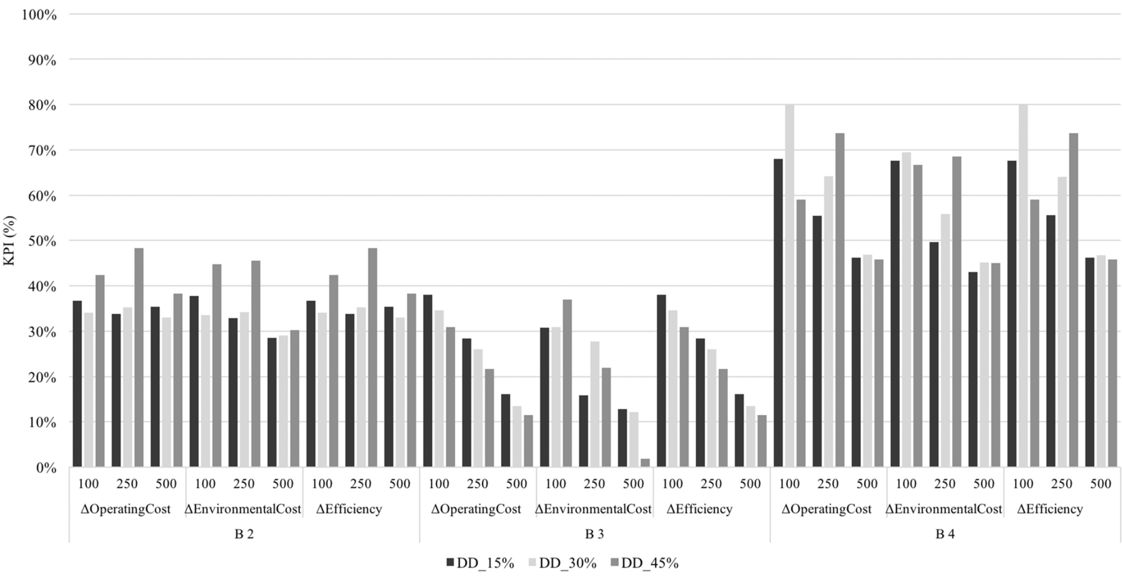

Figure 4.3: Performance of the traditional carrier, when cargo bikes and lockers are adopted.

The integration of different transportation modes and new delivery options, the outsourcing between shippers and carriers, combined with issues of the urban freight

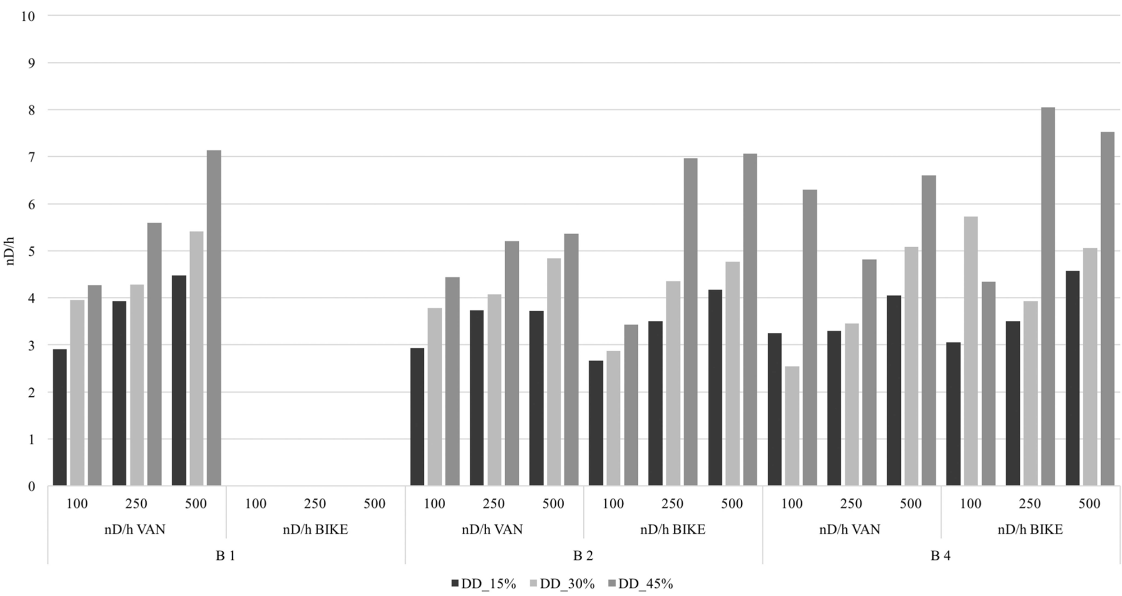

Figure 4.4: Performance of the green carrier. $B3$ is not reported, not involving any green vehicle for the delivery.

transportation, bring to a multi-disciplinary challenge in modeling, optimizing and monitoring the overall system. Thus, new complex and effective planning models and methods become essential to deal with the different decisional levels along different axes: time horizon of the decisions (i.e., strategic, real tactical and short-term tactical, operational), data flows, size of the area under study, and governance [189].

In particular, in Chapter 5, we present one of the most critical decisions in the supply chain management, due to its huge impact on the distribution and operating costs of the companies [49]. It concerns the tactical capacity planning problem faced by a shipper, of securing transportation and warehousing capacity of multiple types (e.g., containers, space in vans or in cargo bikes, space in the warehouse) of different sizes and characteristics (i.e., costs) from a carrier under uncertainty. This uncertainty could regard the demand of loads to be transported or stored, the cost and the availability of future additional capacity, when needed, and the availability of contracted capacity.

Chapter 5

Capacity planning problem under uncertainty

According to Crainic, Ricciardi, and Storchi [56], similarly to any complex transportation system, urban freight transportation and logistics systems require planning decisions at strategic, tactical and operational levels. In this chapter, we focus on a tactical decision that has a huge relevance in supply chain management, concerning the capacity planning problem. Generally, manufacturing and distribution firms do business with logistics service provider, bypassing the direct negotiation with carriers. Consequently, for the sake of simplicity of exposition, but without loss of generality, we refer to the shipper as a retail firm, a producer or a supplier of goods that requires capacity (e.g., containers, ship or train slots, vans, motor carrier tractors, warehousing space) for its raw material, intermediate or final products to meet customer demand. We identify as carrier a service provider (it may also be a third-party logistics company) that provides transportation and warehousing services. Due to the regularity of operations in the supply chain and their cost-efficiency orientation, shippers negotiate in advance a tactical plan to use the needed capacity repeatedly in each period (i.e., one month) of a certain planning horizon (i.e., one year).

The tactical planning assumes a certain level of look-ahead capability and the inclusion of an evaluation of future events, incorporating the uncertainty in the decisions. The uncertainty relates to the demand of loads (e.g., number, weight, volume), the cost and the availability of future additional capacity when needed, and the availability of contracted capacity. In particular, we consider that the contracted capacity could not be (entirely or partially) available at the shipping day for different unfavorable situations (e.g., different characteristics of demand from the estimations, failure or damage of capacity resources).

This tactical capacity planning problem we address is not relevant only in the urban distribution, but also in the long-haul transportation. In fact, before reaching the customers located in the final leg of the supply chain, goods are stored in different warehouses, satellites or UDCs and moved using various transportation modes along the network. Thus, it is clear the influence that decisions on the long-haul transportation have on the urban level, and in the interests of completeness of the information, we give the overall argumentation of the problem in both the contexts.

Looking at the literature, we observe that very few studies have addressed tactical planning problems in logistics. Although various studies in the literature discuss the logistics capacity planning problem between shipper and carrier (e.g., [49, 48]), most of them are devoted to operational decisions, while few contributions deal with strategic and tactical planning applications.

Moreover, to the best of our knowledge, there are no studies that address all the above-presented issues in a single model, including the different sources of uncertainty, which are relevant to both the long-haul transportation and urban distribution contexts. In particular, the case where there is uncertainty on the availability of the contracted capacity at the moment when operations are to be conducted is completely novel. This chapter is a first attempt to contribute to filling this gap by:

- presenting an integrated model that considers different stochastic issues that affect the capacity planning. In particular, we model the described problem as an extended Stochastic Variable Cost and Size Bin Packing Problem [49] by including the possibility that capacity that is planned turns out to be lower. The proposed model thus explicitly represents the uncertainty affecting the actual volume of the contracted capacity resources.

- Applying a progressive hedging-based heuristic to solve the developed stochastic optimization model.

- Conducting an extensive set of computational experiments, using data that reflects the main issues involved in the problem for both the urban distribution and the long-haul transportation contexts, to assess how various sources of uncertainty affect capacity planning (especially the random variability related to contracted capacity).

This chapter is organized as follows. In Section 5.1, we present the logistics capacity-planning problem we address. Then, in Sections 5.2 and 5.3, we discuss the stochastic two-stage formulation of the problem and the solution approach based on the PH algorithm. Section 5.4 presents the experimental plan, with emphasis on the instance sets and analyzes the computational results, providing some relevant managerial insights.

5.1 Tactical planning to secure capacity of multiple types under uncertainty

In this section, we detail the logistics capacity planning problem we address in this chapter. In the first two subsections, we present the problem setting and how this problem appears in two different contexts: the urban distribution and the long-haul transportation. In the third section, we provide a compact description of the general issue.

5.1.1 Urban distribution

In the urban distribution, we observe a continuous growth of the e-commerce importance and of the customers' obsession of fast and cheap deliveries. To answer them, enterprises and particularly the e-commerce giant platforms (e.g., Alibaba and Amazon) are moving from a push cost-driven supply to time and cost pull-driven approach (i.e., demand-driven logistics). Part of that answer is to create distribution centers close to urban areas and to distribute from there through private or, more often, contracted capacity. The latter option requires to negotiate and secure the needed distribution capacity to perform recurring activities over the planning horizon. The freight consolidated into containers for long-distance coming from regional, national and international hubs are collected and consolidated before the distribution, in UCCs located in a strategic node on the outskirts of the urban zone. Then, freight coming from the UCCs and, eventually, other external points, are transferred to satellite facilities and consolidated into vehicles adapted for their usage in dense city zones. On the one hand, the two-tier system minimizes the truck movements within the city and allows to obtain benefits regarding the congestion and externalities, as well as the costs savings due to the economy of scale. On the other hand, it requires a more complex decisional process to make more efficient this system with many interacting goals, players and activities, and to manage repetitive operations and scarce resources.

In particular, wholesalers and retailers negotiate with a carrier to secure capacity to support their procurement and sales processes and thus, to meet the demand coming from retailers or final customers located in the city, in the next cycle of activities. The depots can be grouped in multiple types (e.g., the warehouse or the satellites), and distribution capacity in term of type and size of the fleet of vehicles. The vehicles used to perform the required distribution activities within the city have generally a relatively small capacity (e.g., small vans) to travel along any street in the city-center area and avoid underutilization of the vans' capacity [56]. As discussed in the previous Chapters 3 and 4, they could also be environmental-friendly vehicles according to the emerging business models in the urban distribution, as cargo-bikes. Moreover, these vehicles can be of different types regarding the functionality (e.g., refrigerated or not), box design, loading/unloading technology, capacity and so on. However, efficient operations require a certain standardization, so the number of different types considered is thus assumed to be small [56].

In this context, the characteristics of urban goods distribution, and the limited capacity of urban vehicles and space for storing goods in satellites could affect the availability of booked capacity. For example, situations particularly common in the urban context are the unavailability of vehicles due to mechanical failure or damage, and the insufficient booked capacity due to the presence of parcels not delivered at the end of the day. These parcels cannot be unloaded from the vehicles, which become partially unavailable to load new goods. The latter is particularly common in parcel delivery urban setting, where 12% of parcels require a second-time delivery [246]. This problem is also common in warehousing, where it is mainly due to delays in the collection of the products currently stored. It is particularly important to take this issue into account because it involves the loss of a considerable percentage of capacity.

5.1.2 Long-haul transportation

Concerning the long-haul transportation, globalization, and the opening of broad free-trade economic zones changed the logistics chain dramatically. On the one hand, it has been reorganized around bigger warehouses, and the movement of goods is operated over longer distances, with different modes. On the other hand, the liberalization of the economies increases the competition between firms, and thus the attention paid to controlling costs (especially to the transportation costs). For example, a large Canadian retail chain buys its products from many places, including many suppliers in China. The movement of those commodities from China to Canada is often concentrated in a few ports, where goods are consolidated and shipped by major container-ship of different carriers and then by train to the distribution center near to stores. Due to the long distances and the consolidation of goods in the long-haul transportation, it emerges the need for contracting and securing both transportation and eventually, warehousing capacity from different carriers. In particular, we consider a shipper (i.e., manufacturing firms or wholesalers and retailers) that acquires resources or consumer goods from suppliers located in faraway regions, according to their global procurement policies. Thus, the shipper negotiates to secure in advance capacity, as containers loaded onto long-haul transportation modes (e.g., deep-sea container ship, train, truck) from a long-haul consolidation-based carrier to support their procurement and sales processes. Containers used to move the freight could be of different types defined by their dimensions, the particular environment they offer (e.g., regular, thermal or refrigerated), their form and type of loading [59].

We consider the case of a Canadian wholesale-retail chain that procures and stocks a large variety of products imported from China, to serve a set of customers, through a network of different sized stores. This long-distance procurement process is justified by the global sourcing strategy deployed by the retail chain, to be competitive in the North American market [59]. The imported products are thus moved in containers, consolidated and shipped by the carrier on a vessel from a port of origin in South-East Asia to the port of destination located in Canada. For the retail chain it is important to negotiate with the carrier a tactical plan to secure in advance the needed capacity for regular shipments over the planning horizon (e.g., the vessel leaves the port each week on the same day).

In this context, the characteristics of the transportation mode and the service type and level determine capacity restrictions. Indeed, according to Crainic et al. [59], in the long-haul road transportation, capacity is usually less restricted given that vehicles are more readily available. On the contrary, in maritime and rail modes, the number of available container spaces on ships and trains is limited.

5.1.3 Problem description

In general terms, the logistics capacity planning problem we address, concerns a shipper that need to secure capacity of different types from a carrier, to meet its demand. The capacity types could be transportation modes (e.g., ship or train slots, containers, space in cargo bikes or vans) and carriers or warehousing space, and each type has different characteristics, as the cost, size and functionalities (e.g., refrigerated containers). The shipper negotiates this capacity of multiple types in advance, and it will use it to perform repeatedly the activities (e.g., every week, every month), over a certain planning horizon (e.g., one year, one semester). The output of this negotiation is a medium-term contract that includes the quantity of capacity and the clauses concerning additional logistics services. Given the time lag that usually exists between the signing of the contract and logistics operations, the uncertainty affects the contract negotiation [49].

The first source of uncertainty is the demand. In fact, at each application of the plan, demand fluctuation or characteristics of the goods to be delivered different from the expected, can violate the booked capacity, compromising contract fulfillment. On the contrary, in this analysis we assume that, if the demand is lower than the estimated, it is not allowed to deploy re-selling strategies of the overcapacity on the market.

Another source of uncertainty regards the availability (e.g., number and precise characteristics as the size) and the actual cost of the contracted capacity each time the contract is applied. In fact, due to unfavorable situations (e.g., mechanical failures of vehicles or damage), the capacity may be entirely or partially unavailable at the shipping day and thus lower than that planned. These situations require the negotiation of additional future capacity in the spot market, and an adjustment of the plan (e.g., rearrange and relocate loads). However, additional capacity may not be available when required as well, and thus must be considered stochastic. In case of unavailability of the booked capacity, additional costs are incurred to rearrange loads and store goods. These costs depend on the goods to relocate and can thus be considered proportional to the total lost capacity. Therefore, due to its impact on the operational and economic performance of a company, the problem of losses in planned capacity cannot be ignored, and the actual volume of the capacity resource must be considered stochastic.

Most of the research deals only partially with the requirements of capacity planning, indeed a few papers focus on stochastic capacity planning and the different sources of uncertainty involved. The papers by Crainic et al. [49, 48] propose first attempts to address capacity planning problem settings found in strategic and tactical applications. In particular, the authors present two version of the Stochastic Variable Cost and Size Bin Packing Problem (SVCSBPP) in a long-haul transportation context, through the explicit representation of the uncertainty on future needs in terms of demand for loads and also on the availability (existence and number) of the capacity of various characteristics, respectively. Thus, to our knowledge, the uncertainty on the availability of booked capacity is not considered in the literature. Moreover, there are no studies addressing all the above-presented issues in a single model, which can be applied and validated in both the long haul transportation and urban distribution applications. To contribute to filling this gap, we model the capacity planning problem described in this section, by proposing a new modeling framework. It takes the form of a stochastic bin packing problem, called the *Stochastic Variable Cost and Size Bin Packing Problem with Loss Capacity* (SVCSBPP_L), which generalizes prior work on the SVCSBPP proposed by [49]. Although the SVCSBPP model considers different sources of uncertainty, it supposes that all the booked capacity is available at the shipping or storage date. However, following the discussion above, such a hypothesis is unlikely to be observed in the urban distribution and the long-haul transportation. Our model enhances the current literature, taking into account the actual volumes of the contracted resource as a stochastic parameter.

5.2 Model formulation

This section is devoted to the presentation of the mathematical formulation of the SVCSBPP_L model, which is based on a two-stage stochastic programming formulation with recourse [24]. The first stage concerns the tactical planning decision as the selection *a priori* of the capacity to be made available to move or store the estimated demand of loads, called items. This capacity is expressed in terms of bins characterized by a specific type, volume, and fixed cost defined by the contract (e.g., containers, boxes, vans, etc.). This latter represents a specific price offered by the carrier, and its value is affected by different factors such as bin size and type (e.g., refrigerated bin), additional services, and the time period. The second stage refers to the operational decisions, i.e., the recourse actions that concern the adjustments and thus the acquisition of additional capacity (extra bins) when the actual demand information is revealed. These actions are carried out repeatedly over the planning horizon to cope with unfavorable situations, here defined as random events, which affect the result of the first stage (i.e., booked capacity not sufficient or not available). The extra bins must be purchased at spot-market value, i.e., a higher cost than the fare negotiated initially [49].

Let T be the set of bin types, which are defined according to the volume and fixed cost associated with the bins that are available at the first stage. For $t \in T$, let V^t and f^t be respectively the volume and fixed cost associated with bins of type t. We define $\mathscr{J}^t$ to be the set of available bins of type t and $\mathscr{J} = \bigcup_t \mathscr{J}^t$ to be the set of available bins at the first stage.

Let set Ω be the sample space of the random event, where $\omega \in \Omega$ defines a particular realization. The vector ξ contains the stochastic parameters defined in the model, and $\xi(\omega)$ represents a given realization of this random vector. Let y_j^t be the first-stage variable, which is equal to 1 if bin $j \in \mathscr{J}^t$ is selected and 0 otherwise.

We define c^t as the extra cost to pay for the loss of a unit of capacity in the first-stage bin of type $t \in T$. This cost is the additional cost required to react to the reduction of the available volume of first-stage bins, rearranging the loads or the storage of goods.

Moreover, let $\mathscr{T}$ be the set of bin types available at the second stage, and V^τ be the volume of bins of type $\tau \in \mathcal{T}$.

We consider the following stochastic parameters in $\xi(\omega)$: $\mathcal{V}_j^t(\omega)$, the actual volume of first-stage bin $j \in \mathcal{J}^t$ of type t, where $0 \le \mathcal{V}_j^t(\omega) \le V^t$; $\mathcal{K}^\tau(\omega)$, the set of available bins of type τ at the second stage; $\mathcal{K}(\omega) = \bigcup_\tau \mathcal{K}^\tau(\omega)$, the set of available bins at the second stage; $g^\tau(\omega)$, the cost associated with bins of type $\tau \in \mathcal{T}$; $\mathcal{I}(\omega)$, the set of items to be packed; and $v_i(\omega)$, $i \in \mathcal{I}(\omega)$, the item volumes.

The second-stage variables are defined as follows: $z_k^\tau(\omega) = 1$ if bin $k \in \mathcal{K}^\tau(\omega)$ is selected, 0 otherwise; $x_{ij}(\omega) = 1$ if item $i \in \mathcal{I}(\omega)$ is packed in bin $j \in \mathcal{J}$, 0 otherwise; $x_{ik}(\omega) = 1$ if item $i \in \mathcal{I}(\omega)$ is packed in bin $k \in \mathcal{K}(\omega)$, 0 otherwise.

The two-stage model of the SVCSBPP$_L$ may then be formulated as:

$$\min_y \sum_{t\in T} \sum_{j\in\mathcal{J}^t} f^t y_j^t + E_\xi \left[Q\left(y, \xi(\omega)\right)\right] \tag{5.1}$$

$$\text{s.t.} \quad y_j^t \ge y_{j+1}^t, \qquad \forall t \in T, j = 1, \dots, |\mathcal{J}^t| - 1, \tag{5.2}$$

$$y_j^t \in \{0,1\}, \qquad \forall t \in T, j \in \mathcal{J}^t. \tag{5.3}$$

where

$$Q(y, \xi(\omega)) = \min_{z(\omega), x(\omega)} \sum_{\tau\in\mathcal{T}} \sum_{k\in\mathcal{K}^\tau(\omega)} g^\tau(\omega) z_k^\tau(\omega) + \sum_{t\in T} \sum_{j\in\mathcal{J}^t} c^t (V^t - \mathcal{V}_j^t(\omega)) y_j^t \tag{5.4}$$

$$\text{s.t.} \quad \sum_{j\in\mathcal{J}} x_{ij}(\omega) + \sum_{k\in\mathcal{K}(\omega)} x_{ik}(\omega) = 1, \qquad \forall i \in \mathcal{I}(\omega), \tag{5.5}$$

$$\sum_{i\in\mathcal{I}(\omega)} v_i(\omega) x_{ij}(\omega) \le \mathcal{V}_j^t(\omega) y_j^t, \qquad \forall\, t \in T, j \in \mathcal{J}^t, \tag{5.6}$$

$$\sum_{i\in\mathcal{I}(\omega)} v_i(\omega) x_{ik}(\omega) \le V^\tau z_k^\tau(\omega), \qquad \forall\, \tau \in \mathcal{T}, k \in \mathcal{K}^\tau(\omega), \tag{5.7}$$

$$x_{ij}(\omega) \in \{0,1\}, \qquad \forall\, i \in \mathcal{I}(\omega), j \in \mathcal{J}, \tag{5.8}$$

$$x_{ik}(\omega) \in \{0,1\}, \qquad \forall\, i \in \mathcal{I}(\omega), k \in \mathcal{K}(\omega), \tag{5.9}$$

$$z_k^\tau(\omega) \in \{0,1\}, \qquad \forall\, \tau \in \mathcal{T}, k \in \mathcal{K}^\tau(\omega). \tag{5.10}$$

The objective function (5.1) minimizes the sum of the total fixed cost of the tactical capacity plan and the expected cost associated with the extra capacity added during the operation.

Usually, packing problems present a strong symmetry in the solution space, and two solutions are considered symmetric (and equivalent) if they involve the same set of first-stage bins in different orders. However, when we consider the available capacity of first-stage bins as a source of uncertainty, this is no longer true. In effect, each bin of type $t \in T$ may have a different actual volume, and we need to characterize it properly. We thus introduce constraint (5.2) to break the symmetry and ensure order in the selection of bins of type $t \in T$, i.e., bin $j \in \mathcal{J}^t$ can be selected at the first stage only if bin $j-1 \in \mathcal{J}^t$ has already been selected. Finally, constraint (5.3) imposes the integrality requirements on y.

In the second stage, the term $Q\left(y,\xi(\omega)\right)$ represents the extra cost paid for the capacity that is added at the second stage, given the tactical capacity plan y and the vector $\xi(\omega)$. Thus, the objective function (5.4) minimizes the sum of the cost associated with the extra bins selected at the second stage and the additional cost paid because of the overall lost capacity. Constraint (5.5) ensures that each item is packed in a single bin. Constraints (5.6) and (5.7) ensure that the total volume of items packed in each bin does not exceed the actual volume of the first and second-stage bins. Finally, constraints (5.8) to (5.10) impose the integrality requirements on all second-stage variables.

5.3 Progressive hedging-based heuristic

In this section, we present the adopted solving strategy implemented through an accurate and effective heuristic based on the PH method [199, 49]. Algorithm 1 presents the proposed heuristic for the SVCSBPP$_L$. The original algorithm structure is known and is fully described in [49].

As summarized in the Algorithm 1, the heuristic applies first a horizontal decomposition technique named Scenario Decomposition (SD). This method, based on augmented Lagrangian relaxation, separates the stochastic problem by scenario. This decomposition reduces the computational efforts of solving scenario subproblems and thus, it can be particularly helpful in large-scale problem instances. Furthermore, Lagrangian multipliers are used here to penalize a lack of implementability due to differences in the first-stage variable values among scenario subproblems.

In particular, following the decomposition scheme proposed by [199] our model is decomposed into deterministic VCSBPP subproblems with modified fixed costs $f_b^{\overline{\tau}s}$ and an additional constraint (5.12) that ensures an order in the selection of bins of a certain type $\overline{\tau} \in \overline{\mathscr{T}}$.

In the following, we retrieve a brief description of the notation and formulation of the scenario subproblems, while the interested reader may refer to the Appendix A for an in-depth discussion of the complete procedure for scenario decomposition and the PH heuristic.

A set $\mathscr{S}$ of representative scenarios $s \in \mathscr{S}$ is obtained by sampling. For each scenario s, let $\mathscr{B}^{\overline{\tau}s} = \mathscr{J}^{\overline{\tau}} \cup \mathscr{K}^{\overline{\tau}s}$ be the set of available bins of type $\overline{\tau}$ in the subproblem and $\mathscr{B}^s = \bigcup_{\overline{\tau}} \mathscr{B}^{\overline{\tau}s}$ be the whole set of bins available in the subproblem. For $b \in \mathscr{B}^{\overline{\tau}s}$, let $\mathcal{V}_b^{\overline{\tau}s}$ be the actual volume of bin b (for $b \in \mathscr{K}^{\overline{\tau}s}$, $\mathcal{V}_b^{\overline{\tau}s} = V^{\overline{\tau}}$) and let $f_b^{\overline{\tau}s}$ define the fixed cost associated with bin b. The related decision variable becomes $y_b^{\overline{\tau}s} = 1$ if bin $b \in \mathscr{B}^{\overline{\tau}s}$ of type $\overline{\tau} \in \overline{\mathscr{T}}$ is selected, 0 otherwise. Moreover, if an item $i \in \mathscr{I}^s$ is packed in the bin b, x_{ib}^s is equal to 1, 0 otherwise. Thus, the scenario subproblems can be expressed as follows:

Algorithm 1 PH-based meta-heuristic for the SVCSBPP$_L$

Scenario decomposition
Generate a set of scenarios $\mathscr{S}$;
Decompose the resulting deterministic model (A.1)–(A.10) by scenario using augmented Lagrangian relaxation;

Phase 1
$\nu \leftarrow 0$; $\lambda_b^{\bar{\tau}s\nu} \leftarrow 0$; $\rho_b^{\bar{\tau}\nu} \leftarrow f^{\bar{\tau}}/10$;
while Termination criteria not met **do**
  For all $s \in \mathscr{S}$, solve the corresponding VCSBPP subproblem $\rightarrow y_b^{\bar{\tau}s\nu}$;
  Compute temporary global solution
    $\bar{y}_b^{\bar{\tau}\nu} \leftarrow \sum_{s \in \mathscr{S}} p_s y_b^{\bar{\tau}s\nu}$
    $\bar{\delta}^{\bar{\tau}\nu} \leftarrow \sum_{s \in \mathscr{S}} p_s \delta^{\bar{\tau}s\nu}$
  Penalty adjustment
    $\lambda_b^{\bar{\tau}s\nu} = \lambda_b^{\bar{\tau}s(\nu-1)} + \rho_b^{\bar{\tau}(\nu-1)}(y_b^{\bar{\tau}s\nu} - \bar{y}_b^{\bar{\tau}\nu})$
    $\rho_b^{\bar{\tau}\nu} \leftarrow \alpha \rho_b^{\bar{\tau}(\nu-1)}$

  if consensus is at least $\sigma_{\%}$ **then**
    Adjust the fixed costs $f^{\bar{\tau}s\nu}$ according to (A.37);
  end if
  Bundle fixing
    $\bar{\delta}_m^{\bar{\tau}\nu} \leftarrow \min_{s \in \mathscr{S}} \delta^{\bar{\tau}s\nu}$
    $\bar{\delta}_M^{\bar{\tau}\nu} \leftarrow \max_{s \in \mathscr{S}} \delta^{\bar{\tau}s\nu}$
    Apply variable fixing;
  $\nu \leftarrow \nu + 1$
end while

Phase 2
if consensus not met for a single bin type $\bar{\tau}'$ ($\bar{\delta}_m^{\bar{\tau}'} < \bar{\delta}_M^{\bar{\tau}'}$) **then**
  Identify the consensus number of bins δ of type $\bar{\tau}'$ by enumerating $\delta \in \left[\bar{\delta}_m^{\bar{\tau}'}, \bar{\delta}_M^{\bar{\tau}'}\right]$ (and variable fixing)
else
  Fix consensus variables in model (A.1)–(A.10);
  Solve restricted (A.1)–(A.10) model using a MIP solver.
end if

$$\min_{y,x} \quad \sum_{\overline{\tau}\in\overline{\mathscr{T}}} \sum_{b\in\mathscr{B}^{\overline{\tau}s}} f_b^{\overline{\tau}s} y_b^{\overline{\tau}s} \tag{5.11}$$

$$\text{s.t.} \quad y_b^{\overline{\tau}s} \geq y_{b+1}^{\overline{\tau}s}, \qquad \forall\, \overline{\tau} \in \overline{\mathscr{T}}, b = 1, \ldots, |\mathscr{B}^{\overline{\tau}s}| - 1, \tag{5.12}$$

$$\sum_{b\in\mathscr{B}^s} x_{ib}^s = 1, \qquad \forall\, i \in \mathscr{I}^s, \tag{5.13}$$

$$\sum_{i\in\mathscr{I}^s} v_i^s x_{ib}^s \leq V_b^{\overline{\tau}s} y_b^{\overline{\tau}s}, \qquad \forall\, \overline{\tau} \in \overline{\mathscr{T}}, b \in \mathscr{B}^{\overline{\tau}s}, \tag{5.14}$$

$$y_b^{\overline{\tau}s} \in \{0,1\}, \qquad \forall \overline{\tau} \in \overline{\mathscr{T}}, b \in \mathscr{B}^{\overline{\tau}s}, \tag{5.15}$$

$$x_{ib}^s \in \{0,1\}, \qquad \forall\, i \in \mathscr{I}^s, b \in \mathscr{B}^s, \tag{5.16}$$

As already stated by [44, 49] it is time-consuming to solve a large VCSBPP to optimality using a commercial MIP solver. Moreover, due to the specific characteristics of the bin packing problem addressed (e.g., constraint 5.12 that imposes an order in the selection of bins of a certain type) and because there are multiple equivalent solutions, we cannot use the standard PH algorithm to solve subproblems as [50, 57]. For this reason, we adopted a version of the PH heuristic, proposed by [49] that includes a procedure to reach the consensus among subproblems based on a variable-bundle fixing strategy.

After the SD, the first phase of the PH aims to induce consensus relative to the first-stage decision variables among the scenario subproblems ((i.e., consensus is defined as scenario solutions being similar with regard to the first-stage decisions with the overall capacity plan and thus, being similar among themselves). At each iteration, the subproblems are first solved separately. Their solutions are then aggregated into a temporary overall solution. The search process is gradually guided toward scenario consensus. To induce consensus among the scenario subproblems we adjust the penalties in the objective function at each iteration. In doing so, we propose two strategy. The first is based on the Lagrangian multipliers, which are used to penalize the lack of implementability due to the differences/dissimilarity in the first-stage variables values among scenario subproblems (between local scenario solutions and the overall solution). The second penalty adjustment strategy is a heuristic which directly tunes the fixed costs of bins of the same type. The goal is to accelerate the search process when the overall solution is close to consensus. Then, we introduce a variable bundle-fixing strategy to guide the search process, restricting the number of bins of each type that can be used, through lower and upper bounds.

Finally, the second phase computes the final solution solving a restricted SVCSBPP$_L$ obtained by fixing the first-stage variables for which consensus has been reached (i.e., the bins used in all the scenario subproblems). The range of first-stage variables for which consensus is not reached within certain prescribed computational conditions (i.e., termination criteria), is reduced through bundle fixing, and the resulting MIP is solved exactly.

5.4 Experimental plan

This section describes the extensive set of experiments. First, it begins by presenting the instance sets used to qualify our model and the solution procedure (Section 5.4.1). Then, in the remaining part of the section, we discuss the main computational results.

We performed an extensive set of experiments with a threefold aim:

- analyze the new logistics capacity planning problem in the urban distribution and long-haul transportation, and how the different sources of stochasticity we address, are relevant in both contexts;
- measure the impact of uncertainty and analyzing the usefulness of building a stochastic programming model;
- study the relationship between the problem characteristics and parameters, and the structure of the capacity plan, with the aim of drawing managerial insights.

5.4.1 Instance set

Since, to the best of our knowledge, there is no prior study of the capacity planning problem with uncertainty on the actual volume of contracted capacity, we generated the new test instance set T, starting from a basic instance set named B. The set B represents the cases without reduction of the available first-stage capacity. It has been created by selecting, from the vast literature on bin packing problems [164, 50, 61, 49, 109], the characteristics that better suit our problem settings. To describe our specific capacity-planning problem, taking as a reference the instances of the set B, we have generated different instances in the set T, including additional characteristics related to the actual volume of first-stage bins, and the introduction of extra cost to compensate for the loss of capacity in first-stage bins. Table 5.1 presents the details of the instances sets T and B. For further information about the characteristics the interested reader may refer to Crainic et al. [49].

An extensive computational campaign supports the claim of validity and quality for the proposed model in both the long-haul transportation and urban distribution. In particular, in the set T, the instances related to the long-haul transportation have been differentiated from those in the urban distribution, considering the parameters that better characterize each context (e.g., the type of capacity loss). As highlighted in Table 5.1, the sets of problem instances are similar in the long-haul transportation and urban distribution contexts. In particular, the characteristics related to the basic instances (i.e., the volume and number of items, number of bins, availability in the first-stage, and related costs) and our specific problem (i.e., the availability and cost of bins at the second stage, the actual volume of first-stage bins, and the extra cost resulting from a loss of capacity) are common to the two contexts. The most significant difference is the type of capacity loss. Indeed, in the set T, we considered different entities of volume reduction according to the contexts.

In the case of long-haul transportation, the loss of capacity is evenly distributed among all the bins belonging to the set. It means that every first-stage bin loses a percentage of its volume. Uniform capacity losses are generally due to the limited availability of historical information about the partners and processes involved (e.g., the shipper negotiates with a new carrier in the market) typical of the long-haul transportation. In the case of urban distribution, the loss of volume is localized. It means that only few first-stage bins lose their entire capacity and become unusable, while the others are unaffected. The overall reduction of capacity among all the bins of a certain type is equal to a percentage of the total volume. In particular, when the reduction of capacity is uniformly distributed, every first-stage bins loses a percentage of its volume equal to the parameter BL defined in Table 5.1. Localized capacity losses are caused by mechanical failure of vehicles or other issues (e.g., undelivered parcels in the previous operational day). These events make the capacity of the vehicle totally or partially unavailable. The more accurate information flow in the urban context allows to better identify the unavailable vehicles. Thus, localized capacity losses are typical of the urban distribution.

For each combination of the parameters of set B, defined in Table 5.1, we generated 10 instances yielding a total of 180 instances. A total of $s = 1, \ldots, 100$ scenarios is used in the experiments. According to [131], this scenario tree dimension satisfies the stability conditions and thus, ensures the reliability of the solutions when a different set of scenarios is considered.

As mentioned above, set B represents standard cases, without reduction of the available capacity booked at the first stage. These instances are characterized by the availability and cost of the bins, the number and volume of the items, and the number of bin types. Concerning this last characteristic, in [49] the authors consider a higher number of types (up to ten types). On the contrary, we decided to focus only on two sets of bin types, T3 and T5, with three and five bin types, respectively (see Table 5.1). This choice reflects the current practice in the industry (both in long-haul transportation and urban distribution), where few types and modular capacity resources are usually adopted.

For each of the 180 basic instances, we developed 288 test instances originated by the combinations of parameters that characterize the set T. This gives us a total of 51840 instances composing the set T. These new instances differ from the corresponding basic instance for the actual volume of first-stage bins and the introduction of extra cost to compensate for the loss of capacity in first-stage bins. Indeed, in addition to the previous parameters, set T is also characterized by the percentage of scenarios affected by capacity losses (SL), bin types affected by losses of capacity (TL), the entity and the type of volume reduction for each bin affected by a loss of volume (BL), and the extra cost to compensate for the loss.

This two-step instance generation is justified by our aim to explore the structure of capacity planning solutions for a wide range of configurations [49], as described in depth in the next section.

Characteristic	**Set**	**Value**	
		Long-haul transportation	*Urban distribution*
Number of items	B,T	Uniformly distributed in the range $[100,500]$	Uniformly distributed in the range $[100,500]$
Volume of items	B,T	Small (S): $[5,10]$ Medium (M): $[15,25]$ Big (B): $[20,40]$	Small (S): $[5,10]$ Medium (M): $[15,25]$ Big (B): $[20,40]$
Number of bins	B,T	3 bin types (T3) with volumes equal to [50,100,150] 5 bin type (T5) with volumes equal to [50,80,100,120,150] set $\mathscr{T}$ is equal set T	3 bin types (T3) with volumes equal to [50,100,150] 5 bin type (T5) with volumes equal to [50,80,100,120,150] set $\mathscr{T}$ is equal set T
Availability of first-stage bins	B,T	$\\|\mathscr{J}^t\\|$ equal to $\lceil \frac{1}{V^t} \max_{s\in\mathscr{S}} \sum_{i\in\mathscr{I}^s} v_i^s \rceil$	$\\|\mathscr{J}^t\\|$ equal to $\lceil \frac{1}{V^t} \max_{s\in\mathscr{S}} \sum_{i\in\mathscr{I}^s} v_i^s \rceil$
Availability of second-stage bins	B, T	Availability class 1 (AV1): $\\|\mathscr{K}^{ts}\\|$ uniformly distributed in the range $[0, \\|\mathscr{J}^t\\|]$ Availability class 2 (AV2): $\\|\mathscr{K}^{ts}\\|$ uniformly distributed in the range $[\frac{\\|\mathscr{J}^t\\|}{2}, \\|\mathscr{J}^t\\|]$ Availability class 3 (AV3): $\\|\mathscr{K}^{ts}\\|$ equal to $\\|\mathscr{J}^t\\|$	Availability class 1 (AV1): $\\|\mathscr{K}^{ts}\\|$ uniformly distributed in the range $[0, \\|\mathscr{J}^t\\|]$ Availability class 2 (AV2): $\\|\mathscr{K}^{ts}\\|$ uniformly distributed in the range $[\frac{\\|\mathscr{J}^t\\|}{2}, \\|\mathscr{J}^t\\|]$
Cost of first-stage bins	B,T	$f^t = V^t(1+\gamma^t$ where γ^t is uniformly distributed in the range $[-0.3, 0.3]$ [44]	$f^t = V^t(1+\gamma^t$ where γ^t is uniformly distributed in the range $[-0.3, 0.3]$ [44]
Cost of second-stage bins	B,T	$g^\tau = f^t(1+\alpha)$ where α belongs to the set $\{0.3, 0.5, 0.7\}$	$g^\tau = f^t(1+\alpha)$ where α belongs to the set $\{0.3, 0.5, 0.7\}$
Actual volume of first-stage bins	T	SL - Percentage of scenarios affected by capacity losses: $[20\%, 40\%, 60\%, 80\%]$ TL - Probability that a bin type is affected by a capacity reduction: $[50\%, 75\%, 100\%]$ BL - Percentage of the overall loss of capacity among all the first-stage bins of a certain type: $[20\%, 30\%, 40\%, 50\%, 60\%, 70\%]$ Type of capacity loss: Uniform (U)	SL - Percentage of scenarios affected by capacity losses: $[20\%, 40\%, 60\%, 80\%]$ TL - Probability that a bin type is affected by a capacity reduction: $[50\%, 75\%, 100\%]$ BL - Percentage of the overall loss of capacity among all the first-stage bins of a certain type: $[20\%, 30\%, 40\%, 50\%, 60\%, 70\%]$ Type of capacity loss: Localized (L)
Extra cost due to the reduction of a unit of capacity	T	$c^t = \frac{f^t}{V^t}(\alpha^t)$ where α^t is the constant used to compute the cost of extra bins of type $t \in T$	$c^t = \frac{f^t}{V^t}(\alpha^t)$ where α^t is the constant used to compute the cost of extra bins of type $t \in T$

Table 5.1: Characteristics of sets B and T.

5.4.2 Assessment of the model

As stated in Section 5.1, much of the literature does not consider uncertainty in capacity planning problems. In contrast, our aim in this section is to evaluate and show the benefits of modeling uncertainty using the two-stage formulation with recourse for the SVCSBPP$_L$ model. We treat this topic by considering the two most relevant stochastic programming measures in the literature:

- Expected Value of Perfect Information ($EVPI$). This measure represents the decision maker's willingness to pay for complete information about the future;
- Value of the Stochastic Solution (VSS). This measure is the difference between the result of using an expected value solution (EEV) and the recourse problem solution (RP) [23].

In the first two subsections, we evaluate how the values of the $EVPI$ and VSS change in long-haul transportation and urban distribution, depending on the different parameters characterizing the set T in these contexts, such as the availability of second-stage bins, the extra cost due to loss of capacity, and the entity of actual volume reduction of first-stage bins. In the third subsection, we analyze the value of considering the actual availability of the planned capacity as stochastic.

Expected value of perfect information

In this section, we present the values of the $EVPI$. Table 5.2 shows the average and maximum $EVPI$ percentages for the two sets of instances T3 and T5 (Column 1), computed as $EVPI/RP \cdot 100$, where RP is the value of an optimal solution of the 2-stage with recursion model. These percentages are grouped by availability class of second-stage bins (Column 2), value of alpha (Column 3), and the application type (Columns 4 and 5 for the urban distribution and Columns 6 and 7 for the long-haul transportation).

The average percentage $EVPI$ is always greater than 8.09%, highlighting the benefit of having information about the future in advance. It is particularly significant when the availability of extra bins is limited (AV1), and the costs of second-stage bins are high. In fact, in the long-haul transportation, where the losses are uniform, we obtain the highest values of average and maximum $EVPI$ when the availability class is A1 and alpha is equal to 0.7. In this situation, the maximum percentage of $EVPI$ reaches 74.27%. This means that it would be particularly important to have complete information about the future when numerous first-stage bins are likely to lose part of their available capacity and, at the same time, second-stage bins are rather expensive and may not be available in sufficient numbers to load all items for delivery.

Set	**Availability**	**Alpha**	**Urban distribution**		**Long-haul transportation**	
			$EVPI[\%]$	$EVPI_{max}[\%]$	$EVPI[\%]$	$EVPI_{max}[\%]$
T3	**AV1**	**0.3**	13.98	60.76	22.20	77.35
		0.5	18.65	48.07	25.47	75.24
		0.7	21.97	36.69	26.80	74.27
	AV2	**0.3**	9.05	13.85	10.19	20.23
		0.5	15.26	19.12	16.14	29.96
		0.7	19.34	23.71	19.82	35.28
	AV3	**0.3**	9.47	14.52	10.11	20.30
		0.5	15.79	20.38	16.18	29.43
		0.7	19.90	24.61	19.91	35.95
T5	**AV1**	**0.3**	12.13	15.71	13.28	54.26
		0.5	17.73	21.24	19.16	50.83
		0.7	21.44	25.11	22.74	47.86
	AV2	**0.3**	8.09	13.62	9.61	19.27
		0.5	15.23	21.60	16.45	31.17
		0.7	19.59	25.32	20.40	36.60
	AV3	**0.3**	8.97	13.66	9.48	20.72
		0.5	15.84	19.88	16.57	30.17
		0.7	20.20	25.57	21.07	37.25

Table 5.2: $EVPI$ for different availability classes, values of alpha, and types of losses.

Tables from 5.3 to 5.5 report the average and maximum percentages $EVPI$, showing how different parameters such as the level of the volume reduction, the percentage of scenarios affected by capacity losses and the probability that a bins type has a capacity reduction, affect the $EVPI$. In the urban distribution, where the losses are localized among the bins, the average percentage $EVPI$ decreases with an increase of SL and TL. In this case, having information about the future is valuable, particularly when the reduction of actual volume is less likely. For example, Table 5.3 highlights that when SL and TL are respectively equal to 20% and 50%, and BL is between 60% and 70%, the average and maximum percentages of $EVPI$ are 16.90% and 31.99% for instances with three bin types (set T3), and 16.15% and 24.90% for instance with five bin types (set T5).

The results obtained considering the instances in T5 are not affected by the availability of the second-stage bins, regardless of the context (long-haul transportation or urban distribution) (see Tables 5.3 and 5.5). On the contrary, Table 5.4 shows that in the long-haul transportation, when there we consider three types of bins (set T3) the impacts of the number of scenarios affected by the uncertainty and the probability that a bin types has a capacity reduction depend on the availability of second-stage bins. The knowledge of the future becomes particularly important if all the parameters determining the actual volumes of first-stage bins are high because of the considerable risk of not being able to pack all items. For example, the average percentage of $EVPI$ reaches 46.16% when SL, TL, and BL are equal to 80%, 100%, and 70%, respectively (see Table 5.4).

We now examine to what extent the first-stage decisions of the recourse problem and the EV formulation differ. As already highlighted by Crainic et al. [49], the EV problem generally overestimates the future demand to be loaded (i.e., the total volume of the items is larger than the actual volume) and the availability of extra bins (i.e., a larger set of bins is assumed available for the recourse action). Moreover, when SL and TL are low, the EV formulation underestimates the reduction of available capacity (i.e., the total volume of first-stage bins available to load items is larger than the actual available volume). This behavior can lead to two situations. First, EV may plan for a set of bins that are not required for the set of scenarios considered. Thus, the capacity plan is more expensive even if the solution is feasible and implementable. Second, EV may plan for an insufficient capacity for a subset of scenarios in which the actual availability of bins is limited. In this case, the capacity plan is infeasible for these scenarios. While, for the basic problem the percentage of infeasible instances is equal to 10% for set T3 and availability AV1, and 0% for the other groups introducing the losses of volume, infeasibility may change according to the values of the different instances parameters.

Table 5.6 shows that when we consider uniform losses and availability class A1, the number of infeasible instances grows considerably for both sets T3 and T5 as SL, TL, and BL increase. Indeed, when all the parameters that determine the actual volumes of first-stage bins are at their maximum values (i.e., SL, TL, and BL are 60-80%, 100%, and 60-70%, respectively), the percentage of infeasible instances reaches 30%.

Adding a further level of investigation, when we consider the additional cost of second-stage bins at its maximum value (i.e., alpha is equal to 0.7) and a loss of capacity that concerns a low percentage of scenarios but of a considerable entity (i.e., SL, TL, and BL are 20%-40%, 75%-100%, and 60%-70%, respectively), all the instances are infeasible (see Table 5.6). These outcomes highlight the need for considering uncertainty in capacity planning when the availability of second-stage bins may be limited.

Value of the stochastic solution

In this section, we focus on the VSS. Table 5.7 shows the average and maximum VSS percentages for the two sets of instances T3 and T5 (Column 1), computed as $VSS/RP \cdot 100$ and grouped by availability class (Column 2), value of alpha (Column 3), and the application type (Columns 4 and 5 for the urban distribution and Columns 6 and 7 for the long-haul transportation).

The average VSS percentage is always greater than 4.93% and reaches its maximum value at 17.96%. These percentages highlight that the gap between the expected-value solution and the stochastic solution is always significant.

Similarly to the $EVPI$ analysis, we will discuss the impact on VSS of the parameters that determine the actual volume of the first-stage bins. In particular, Tables from 5.8 to 5.10 report the average and maximum percentages VSS, showing how different parameters such as the level of the volume reduction, the percentage of scenarios affected by capacity losses and the probability that a bins type has a capacity reduction, affect the VSS.

Starting with a focus on the urban distribution, Table 5.8 shows that the average VSS decreases as SL increases for both sets T3 and T5. The maximum values of VSS are reached when SL is equal to 20% and BL is 70%. In this case, the average and maximum percentages of VSS are 15.49% and 44.49% for T3 and 13.82% and 45.00% for T5. Concerning the urban distribution, where the losses are localized, the stochastic approach is more valuable when there is a low probability of losing a large number of entire bins, which is the case of unavailability of vans. In the case of the long-haul transportation (Table 5.9), when we consider instance set T3, the experimental tests revealed that when SL and TL are low, VSS increases as BL increases. On the contrary, when all the parameters have high values, VSS drops sharply. In particular, when we consider the availability class AV1 and SL, TL and BL are respectively equal to 80%, 75%, and 70%, and the average VSS percentage falls to 0%. This behavior might suggest that when the availability of second-stage bins is limited and a considerable amount of capacity is likely to be lost in first-stage bins, the stochastic problem is not worth solving from a pure cost point of view, while the eventual infeasibility may be the real issue.

As in instance set T3, and even in instance set T5 (see Table 5.10), when SL and TL are low, the value of VSS increases as BL increases. In particular, the average percentage of VSS reaches 21.95% when SL, TL, and BL are respectively equal to 20%, 100%, and 70%, while the maximum percentage of VSS reaches 88.36%, with SL, TL, and BL respectively equaling 40%, 100%, and 70%. On the contrary, when SL and TL are high, the value of VSS decreases as BL increases and falls to 1.88% when SL, TL, and BL are respectively equal to 80%, 75%, and 70%.

SL[%]	TL[%]	BL[%]	Set T3 $EVPI$[%]	Set T3 $EVPI_{max}$[%]	Set T5 $EVPI$[%]	Set T5 $EVPI_{max}$[%]
20	**50**	**20-30**	16.26	26.62	15.77	23.91
		40-50	16.24	28.09	16.00	23.63
		60-70	16.90	31.99	16.15	24.90
	75	**20-30**	16.30	26.65	15.94	23.90
		40-50	16.33	28.47	15.95	23.31
		60-70	17.06	33.43	16.08	25.32
	100	**20-30**	16.45	26.13	15.93	23.84
		40-50	16.22	28.67	15.80	23.30
		60-70	17.00	33.75	16.00	24.48
40	**50**	**20-30**	16.33	26.54	15.98	23.97
		40-50	16.10	29.08	15.79	23.23
		60-70	17.05	33.93	16.16	25.57
	75	**20-30**	16.32	26.66	15.91	23.94
		40-50	15.99	29.99	15.61	23.16
		60-70	16.66	34.84	15.91	24.34
	100	**20-30**	16.25	26.35	15.92	23.60
		40-50	15.68	30.20	15.20	22.81
		60-70	16.03	35.49	15.40	23.29
60	**50**	**20-30**	16.23	26.70	16.07	23.75
		40-50	15.92	30.10	15.47	23.38
		60-70	16.52	48.07	15.99	24.46
	75	**20-30**	16.22	26.46	15.88	23.85
		40-50	15.47	28.95	15.06	22.81
		60-70	15.75	60.76	15.23	23.27
	100	**20-30**	16.11	26.50	15.79	23.56
		40-50	15.08	28.00	14.54	22.73
		60-70	14.59	50.01	14.21	21.93
80	**50**	**20-30**	16.23	26.55	15.95	23.79
		40-50	15.48	29.18	15.20	23.10
		60-70	15.84	36.60	15.47	23.81
	75	**20-30**	16.05	26.47	15.73	23.83
		40-50	15.04	30.29	14.46	22.61
		60-70	14.76	51.06	14.20	23.17
	100	**20-30**	15.87	25.68	15.48	23.50
		40-50	14.28	26.51	13.90	22.61
		60-70	12.99	28.73	12.81	21.73

Table 5.3: The impact of SL, TL and BL on $EVPI$ in the urban distribution setting.

SL[%]	TL[%]	BL [%]	AV1 $EVPI$[%]	AV1 $EVPI_{max}$[%]	AV2-AV3 $EVPI$[%]	AV2-AV3 $EVPI_{max}$[%]
20	**50**	**20-30**	18.12	25.59	15.61	24.23
		40-50	20.27	34.30	17.28	27.36
		60-70	25.21	63.69	19.79	29.42
	75	**20-30**	17.73	24.95	14.93	23.54
		40-50	20.67	38.63	16.66	24.65
		60-70	26.03	63.14	19.80	29.13
	100	**20-30**	16.58	24.60	13.68	22.41
		40-50	19.01	37.97	15.02	21.84
		60-70	27.83	61.04	18.59	25.83
40	**50**	**20-30**	18.30	25.66	15.67	26.48
		40-50	23.20	40.98	18.45	29.05
		60-70	30.92	63.53	22.30	32.52
	75	**20-30**	17.01	24.10	14.31	22.53
		40-50	22.16	40.79	17.31	26.21
		60-70	32.49	64.40	21.30	31.79
	100	**20-30**	14.75	22.89	11.56	21.09
		40-50	19.43	38.07	13.42	20.23
		60-70	35.60	65.67	16.50	25.29
60	**50**	**20-30**	18.29	29.49	15.44	26.84
		40-50	25.35	50.96	19.16	31.13
		60-70	34.46	74.27	23.01	35.04
	75	**20-30**	17.09	35.24	13.29	22.41
		40-50	24.91	52.88	16.71	27.18
		60-70	40.30	76.84	19.65	30.42
	100	**20-30**	13.85	33.34	8.91	19.27
		40-50	22.10	57.15	9.56	16.96
		60-70	43.53	77.34	10.39	18.53
80	**50**	**20-30**	18.54	34.95	15.02	27.57
		40-50	27.77	56.97	19.09	32.17
		60-70	37.34	75.52	22.34	35.95
	75	**20-30**	16.58	34.37	12.09	22.42
		40-50	25.22	53.94	14.95	25.70
		60-70	42.52	75.24	16.00	28.90
	100	**20-30**	12.09	31.38	6.27	16.55
		40-50	22.20	56.19	3.97	9.24
		60-70	46.16	77.35	4.14	8.15

Table 5.4: The impact of SL, TL and BL on $EVPI$ for instance set T3 in the long-haul transportation setting.

SL[%]	TL[%]	BL [%]	$EVPI$[%]	$EVPI_{max}$[%]
20	**50**	**20-30**	16.05	24.71
		40-50	17.93	27.18
		60-70	20.51	31.33
	75	**20-30**	15.39	23.33
		40-50	17.65	27.78
		60-70	20.70	30.36
	100	**20-30**	13.87	22.11
		40-50	15.19	21.97
		60-70	18.51	27.49
40	**50**	**20-30**	16.28	25.73
		40-50	19.47	30.75
		60-70	23.47	35.77
	75	**20-30**	15.03	25.03
		40-50	18.53	28.08
		60-70	22.84	33.54
	100	**20-30**	11.83	19.62
		40-50	13.75	20.66
		60-70	17.41	26.68
60	**50**	**20-30**	16.31	27.08
		40-50	20.49	32.35
		60-70	24.92	36.79
	75	**20-30**	14.29	24.45
		40-50	18.46	31.79
		60-70	22.14	34.89
	100	**20-30**	9.42	18.44
		40-50	10.34	17.39
		60-70	12.04	30.31
80	**50**	**20-30**	16.14	28.30
		40-50	21.23	34.39
		60-70	25.04	43.02
	75	**20-30**	13.32	26.15
		40-50	17.44	32.46
		60-70	19.51	50.83
	100	**20-30**	7.07	16.82
		40-50	5.33	27.16
		60-70	6.61	54.26

Table 5.5: The impact of SL, TL and BL on $EVPI$ for instance set T5 in the long-haul transportation setting.

Alpha	SL[%]	TL[%]	Set T3 BL[%] 20-30	Set T3 BL[%] 40-50	Set T3 BL[%] 60-70	Set T5 BL[%] 20-30	Set T5 BL[%] 40-50	Set T5 BL[%] 60-70
0.3	**20**	**50**	12.50	10.00	25.00	0.00	0.00	0.00
		75	10.00	20.00	47.50	0.00	0.00	0.00
		100	8.75	43.75	82.50	0.00	0.00	0.00
	40	**50**	12.50	12.50	32.50	0.00	0.00	0.00
		75	10.00	15.00	40.00	0.00	2.50	10.00
		100	6.25	25.00	77.50	0.00	5.00	22.50
	60-80	**50**	12.50	15.00	30.00	0.00	3.75	12.50
		75	10.00	17.50	12.50	1.25	16.25	28.75
		100	8.75	15.00	53.75	6.25	27.5	30.00
0.5	**20**	**50**	12.50	20.00	32.50	0.00	0.00	0.00
		75	10.00	22.50	70.00	0.00	0.00	0.00
		100	15.00	75.00	98.75	0.00	0.00	0.00
	40	**50**	15.00	20.00	32.50	0.00	0.00	0.00
		75	10.00	12.50	50.00	0.00	0.00	2.50
		100	8.75	52.50	98.75	0.00	0.00	25.00
	60-80	**50**	12.50	17.50	25.00	0.00	0.00	15.00
		75	10.00	12.50	35.00	0.00	13.75	26.25
		100	8.75	30.00	85.00	0.00	25.00	30.00
0.7	**20**	**50**	10.00	20.00	40.00	0.00	0.00	0.00
		75	5.00	35.00	100.00	0.00	0.00	0.00
		100	35.00	92.50	98.75	0.00	0.00	0.00
	40	**50**	10.00	20.00	30.00	0.00	0.00	0.00
		75	5.00	15.00	100.00	0.00	0.00	0.00
		100	10.00	77.50	100.00	0.00	0.00	5.00
	60-80	**50**	10.00	20.00	30.00	0.00	0.00	3.75
		75	5.00	15.00	55.00	0.00	2.50	23.75
		100	10.00	65.00	97.50	0.00	12.50	30.00

Table 5.6: Percentage of infeasible instances when the availability class is AV1 in the long-haul transportation setting.

Set	Availability	Alpha	Urban distribution		Long-haul transportation	
			$VSS[\%]$	$VSS_{max}[\%]$	$VSS[\%]$	$VSS_{max}[\%]$
T3	**AV1**	**0.3**	11.29	23.53	13.79	33.85
		0.5	8.37	20.04	10.58	31.47
		0.7	5.63	15.49	8.47	56.65
	AV2	**0.3**	15.75	44.49	17.57	55.13
		0.5	12.20	30.92	13.95	55.03
		0.7	9.41	38.24	12.59	80.40
	AV3	**0.3**	15.67	43.82	17.02	62.07
		0.5	10.34	35.99	13.52	50.98
		0.7	8.08	29.52	11.90	80.83
T5	**AV1**	**0.3**	12.00	29.73	14.50	38.40
		0.5	7.79	22.61	12.02	49.84
		0.7	4.93	16.35	9.88	74.71
	AV2	**0.3**	14.12	45.00	16.17	58.54
		0.5	9.95	31.21	12.93	63.77
		0.7	6.70	22.28	11.40	88.36
	AV3	**0.3**	14.54	33.51	17.96	57.93
		0.5	9.07	34.95	14.67	48.97
		0.7	5.34	27.67	11.48	63.08

Table 5.7: VSS for different availability classes, values of alpha, and types of losses.

SL[%]	BL[%]	Set T3		Set T5	
		VSS[%]	VSS_{max}[%]	VSS[%]	VSS_{max}[%]
20	**20**	9.31	23.61	8.24	22.61
	30	9.21	24.83	7.98	23.48
	40	9.83	28.23	8.25	27.30
	50	12.24	32.97	10.26	32.69
	60	14.03	38.92	12.74	38.68
	70	15.49	44.49	13.82	45.00
40	**20**	9.24	23.61	7.88	22.61
	30	8.86	24.80	7.78	23.15
	40	9.31	29.54	7.95	27.27
	50	11.65	36.34	9.84	34.15
	60	13.11	40.16	11.20	39.31
	70	13.02	42.68	11.28	40.68
60	**20**	9.14	23.61	7.71	22.61
	30	8.71	23.27	7.68	22.44
	40	8.93	22.39	8.04	22.74
	50	11.12	25.71	9.55	23.97
	60	12.49	31.96	10.61	30.59
	70	12.08	38.24	10.42	27.85
80	**20**	9.09	23.61	7.75	22.61
	30	8.70	22.63	7.74	22.44
	40	9.03	22.36	8.09	22.83
	50	11.10	25.71	9.61	24.03
	60	12.39	32.66	10.45	31.22
	70	11.80	30.58	10.29	27.41

Table 5.8: The impact of SL, TL and BL on VSS in the urban distribution setting.

SL[%]	**TL[%]**	**BL[%]**	**AV1**		**AV2-AV3**	
			$VSS[\%]$	$VSS_{max}[\%]$	$VSS[\%]$	$VSS_{max}[\%]$
20	**50**	**20-30**	6.41	21.52	10.42	25.14
		40-50	8.32	23.05	13.19	29.33
		60-70	11.65	26.89	17.51	35.35
	75	**20-30**	6.19	19.88	10.41	27.02
		40-50	11.16	23.43	15.84	30.57
		60-70	12.00	25.33	19.47	41.04
	100	**20-30**	8.10	23.15	12.01	26.96
		40-50	12.08	22.68	17.08	32.72
		60-70	13.15	27.41	22.58	43.59
40	**50**	**20-30**	8.31	21.81	11.98	27.75
		40-50	12.02	27.09	17.47	36.46
		60-70	13.14	33.15	22.21	43.40
	75	**20-30**	10.28	22.39	13.57	27.58
		40-50	12.27	25.54	18.86	39.70
		60-70	14.24	31.47	21.90	57.95
	100	**20-30**	10.24	23.03	14.58	32.92
		40-50	11.75	23.87	20.65	47.63
		60-70	15.74	32.00	15.03	62.07
60	**50**	**20-30**	9.92	27.21	14.00	33.47
		40-50	12.41	24.71	19.64	40.68
		60-70	16.17	36.68	19.85	80.83
	75	**20-30**	10.52	24.11	14.74	32.86
		40-50	12.32	26.85	18.68	53.22
		60-70	23.70	31.38	8.00	78.57
	100	**20-30**	10.67	24.83	15.64	36.01
		40-50	11.27	26.44	14.18	62.05
		60-70	0.25	0.75	3.33	8.33
80	**50**	**20-30**	10.18	23.70	15.01	32.25
		40-50	12.44	28.37	19.10	56.13
		60-70	28.13	37.55	8.22	80.40
	75	**20-30**	10.36	23.92	14.96	35.19
		40-50	16.85	56.65	13.11	74.73
		60-70	0.00	0.00	1.95	30.88
	100	**20-30**	9.46	23.52	14.78	44.59
		40-50	8.45	20.00	6.46	52.34

Table 5.9: The impact of SL, TL and BL on VSS for instance set T3 in the long-haul transportation setting.

SL[%]	TL[%]	BL [%]	VSS[%]	VSS_{max}[%]
20	**50**	**20-30**	8.03	24.23
		40-50	10.12	35.71
		60-70	15.79	41.69
	75	**20-30**	7.94	24.87
		40-50	14.92	37.66
		60-70	19.66	43.39
	100	**20-30**	11.16	35.40
		40-50	17.18	39.62
		60-70	21.95	43.35
40	**50**	**20-30**	10.16	33.00
		40-50	16.80	38.14
		60-70	19.90	43.09
	75	**20-30**	13.56	35.41
		40-50	17.88	37.49
		60-70	20.48	58.54
	100	**20-30**	14.40	35.04
		40-50	18.47	45.31
		60-70	10.66	88.36
60	**50**	**20-30**	13.39	34.73
		40-50	18.10	38.91
		60-70	19.28	57.73
	75	**20-30**	14.51	35.28
		40-50	18.04	78.50
		60-70	7.17	84.46
	100	**20-30**	14.30	34.40
		40-50	11.27	64.27
		60-70	3.11	23.86
80	**50**	**20-30**	14.66	35.38
		40-50	17.49	74.47
		60-70	10.46	85.88
	75	**20-30**	14.41	35.69
		40-50	11.61	63.08
		60-70	1.88	19.62
	100	**20-30**	13.71	55.57
		40-50	4.46	51.44
		60-70	2.68	6.56

Table 5.10: The impact of SL, TL and BL on VSS for instance set T5 in the long-haul transportation setting.

Considering stochasticity on the availability of planned capacity

As stated, the uncertainty on the availability of contracted capacity at the operational time is not addressed in the literature. Thus, this subsection is devoted to studying how considering the actual availability of the planned capacity as a stochastic parameter is valuable. In doing so, in the Figures 5.1 to 5.3 , we compare our results concerning $EVPI$ and VSS, with those obtained in [49], that considered two sources of uncertainty (i.e., numbers and volumes of items, and the availability and cost of extra bins), disregarding the stochasticity related to the actual volumes of first-stage bins.

In particular, the bar charts depict for each bin type (T3 and T5), the average and maximum $EVPI$ and VSS percentages in the cases of disregarding uncertainty on actual availability of booked capacity (Figure 5.1), considering this source of uncertainty in the urban distribution (Figure 5.2), and in the long-haul transportation (Figure 5.3), respectively.

Given the same characterization of the set T, both studies emphasize the usefulness of the stochastic formulation approach. Furthermore, in our case, taking into account the actual volumes of bins as a stochastic parameter leads to a significant improvement of both average and maximum values of $EVPI$ and VSS for all sets considered. For example, the average percentage VSS obtained without considering the additional uncertainty regarding actual volumes is about 6% and increases to 10% and 14% for localized and uniform losses, respectively. This range is sufficiently broad to justify considering the actual volumes of first-stage bins as stochastic rather than deterministic.

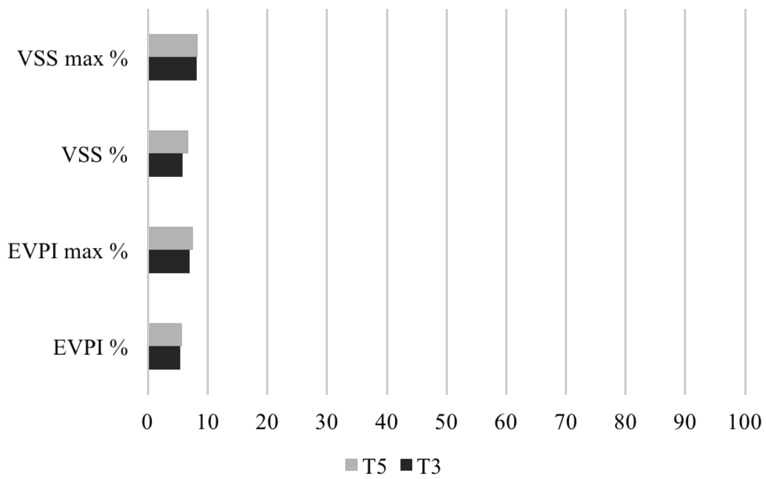

Figure 5.1: $EVPI$ and VSS comparison without uncertainty on actual availability of booked capacity.

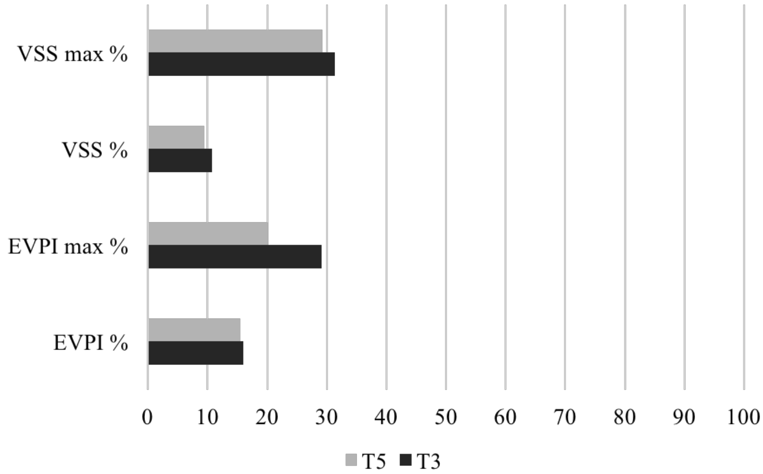

Figure 5.2: $EVPI$ and VSS comparison with uncertainty on actual availability of booked capacity in the urban distribution setting.

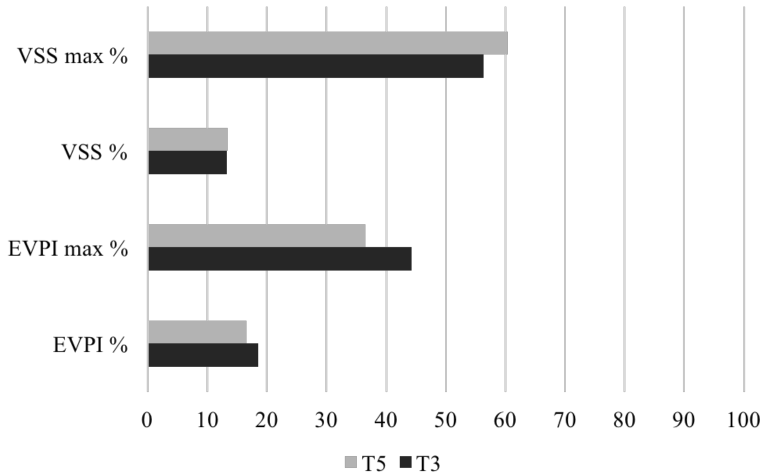

Figure 5.3: $EVPI$ and VSS comparison with uncertainty on actual availability of booked capacity in the the long-haul transportation setting.

5.4.3 Capacity-planning solution analysis

In this section, we present the capacity-planning solutions and analyze their relationship with the characteristics of the problem. In particular, we study how solutions vary depending on the attributes of the urban distribution and long-haul transportation problem settings, with emphasis on the actual volumes of first-stage bins.

As stated, the purpose is to determine whether the basic structure of the capacity planning exists and to investigate the dependence of the plan on the attributes.

For each combination of instance sets, availability classes, and other characteristics of the sets, we computed the following measures:

- average number of bin types used in the capacity plan N_t;
- average percentage of the capacity booked at the first stage Cap_{FS};
- average percentage of the objective function value achieved at the first stage Obj_{FS};
- average percentage of the fill level of the bins at the first stage f_{FS}.

In more details, we compare the model presented in this chapter with the results of the model in [49], where the loss of capacity was not considered.

Table 5.11 summarizes the ranges in which the measures vary for each capacity-planning solution according to the set of bin types (Column1), the combinations of the availability of extra bins on the spot market (Column 2). Columns from 3 to 6 show the values of these measures obtained in the long-haul transportation, while Columns from 7 to 10 refer to the urban distribution.

		No loss of volume [49]							
Set	*Availability*	Cap_{FS}	Obj_{FS}	f_{FS}	N_t				
T3	AV1	72%-84%	63%-73%	83%-89%	1.10-1.20				
	AV2(AV3)	61%-82%	53%-71%	85%-93%	1.00-1.10				
T5	AV1	67%-84%	59%-73%	85%-92%	1.33-1.44				
	AV2(AV3)	64%-83%	57%-73%	84%-92%	1.00-1.20				
		With losses of available volume							
		Long-haul transportation				Urban distribution			
Set	*Availability*	Cap_{FS}	Obj_{FS}	f_{FS}	N_t	Cap_{FS}	Obj_{FS}	f_{FS}	N_t
T3	AV1	60%-83%	48%-73%	71%-95%	1.20-3	66%-84%	59%-75%	80%-93%	1.40-2.80
	AV2(AV3)	0%-79%	0%-61%	>79%	0-1.60				
T5	AV1	6%-81%	5%-71%	84%-98%	0.30-3	55%-81%.	83%-95%.	48%-72%	1.70-3.90
	AV2(AV3)	0%-81%	0%-72%	87%-99%	0-1.80				

Table 5.11: Capacity-planning solutions.

When all the parameters that determine the actual volume of first-stage bins are equal, the resulting structures of the capacity-planning solutions are the same for availability classes AV2 and AV3. For this reason, we present the results of instances with availability class AV2 and AV3 together. For further details and the complete tables concerning the figures and results reported in this section, the interested reader could refer to the work by Lerma [139].

In the following paragraphs, we first present the structure of the capacity-planning solutions of the problem by Crainic et al. [49] and then we discuss to what extent the structure of the solution changes in the long haul transportation and urban distribution when we take into account the actual volume of first-stage bins.

Solution analysis of the basic problem When the availability of second-stage bins is limited, N_t increases (1.20 for set T3 and 1.44 for set T5). The percentages of instances that book more than one bin type at the first stage in instance sets T3 and T5 are respectively equal to 15% and 25%. However, the bins included in the capacity plan are of the same type, and only one or two bins are of different types. This relates to the cost-orientation of firms, which aim to avoid the higher loading/unloading costs generated by non-standardized loading schemes.

The percentages of Cap_{FS} and Obj_{FS} are respectively around 75% and 65%, indicating that when there is no loss of volume in first-stage bins, a capacity sufficient to limit the adjustment (when the actual demand becomes known) is booked *a priori*.

Impact of losses of available volume Considering the actual volume of first-stage bins, the structure of the capacity plan varies in the long-haul transportation and urban distribution. In particular, the different types of capacity reductions in the two contexts affect the capacity plan, as well as the availability of extra bins on the spot market, and the percentage of lost capacity. This confirms the need to take into account the reductions of available planned capacity in the capacity-planning applications. Table 5.12 examines, for each set of bin types (Column 1) and availability class (Column 2), the sensitivity of the average percentage of booked capacity (Columns 4 and 5) to the different values of the parameter alpha (Column 3).

The results show that the extra cost paid in the second stage for the recourse action affects the managerial decisions concerning how much capacity to contract, particularly in the long haul transportation. In this context, as freight demand rises and the supply falls due to the reduced availability of data and information, the spot market rates rise and the shipper will suffer from the higher second-stage costs. Thus, due to the limited alternatives in terms of recourse action, the shipper books in advance more capacity. In fact, in this case, the booked capacity is doubled when alpha reaches the highest value, 0.7, in almost all the sets and availability classes. On the contrary, in the urban distribution, the shipper should book almost the same capacity (more than 60%) in advance without significant variations, depending on the value of alpha.

Long-haul transportation. As discussed in the Section 5.4.1, in the long-haul transportation losses are uniformly distributed among the bins. In this context, when there are only three types of bins and the availability of second-stage bins is limited (AV1), the structure of the capacity-planning solution is always the same, regardless of the likelihood of losses and the percentage of lost capacity. The number of bins available at the second stage may be limited because the shipper cannot switch to another carrier. The shipper is therefore forced to buy a large portion of capacity at the first stage, although it is quite likely that this capacity will not be fully available.

Figures 5.4 to 5.7 depicts the average values of the measures Cap_{FS} and N_t when the losses are uniformed distributed, the sets are T3 and T5, and availability class AV1 and

Set	$Availability$	α	**Long-haul transportation** Cap_{FS}	**Urban distribution** Cap_{FS}
T3	AV1	0.3	35.44%	70.09%
	AV1	0.5	53.36%	78.44%
	AV1	0.7	69.03%	86.78%
	AV2(AV3)	0.3	26.49%	61.24%
	AV2(AV3)	0.5	42.01%	69.30%
	AV2(AV3)	0.7	53.50%	75.01%
T5	AV1	0.3	30.32%	61.96%
	AV1	0.5	45.71%	70.43%
	AV1	0.7	57.01%	75.64%
	AV2(AV3)	0.3	26.99%	62.98%
	AV2(AV3)	0.5	42.91%	69.99%
	AV2(AV3)	0.7	53.66%	76.16%

Table 5.12: Sensitivity of booked capacity to α.

AV2. For further details concerning the results, the interested reader could refer to [139].

As shown in the Table 5.11, Cap_{FS} is always between 60% and 83%. While, Figure 5.4 and 5.5 highlight as the value of Cap_{FS} depends on the percentage of lost volume in all BL bins. Thus, the risk of having a limited availability of extra bins and the need to load all items lead to booking much of the capacity in advance, although the actual available capacity will most likely be lower than planned.

On the one hand, when the percentage of lost volume is low, the percentage of capacity booked at the first stage depends on the value of Alpha. In particular, the capacity booked in advance is greater when the premium cost of extra bins is high. On the other hand, when the values of BL, SL, and TL are high, the percentage of first-stage capacity is always the same, whatever the cost of second-stage bins.

The impact on the objective function of the first-stage (Obj_{FS}) is quite different, ranging from 48% to 73%. Actually, this is mainly due to the different impact of the cost of extra bins and not to a real change of the solution structure.

The average N_t used in the capacity plan is always greater than 1.2, and its maximum value is equal to 3, obtained when the probability TL is equal to 75%. In particular, when SL, TL, and BL are respectively equal to 60%, 75%, and 60-70%, the number of bin types included in the plan is always greater than 2.7. This means that when numerous scenarios are affected by large reductions of volume, which nevertheless do not affect all types of vehicles, nearly all bin types are included in the capacity plan. The downside of this capacity plan is that loading/unloading costs increase because it becomes impossible to use standardized loading schemes.

The availability class AV2 indeed implies that the number of bins of a certain type available at the second stage is, in the worst case scenario, equal to half the number of bins of that type available in advance. The structure of the capacity-planning solution, for instance set T3 with availability class AV2 and uniform losses, varies considerably depending on the values assumed by the parameters SL, TL, and BL. The percentage of capacity booked at the first stage is greater when alpha is high and thus when the premium cost of extra bins is high.

When we consider instance set T5 with availability class AV2, the percentage of capacity booked at the first stage varies between 0% and 81%. The percentage of Cap_{FS} increases with the premium cost of extra bins and decreases as the parameters SL, TL, and BL increase. When the percentage of scenarios affected by capacity losses is equal to 20%, the average percentage Cap_{FS} is always greater than 29%; when at least one SL and TL is high, the percentage Cap_{FS} reaches 0% for high levels of loss. In particular, when SL and TL are set at their maximum values, no capacity is booked at the first stage if the percentage of lost volume is greater than or equal to 50%, whatever the cost of second-stage bins.

The average number of first-stage bin types used in the plan increases with alpha. Moreover, the average number of bin types N_t is always below 1.8. It means that in this case, in the long-haul transportation there is a higher level of standardization and thus, almost all the bins included in the capacity plan are the same type, whatever the probability and entity of the volume losses.

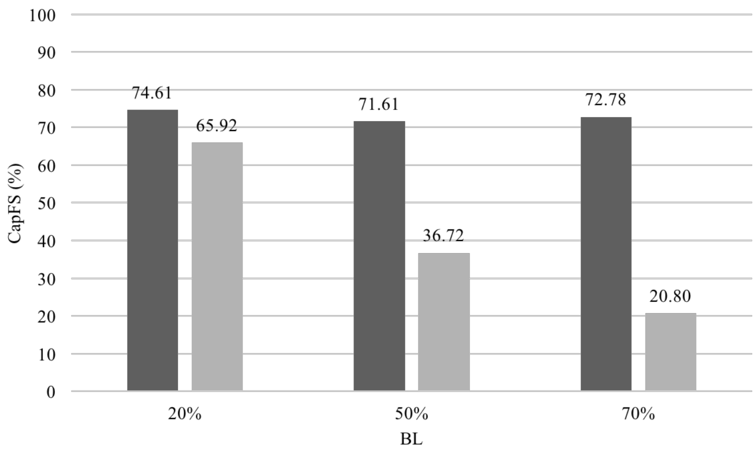

Figure 5.4: Average values of Cap_{FS} in the long-haul transportation setting, when the instance set is T3, and availability classes are AV1 (dark grey) and AV2 (light grey).

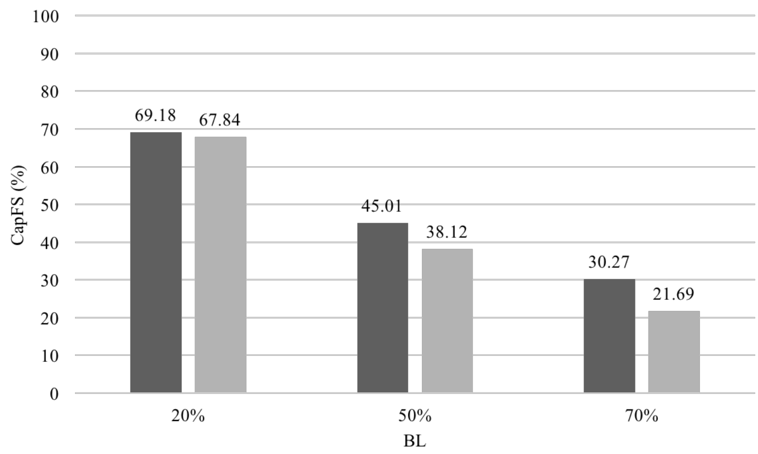

Figure 5.5: Average values of Cap_{FS} in the long-haul transportation setting, when the instance set is T5, and availability classes are AV1 (dark grey) and AV2 (light grey).

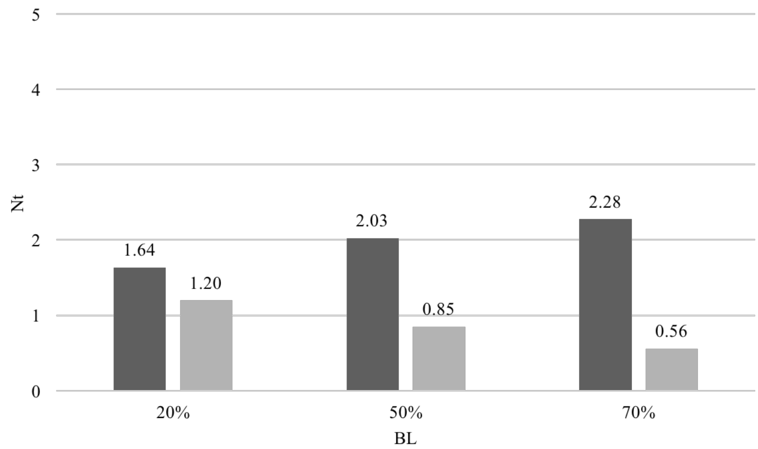

Figure 5.6: Average values of N_t in the long-haul transportation setting, when the instance set is T3, and availability classes are AV1 (dark grey) and AV2 (light grey).

Urban distribution. Regarding the urban distribution, where the losses of volume are localized, the structures of the capacity plan, when all the parameters that determine the actual volume of first-stage bins are equal, are nearly the same for all the availability classes.

Figure 5.8 to 5.11 depicts the average values of the measures Cap_{FS} and N_t when the losses are localized, the sets are T3 and T5, and availability class AV1 and AV2. For further details concerning the results, the interested reader could refer to the work by Lerma [139].

In general, the results highlight as in the urban distribution, the number of bin types used N_t is greater than 2 and reaches 3, compared in the long-haul transportation. This

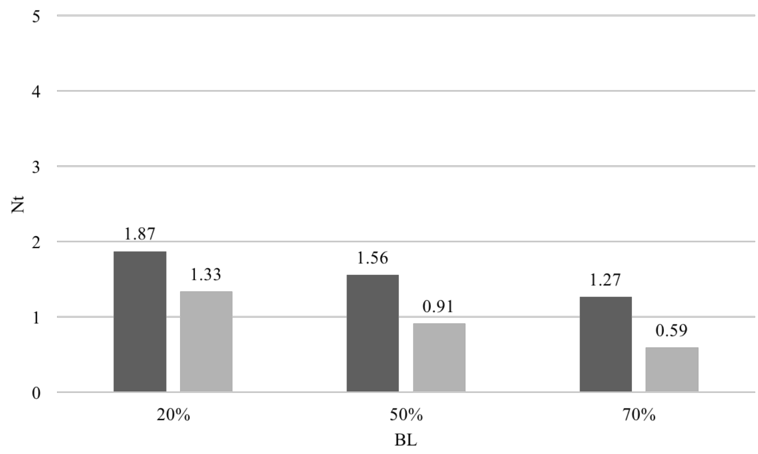

Figure 5.7: Average values of N_t in the long-haul transportation setting, when the instance set is T5, and availability classes are AV1 (dark grey) and AV2 (light grey).

trend is justified by the availability of new transportation modes (e.g. cargo-bikes) to overcome the complexities of urban centers.

In instance set T3 and availability class AV1, the percentage Cap_{FS} is between 66% and 84% (Table 5.11). Its value varies with the premium cost of extra bins in the spot market and decreases as the level of loss increases (as shown in Figures 5.8 and 5.9), while it remains the same whatever the parameter SL and TL. Thud, the capacity booked at the first stage does not depend on the probability of being affected by losses. Even if the percentage of lost volume in each bin is equal to 70%, at least 66% of the capacity is booked in advance. This aspect is also confirmed by the measure Obj_{FS}. This percentage varies between 59% and 75%. The average number of bin types N_t used in the capacity plan is 2.10 and reaches 3, varying according to the level of loss, showing how the flexibility of having a larger set of bin sizes is a good choice when a precise information about the capacity loss distribution is available (as normally in urban and last-mile distribution). The average percentage fill level related to the actual volume of first-stage bins is always between 80% and 93%. In particular, when the percentage of lost volume is greater than or equal to 50%, the average percentage fill level is greater than 84%. When the probability of loss volume is higher, the fill rate decreases, due to a massive usage of the largest bins. For example, considering vehicles with relatively small capacity adopted in urban areas, as the cargo-bikes, when there is a high probability of loss volume, they most likely will be unavailable. Thus, the shipper will prefer and book in advance larger vehicles as the vans to be used as a recovery option.

When we consider instances with availability classes AV2 or AV3, instead of AV1, the structure of the capacity plan remains the same but the capacity booked at the first stage is slightly lower. This gap grows with the percentage of lost volume.

Similarly to the instances of set T3, also for set T5, the structures of the capacity plan are almost the same for all the availability classes.

The average N_t is greater than 2 when the level of loss is lower than 40%, while when the level of loss is higher, it increases with BL and reaches 3.9. Thus, when the percentage of lost capacity is high, several types of bins are included in the capacity plan. The average percentage f_{FS} related to the actual volume of first-stage bins varies between 83% and 95% and does not depend on the parameters SL, TL, and BL, but decreases with the value of alpha. Given that the f_{FS} ranges between two high values and that the average percentage fill level of second-stage bins is always around 85%, the capacity plan results are effective, requiring only targeted adjustments at the second stage. This effectiveness is confirmed by the low level of capacity lost in the first-stage, which is almost always zero (0.3%).

Finally, when we consider instances with availability classes AV2 or AV3, instead of AV1, the structure of the capacity plan remains the same, but the capacity booked at the first stage is slightly lower.

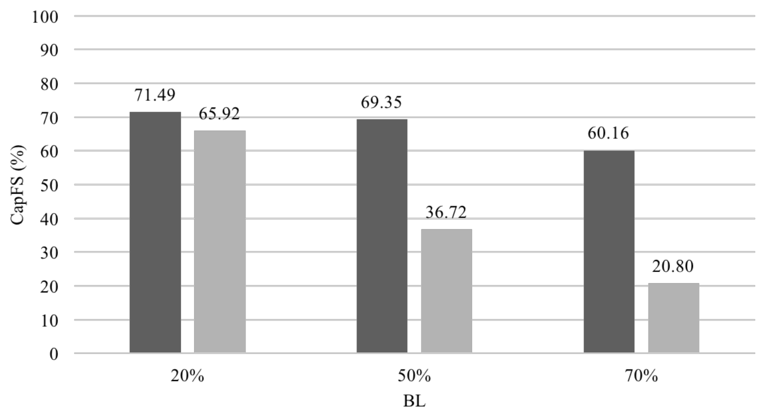

Figure 5.8: Average values of Cap_{FS} in the urban distribution setting, when the instance set is T3, and availability classes are AV1 (dark grey) and AV2 (light grey).

5.4.4 Managerial insights

We complete our analysis by summarizing the main outcomes of our experimental design, and providing some managerial insights useful to the supply-chain partners involved in the logistics segment:

- numerical results show the need to consider uncertainty in capacity-planning applications explicitly. The benefits of using this type of model compared to the complete information problem, i.e., the wait-and-see approach, and the expected value problem, are significant. Indeed, from the numerical analysis, it emerges that the stochastic formulation results in improved operations management (prediction of the capacity needed) and economic benefits in terms of lower operating costs.

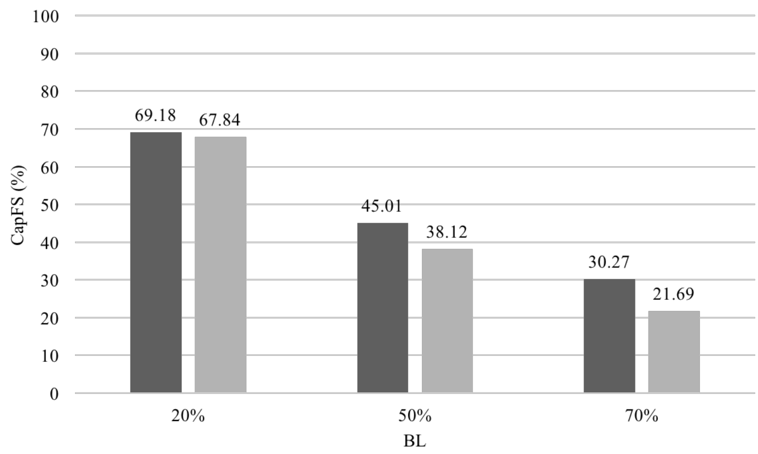

Figure 5.9: Average values of Cap_{FS} in the urban distribution setting, when the instance set is T5, and availability classes are AV1 (dark grey) and AV2 (light grey).

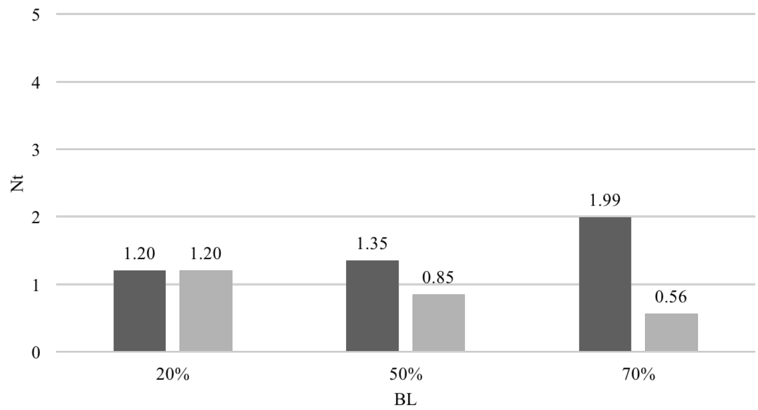

Figure 5.10: Average values of N_t in the urban distribution setting, when the instance set is T3, and availability classes are AV1 (dark grey) and AV2 (light grey).

Moreover, when the availability of bins at the shipping day is limited and there is a low probability of losing a large amount of planned capacity, the expected-value solutions lead to infeasible capacity plans.

- The structure of the capacity plan is affected by the probability of incurring a reduction of available capacity and by the type and entity of the losses, which is different in the urban distribution and the long haul transportation settings.

  In particular, in the long-haul transportation where the losses of available volume are usually uniformly distributed among the bins, if only a few types of bins are available on the spot market, and if the availability of extra bins at the shipping day is limited, the shipper should book almost all the capacity it will need for the

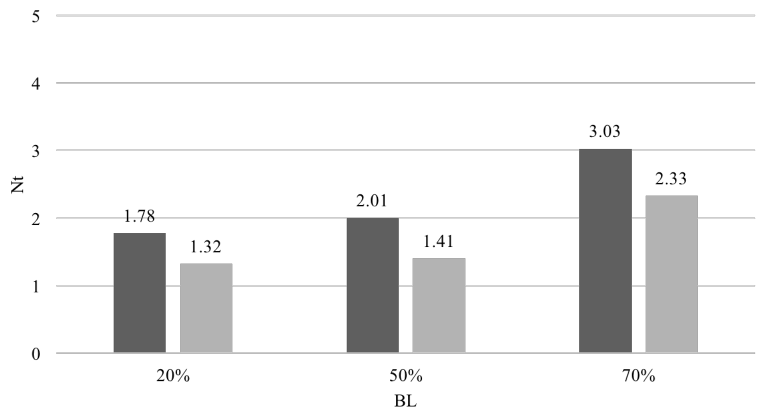

Figure 5.11: Average values of N_t in the urban distribution setting, when the instance set is T5, and availability classes are AV1 (dark grey) and AV2 (light grey).

planning horizon in advance. In particular, if there is a high probability of losing a large amount of capacity, the shipper should book more capacity than needed.

This situation could also impact on the urban distribution, in particular when logistic operations require customized treatments and carrier who has specialized equipment (e.g., refrigerated bins) provides the capacity. The shipper should book thus a large portion of capacity because at the operational day it cannot turn quickly to another carrier.

On the contrary, if there is a high probability of losing a large amount of capacity but the availability of extra bins is not limited, no capacity should be booked in advance. In this situation, the shipper, instead of making a capacity plan, should wait until the shipping date to purchase the necessary capacity at a premium price. Finally, if the reductions of capacity are highly localized as in the urban distribution context (i.e., the losses concern only a few bins or vans that become entirely unusable), the shipper should book, in advance, the same capacity that it would buy if there were no losses of capacity but using different types of bins.

Chapter 6

Conclusions

In this thesis, we have introduced a new multi-disciplinary approach to urban freight transportation and logistics problems arising in the City Logistics and Smart Cities fields.

Nowadays, a competitive and well-functioning urban freight transportation and logistics system requires the commitment and cooperation of public and private stakeholders and actors, as well as the integration of different business and operational models. This requirement calls for a holistic representation of the urban area as a MACS that acts as a "system of systems". It means that this system becomes an integrator, in a modular manner, on the one hand of existing single logistics subsystems, including single and multi-echelon structures, multimodal and intermodal delivery options and low-emission vehicles (e.g., cargo bikes, lockers), and future disruptive innovation (e.g., drones, autonomous vehicles). On the other hand, the system has to integrate a macro-level of interconnections among actors, stakeholders, and subsystems.

This integration will harness the value of behavioral, technological and optimization components to provide a solid basis of cooperation, reliable data to design policies for sustainable logistics. In particular, it brings to a multi-disciplinary challenge in modeling the overall system, in which mixing qualitative and quantitative methods and models from the different research communities are key pillars to cope with the various issues in urban areas and decisional levels.

Prior work has documented the effectiveness of this multi-disciplinary approach in dealing with emerging critical problems arising in urban freight transportation and logistics applications. These problems are the integration of traditional transportation modes (i.e., vans) and, vehicles with low-environmental impact (i.e., cargo bikes) and new delivery options (i.e., lockers), and the multiple-types capacity planning problem in the form of stochastic variable cost and size bin packing problem with uncertainty on the available capacity.

We have addressed these new applications to overcome a noteworthy portion of a gap in the literature concerning the combination of different logistics and transportation business and operational models, and the mixing of managerial and technical perspectives to design public and private policies, and jointly optimize the freight transportation process. This gap in the literature has emerged relevant in both the City Logistics and intermodal system. In fact, analyzing the rich research on intermodal transportation, we found that there is the need for new models, methods and software tools able to represent the complete transportation system, including public governance, individuals and freight movement. This holistic vision, thought the behavioral analysis and the incorporation of a managerial perspective into simulation and optimization tools, represents a significant element in designing sustainable policies appropriate for freight transportation. In this sense, the study has highlighted that policy-making processes receive little attention in the literature. Even when DSSs are available, some other gaps come from the difficult validation of models and methods. Indeed, the results generated by the generalization of classical instances are often not created for urban applications, or on artificial data (i.e., data not coming from any historical or empirical datasets), and thus, not directly compared with real or realistic settings associated to the real urban context and stakeholders. Moreover, there is no standard way of combining data gathered from different sources and, from them, generate new instances for urban applications.

To demonstrate the valuable contribution of this multi-disciplinary approach to the research in urban transportation and logistics, we applied it to deal with the recent trend in the CEP market, related to substitution of traditional single-echelon routing structures with two-echelon ones that include satellites centers and the use of environmentally-friendly vehicles. Indeed, nowadays, there is the practice of outsourcing of the last-mile activities to operators that base their businesses on the adoption of low-emission vehicles and new delivery options.

First, we analyzed the main actors involved in the urban freight transportation system from both business and operational perspectives, to identify synergies, conflicts, and the operational and economic consequences of adopting green vehicles. Most notably, this is the first study to our knowledge that has explicitly investigated the behaviors, costs and revenues structures of these actors, as well as the operational performance of the traditional and green delivery options, based on the main variables that affect the last-mile logistics in urban areas (e.g., distance, delivery time, etc.). This managerial analysis has supported a quantitative analysis of strategic actions and their implementation in operations.

Second, we proposed a new standard optimization–simulation framework for urban freight transportation and logistics that generalizes to many types of problems encountered in urban areas. This tool is able to combine data gathered from different sources and requirements from different stakeholders (e.g., city administrations, companies, city technology infrastructures), building new realistic instance sets.

We have conducted this study through case studies that aimed to evaluate the integration of transportation modes and delivery options to face the demand from e-commerce, in an urban context as the City of Turin (Italy).

Our results provide compelling evidence that the switch to vehicles with a low environmental impact and lockers does not generate benefits in absolute terms, but it needs to be calibrated and assessed, due to the loss of efficiency for traditional subcontractors, that this type of integration could cause. On the one hand, the outsourcing of deliveries to green subcontractors could determine the reduction of CO_2 emissions, economic efficiency for traditional business models, better working condition for drivers, and improvement of quality level required by time-sensitive services. This last benefit is a consequence of the reduction of delivery times and the overcoming of regulatory and infrastructure restrictions in the city (e.g., low-emission zones, traffic, and congestion) by cargo bikes. Moreover, the bikes represent the most suitable vehicles to face online requests for deliveries, due to their high flexibility. On the other hand, the loss of efficiency for traditional subcontractors has to be contained and balanced by an increase in service quality provided by green subcontractors, to maintain an equilibrium in the system. Mitigating this issue and achieving a reasonable level of efficiency in the overall system, require a continuous process of optimization and planning activities implemented by a DSS that considers the requirements of all stakeholders and the evolution of society.

Concerning new planning problems, we addressed the Stochastic Variable Cost and Size Bin Packing Problem with Loss of Available Capacity ($SVCSBPP_L$), which explicitly takes into account the presence of uncertainty on parameters that characterize the system of urban areas and strongly affect the tactical decisions related to the outsourcing process. This analysis has overcome the gap in the literature of comprehensive study of the sources of uncertainty that affect the capacity planning, and particularly, the explicit representation of the uncertainty on the actual volume of contracted capacity resources. The results provided by extensive computational tests shown the usefulness of building a stochastic programming model and explicitly considering the uncertainty on the actual volume of booked capacity. Some managerial insights have been drawn out of the results. In particular, it emerged that the capacity plan depends on the probability of suffering from reductions of available capacity and on the type and the entity of these losses.

Two future directions need to be further investigated. First, concerning this emerging bi-vehicular model, future research should analyze how the dynamics in urban freight transportation systems change after introducing vehicles with a low environmental impact, such as electric and the hybrid vehicles, as well as additional traditional vehicles owned by unprofessional users. This last practice is known as “Crowdsourcing”, and according to the work by Giret et al. [107], it has the aim of reducing the need of dedicated logistic moves (by vans, and/or trucks), by exploiting the citizens’ movements that become temporal deliverers, while increasing the service level with respect to the strict time windows imposed by the demand-driven logistics.

Second, the $SVCSBPP_L$ is based on the hypothesis that a company contracts capacity with only one carrier. In reality, this hypothesis may be not always correct, and it entails the selection of the carriers to activate businesses and the contracting with them to book the necessary capacity before operations start. One can generalize the $SVCSBPP_L$ explicitly introducing the problem of choosing multiple carriers and of determining the quantity of capacity of different types to purchase from each selected carrier.

In this direction, we modeled the new capacity planning problem by proposing a new modeling framework. It takes the form of a stochastic bin packing problem, called the *Stochastic Variable Cost and Size Bin Packing Problem with Supplier Selection* ($SVCSBPP_L$), which generalizes prior work on the $SVCSBPP_L$ proposed in this thesis, introducing the supplier selection problem. The extended model is based on two-stage stochastic programming with recourse formulation.

Currently, we are developing an innovative solution method for this problem based on a constructive heuristic for selecting carriers and determining the quantity of capacity units of different types to book for the next period of activity, and a metaheuristic inspired by the PH idea. An extensive computational campaign is required to analyze the impact of the new problem settings on capacity planning.

Appendix A

PH-based meta-heuristic

A.1 Scenario decomposition

We first reformulate the SVCSBPP$_L$ stochastic (5.1)-(5.10) model using scenario decomposition. Sampling is applied to obtain a set of representative scenarios, namely the set $\mathscr{S}$, and these are used to approximate the expected cost associated with the second stage. For the first stage, let $y_j^{ts} = 1$ if bin $j \in \mathscr{J}^t$ of type $t \in T$ is selected under scenario $s \in \mathscr{S}$ and 0 otherwise. For the second stage, define $\mathscr{K}^s = \bigcup_\tau \mathscr{K}^{\tau s}$, where $\mathscr{K}^{\tau s}$ is the set of extra bins of type $\tau \in \mathscr{T}$ in scenario $s \in \mathscr{S}$, and let $\mathscr{I}^s$ be the set of items to pack under scenario $s \in \mathscr{S}$. Let $g^{\tau s}$ be the cost associated with bins of type $\tau \in \mathscr{T}$ in scenario $s \in \mathscr{S}$, $\mathcal{V}_j^{ts}$ be the actual volume of first-stage bin $j \in \mathscr{J}^t$ under scenario $s \in \mathscr{S}$, and v_i^s be the volume of item $i \in \mathscr{I}^s$ in scenario $s \in \mathscr{S}$. Then, variable $z_k^{\tau s}$ is equal to 1 if and only if extra bin $k \in \mathscr{K}^{\tau s}$ of type $\tau \in \mathscr{T}$ is selected in scenario $s \in \mathscr{S}$, and x_{ij}^s and x_{ik}^s are item-to-bin assignment variable for scenario $s \in \mathscr{S}$.

Given the probability p_s of each scenario $s \in \mathscr{S}$, the SVCSBPP$_L$ problem (5.1)-(5.10) can be approximated by the following equivalent deterministic model:

$$\min_{y,z,x} \sum_{s \in \mathscr{S}} p_s \left[\sum_{t \in T} \sum_{j \in \mathscr{J}^t} f^t y_j^{ts} + \sum_{\tau \in \mathscr{T}} \sum_{k \in \mathscr{K}^{\tau s}} g^{\tau s} z_k^{\tau s} + \sum_{t \in T} \sum_{j \in \mathscr{J}^t} c^t (V^t - \mathcal{V}_j^{ts}) y_j^{ts} \right] \tag{A.1}$$

$$
\begin{aligned}
\text{s.t.}\quad & y_j^{ts} \geq y_{j+1}^{ts}, && \forall\, t \in T, j = 1, \ldots, |\mathscr{J}^t| - 1, s \in \mathscr{S}, && \text{(A.2)}\\
& \sum_{j \in \mathscr{J}} x_{ij}^s + \sum_{k \in \mathscr{K}^s} x_{ik}^s = 1, && \forall\, i \in \mathscr{I}^s, s \in \mathscr{S}, && \text{(A.3)}\\
& \sum_{i \in \mathscr{I}^s} v_i^s x_{ij}^s \leq \mathcal{V}_j^{ts} y_j^{ts}, && \forall\, t \in T, j \in \mathscr{J}^t, s \in \mathscr{S}, && \text{(A.4)}\\
& \sum_{i \in \mathscr{I}^s} v_i^s x_{ik}^s \leq V^\tau z_k^{\tau s}, && \forall\, \tau \in \mathscr{T}, k \in \mathscr{K}^{\tau s}, s \in \mathscr{S}, && \text{(A.5)}\\
& y_j^{ts} = y_j^{ts'}, && \forall\, t \in T, j \in \mathscr{J}^t, s, s' \in \mathscr{S}, && \text{(A.6)}\\
& y_j^{ts} \in \{0,1\}, && \forall\, t \in T, j \in \mathscr{J}^t, s \in \mathscr{S}, && \text{(A.7)}\\
& z_k^{\tau s} \in \{0,1\}, && \forall\, \tau \in \mathscr{T}, k \in \mathscr{K}^{\tau s}, s \in \mathscr{S}, && \text{(A.8)}\\
& x_{ij}^s \in \{0,1\}, && \forall\, i \in \mathscr{I}^s, j \in \mathscr{J}, s \in \mathscr{S}, && \text{(A.9)}\\
& x_{ik}^s \in \{0,1\}, && \forall\, i \in \mathscr{I}^s, k \in \mathscr{K}^s, s \in \mathscr{S}. && \text{(A.10)}
\end{aligned}
$$

Constraints (A.6) are referred as the non-anticipativity constraints. They ensure that the first-stage decisions are not tailored to the scenarios considered in $\mathscr{S}$. Indeed, all the scenario solutions must be equal to produce a single implementable plan. Thus, the non-anticipativity constraints link the first-stage variables to the second-stage variables, so the model is not separable.

To apply Lagrangean relaxation and make the model separable, we need a different expression of the non-anticipativity constraints. Let $\bar{y}_j^t \in \{0,1\}, \forall\, t \in T, j \in \mathscr{J}^t$, be the *global capacity plan*, i.e., the set of bins selected at the first stage. The following constraints are equivalent to (A.6):

$$
\begin{aligned}
& \bar{y}_j^t = y_j^{ts}, && \forall\, t \in T,\ j \in \mathscr{J}^t, s \in \mathscr{S}, && \text{(A.11)}\\
& \bar{y}_j^t \in \{0,1\}, && \forall\, t \in T,\ j \in \mathscr{J}^t. && \text{(A.12)}
\end{aligned}
$$

Constraints (A.11) force the first-stage solution of each scenario to be equal to the global capacity plan. Constraints (A.12) are simply the integrality conditions on the selection of the bins. With this formulation of the non-anticipativity constraints, when we apply Lagrangean relaxation to (A.11), we can penalize individually the difference between the scenario solution and the global solution of each bin in the plan.

Following the decomposition scheme proposed by [199], we relax constraints (A.11) using an augmented Lagrangean strategy. We thus obtain the following objective function for the overall problem:

$$
\begin{aligned}
\min_{y,z,x} \sum_{s \in \mathscr{S}} p_s \Bigg[& \sum_{t \in T} \sum_{j \in \mathscr{J}^t} f^t y_j^{ts} + \sum_{\tau \in \mathscr{T}} \sum_{k \in \mathscr{K}^{\tau s}} g^{\tau s} z_k^{\tau s} + \sum_{t \in T} \sum_{j \in \mathscr{J}^t} c^t (V^t - \mathcal{V}_j^{ts}) y_j^{ts} + \\
& + \sum_{t \in T} \sum_{j \in \mathscr{J}^t} \lambda_j^{ts} (y_j^{ts} - \bar{y}_j^t) + \frac{1}{2} \sum_{t \in T} \sum_{j \in \mathscr{J}^t} \rho_j^t (y_j^{ts} - \bar{y}_j^t)^2 \Bigg]
\end{aligned} \tag{A.13}
$$

where $\lambda_j^{ts}, \forall\, j \in \mathscr{J}^t, \forall\, t \in T$, and $\forall\, s \in \mathscr{S}$, define the Lagrangean multipliers for the relaxed constraints and ρ_j^t is a penalty ratio associated with bin $j \in \mathscr{J}^t$ of type $t \in T$. Within function A.13, let us consider the quadratic term. Given the binary requirements of y_j^{ts} and $\bar{y}_j^t$, the term becomes:

$$\sum_{t\in T}\sum_{j\in\mathcal{J}^t}\rho_j^t\left(y_j^{ts}-\bar{y}_j^t\right)^2=\sum_{t\in T}\sum_{j\in\mathcal{J}^t}\left(\rho_j^t(y_j^{ts})^2-2\rho_j^t y_j^{ts}\bar{y}_j^t+\rho_j^t(\bar{y}_j^t)^2\right)= \tag{A.14}$$

$$=\sum_{t\in T}\sum_{j\in\mathcal{J}^t}\left(\rho_j^t y_j^{ts}-2\rho_j^t y_j^{ts}\bar{y}_j^t+\rho_j^t\bar{y}_j^t\right). \tag{A.15}$$

Therefore, the objective function can be formulated as follows:

$$\begin{aligned}\min_{y,z,x}\sum_{s\in\mathcal{S}}p_s\Bigg[&\sum_{t\in T}\sum_{j\in\mathcal{J}^t}\left(f^t+c^{ts}(V^t-\mathcal{V}_j^{ts})+\lambda_j^{ts}-\rho_j^t\bar{y}_j^t+\frac{\rho_j^t}{2}\right)y_j^{ts}+\\&+\sum_{\tau\in\mathcal{T}}\sum_{k\in\mathcal{K}^{\tau s}}g^{\tau s}z_k^{\tau s}-\sum_{t\in T}\sum_{j\in\mathcal{J}^t}\lambda_j^{ts}\bar{y}_j^t+\frac{1}{2}\sum_{t\in T}\sum_{j\in\mathcal{J}^t}\rho_j^t\bar{y}_j^t\Bigg].\end{aligned} \tag{A.16}$$

Given constraints (A.2)-(A.10) and the objective function (A.16), the relaxed problem is not separable by scenario. However, if the overall plan $\bar{y}_j^t, \forall t\in T$ and $\forall j\in\mathcal{J}^t$, is fixed to a given value vector (i.e., the expected value of the scenario solutions), then the model decomposes according to the scenarios in $\mathcal{S}$ and the scenario subproblems can be expressed as follows:

$$\min_{y,z,x}\quad\sum_{t\in T}\sum_{j\in\mathcal{J}^t}\left(f^t+c^{ts}(V^t-\mathcal{V}_j^{ts})+\lambda_j^{ts}-\rho_j^t\bar{y}_j^t+\frac{\rho_j^t}{2}\right)y_j^{ts}+\sum_{\tau\in\mathcal{T}}\sum_{k\in\mathcal{K}^{\tau s}}g^{\tau s}z_k^{\tau s} \tag{A.17}$$

$$\text{s.t.}\quad y_j^{ts}\ge y_{j+1}^{ts},\qquad \forall\, t\in T, j=1,\ldots,|\mathcal{J}^t|-1, s\in\mathcal{S}, \tag{A.18}$$

$$\sum_{j\in\mathcal{J}}x_{ij}^s+\sum_{k\in\mathcal{K}^s}x_{ik}^s=1,\qquad \forall\, i\in\mathcal{I}^s, s\in\mathcal{S}, \tag{A.19}$$

$$\sum_{i\in\mathcal{I}^s}v_i^s x_{ij}^s\le\mathcal{V}_j^{ts}y_j^{ts},\qquad \forall\, t\in T, j\in\mathcal{J}^t, s\in\mathcal{S}, \tag{A.20}$$

$$\sum_{i\in\mathcal{I}^s}v_i^s x_{ik}^s\le V^\tau z_k^{\tau s},\qquad \forall\,\tau\in\mathcal{T}, k\in\mathcal{K}^{\tau s}, s\in\mathcal{S}, \tag{A.21}$$

$$y_j^{ts}\in\{0,1\},\qquad \forall\, t\in T, j\in\mathcal{J}^t, s\in\mathcal{S}, \tag{A.22}$$

$$z_k^{\tau s}\in\{0,1\},\qquad \forall\,\tau\in\mathcal{T}, k\in\mathcal{K}^{\tau s}, s\in\mathcal{S}, \tag{A.23}$$

$$x_{ij}^s\in\{0,1\},\qquad \forall\, i\in\mathcal{I}^s, j\in\mathcal{J}, s\in\mathcal{S}, \tag{A.24}$$

$$x_{ik}^s\in\{0,1\},\qquad \forall\, i\in\mathcal{I}^s, k\in\mathcal{K}^s, s\in\mathcal{S}. \tag{A.25}$$

Furthermore, by noting that λ_j^{ts} and ρ_j^t are exogenous constants for the model (A.17)-(A.25), we can reformulate each scenario subproblem as follows. We define $\overline{\mathcal{T}}=T\cup\mathcal{T}$ to be the overall set of bin types. For each scenario s, let $\mathcal{B}^{\overline{\tau}s}=\mathcal{J}^{\overline{\tau}}\cup\mathcal{K}^{\overline{\tau}s}$ be the set of available bins of type $\overline{\tau}$ in the subproblem and $\mathscr{B}^s = \bigcup_{\overline{\tau}} \mathscr{B}^{\overline{\tau}s}$ be the whole set of bins available in the subproblem. For $b \in \mathscr{B}^{\overline{\tau}s}$, let $\mathcal{V}_b^{\overline{\tau}s}$ be the actual volume of bin b (for $b \in \mathscr{K}^{\overline{\tau}s}$, $\mathcal{V}_b^{\overline{\tau}s} = V^{\overline{\tau}}$) and let $f_b^{\overline{\tau}s}$ define the fixed cost associated with bin b. The value of $f_b^{\overline{\tau}s}$ is given by

$$f_b^{\overline{\tau}s} = \begin{cases} f^{\overline{\tau}} + c^{\overline{\tau}s}(V^{\overline{\tau}} - \mathcal{V}_b^{\overline{\tau}s}) + \lambda_b^{\overline{\tau}s} - \rho_b^{\overline{\tau}} \bar{y}_b^{\overline{\tau}} + \frac{\rho_b^{\overline{\tau}}}{2} & \overline{\tau} \in \overline{\mathscr{T}}, b \in \mathscr{J}^{\overline{\tau}} \\ g^{\overline{\tau}s} & \overline{\tau} \in \overline{\mathscr{T}}, b \in \mathscr{K}^{\overline{\tau}s}. \end{cases} \tag{A.26}$$

Thus, each scenario subproblem can be reduced to a deterministic VCSBPP with modified fixed costs and an additional constraint that ensures an order in the selection of bins of type $\overline{\tau} \in \overline{\mathscr{T}}$:

$$\min_{y,x} \quad \sum_{\overline{\tau} \in \overline{\mathscr{T}}} \sum_{b \in \mathscr{B}^{\overline{\tau}s}} f_b^{\overline{\tau}s} y_b^{\overline{\tau}s} \tag{A.27}$$

$$\text{s.t.} \quad y_b^{\overline{\tau}s} \geq y_{b+1}^{\overline{\tau}s}, \qquad \forall\, \overline{\tau} \in \overline{\mathscr{T}}, b = 1, \ldots, |\mathscr{B}^{\overline{\tau}s}| - 1, \tag{A.28}$$

$$\sum_{b \in \mathscr{B}^s} x_{ib}^s = 1, \qquad \forall\, i \in \mathscr{I}^s, \tag{A.29}$$

$$\sum_{i \in \mathscr{I}^s} v_i^s x_{ib}^s \leq \mathcal{V}_b^{\overline{\tau}s} y_b^{\overline{\tau}s}, \qquad \forall\, \overline{\tau} \in \overline{\mathscr{T}}, b \in \mathscr{B}^{\overline{\tau}s}, \tag{A.30}$$

$$y_b^{\overline{\tau}s} \in \{0,1\}, \qquad \forall \overline{\tau} \in \overline{\mathscr{T}}, b \in \mathscr{B}^{\overline{\tau}s}, \tag{A.31}$$

$$x_{ib}^s \in \{0,1\}, \qquad \forall\, i \in \mathscr{I}^s, b \in \mathscr{B}^s, \tag{A.32}$$

where $y_b^{\overline{\tau}s} = 1$ if bin $b \in \mathscr{B}^{\overline{\tau}s}$ of type $\overline{\tau} \in \overline{\mathscr{T}}$ is selected, 0 otherwise.

A.2 Phase 1 of the meta-heuristic

A.2.1 Obtaining consensus among subproblems

At each iteration of the meta-heuristic, the solutions of the scenario subproblems are used to build a temporary global solution (the overall capacity plan). *Consensus* is then defined as scenario solutions being similar with regard to the first-stage decisions with the overall capacity plan and, thus, being similar among themselves. This section describes how the overall plan is computed. Moreover, we introduce strategies for the penalty adjustment when nonconsensus is observed and techniques to guide the search process by bounding the number of bins that can be selected at the first stage.

A.2.2 Defining the overall capacity plan

Let ν be the iteration counter in the PH algorithm. At each iteration, the algorithm solves subproblems (A.27)–(A.32), obtaining local solutions $y_b^{\overline{\tau}s\nu}$ $y_j^{\tau s\nu}$, $\forall s \in \mathscr{S}$, $\forall \overline{\tau} \in \overline{\mathscr{T}}$, and $\forall b \in \mathscr{B}^{\overline{\tau}s}$. The subproblem solutions are then combined in the overall capacity plan

$\bar{y}_b^{\overline{\tau}\nu}$ by using the expected value operator, as shown in Equation (A.33). The weight used for each component is the probability p_s associated with the corresponding scenario.

$$\bar{y}_b^{\overline{\tau}\nu} = \sum_{s\in\mathcal{S}} p_s y_b^{\overline{\tau}s\nu}, \quad \forall\overline{\tau}\in\overline{\mathcal{T}}, \forall b\in\mathcal{B}^{\overline{\tau}}. \tag{A.33}$$

Moreover, we define an overall solution based on the number of bins in the capacity plan. Let $\delta^{\overline{\tau}s\nu} = \sum_{b\in\mathcal{B}^{\overline{\tau}}} y_b^{\overline{\tau}s\nu}$ be the total number of bins of type $\overline{\tau}\in\overline{\mathcal{T}}$ in the capacity plan for scenario subproblem $s\in\mathcal{S}$ at iteration ν. Equivalently to (A.33), using the expected value operator on $\delta^{\overline{\tau}s\nu}$ $\forall s\in\mathcal{S}$, we can define the overall capacity plan for each bin type $\overline{\tau}\in\mathcal{T}$ as

$$\bar{\delta}^{\overline{\tau}\nu} = \sum_{s\in\mathcal{S}} p_s\delta^{\overline{\tau}s\nu} = \sum_{s\in\mathcal{S}} p_s \sum_{b\in\mathcal{B}^{\overline{\tau}}} y_b^{\overline{\tau}s\nu} = \sum_{b\in\mathcal{J}^{\overline{\tau}}}\sum_{s\in\mathcal{S}} p_s y_b^{\overline{\tau}s\nu} = \sum_{b\in\mathcal{B}^{\overline{\tau}}} \bar{y}_b^{\overline{\tau}\nu}. \tag{A.34}$$

Equation (A.34) can be used to define the stopping criterion. Thus, we consider consensus to be achieved when the values of $\delta^{\overline{\tau}s\nu}$, $\forall s\in\mathcal{S}$, are equal to $\bar{\delta}^{\overline{\tau}\nu}$.

It is important to note that (A.33) and (A.34) do not necessarily produce a feasible capacity plan. When consensus is not achieved, the overall solution may not satisfy the integrality constraints on the first-stage decision variables. For nonconvex problems such as the SVCSBPP$_L$ using the expected value as an aggregation operator does not guarantee that the algorithm converges to the optimal solution. Moreover, it cannot ensure that a good (feasible) solution will be obtained for the stochastic problem. Therefore, (A.33) and (A.34) are used as reference solutions with the goal of helping the search process of the PH algorithm to identify bins for which consensus is possible. Both are used in the penalty adjustment, while (A.34) is also used in the bounding strategy.

A.2.3 Penalty adjustment strategies

To induce consensus among the scenario subproblems, we adjust the penalties in the objective function at each iteration to penalize a lack of implementability and dissimilarity between local solutions and the overall solution. We propose two different strategies for these adjustments, both working at the local level in the sense that they affect every scenario subproblem separately.

The first strategy was originally proposed by [199]. Using information on the bin selection (i.e., variable $y_b^{\overline{\tau}s\nu}$), it operates on the fixed costs by changing the Lagrangean multipliers. For a given iteration ν, let $\lambda_b^{\overline{\tau}s\nu}$ be the Lagrangean multiplier associated with bin $b\in\mathcal{B}^{\overline{\tau}s}$ for scenario $s\in\mathcal{S}$, and let $\rho_b^{\overline{\tau}\nu}$ be the penalty deriving from the quadratic term. Note that the value of $\rho_b^{\overline{\tau}\nu}$ is variable-specific. At each iteration, we update the values $\lambda_b^{\overline{\tau}s\nu}$ and $\rho_b^{\overline{\tau}\nu}$, $\forall b\in\mathcal{B}^{\overline{\tau}s}$ and $\forall s\in\mathcal{S}$, as follows:

$$\lambda_b^{\overline{\tau}s\nu} = \lambda_b^{\overline{\tau}s(\nu-1)} + \rho_b^{\overline{\tau}(\nu-1)}(y_b^{\overline{\tau}s\nu} - \bar{y}_b^{\overline{\tau}\nu}) \tag{A.35}$$

$$\rho_b^{\overline{\tau}\nu} \leftarrow \alpha\rho_b^{\overline{\tau}(\nu-1)}, \tag{A.36}$$

where $\alpha > 1$ is a given constant and $\rho_b^{\overline{\tau}0}$ is fixed to a positive value to ensure that $\rho_b^{\overline{\tau}\nu} \to \infty$ as the number of iterations ν increases.

We initialize $\lambda_b^{s0} = 0$ for each scenario $s \in \mathscr{S}$. Equation (A.35) can then reduce, increase, or maintain this contribution according to the difference between the value of the bin-selection variables in the subproblem solutions and the overall capacity plan. The initial choice of $\rho_b^{\overline{\tau}0}$ is important. An inaccurate choice may cause premature convergence to a solution that is far from optimal or cause slow convergence of the search process. To avoid this, we set $\rho_b^{\overline{\tau}0}$ proportional to the fixed cost associated with the bin-selection variable: $\rho_b^{\overline{\tau}0} = max(1, f^{\overline{\tau}}/10)$, $\forall b \in \mathscr{B}^{\overline{\tau}s}$ and $\forall \overline{\tau} \in \overline{\mathscr{T}}$. The value of $\rho_b^{\overline{\tau}0}$ increases according to (A.36) as the number of iteration grows.

The second penalty adjustment is a heuristic strategy, which directly tunes the fixed costs of bins of the same type. The goal of this strategy is to accelerate the search process when the overall solution is close to consensus. When consensus is close, the difference between the subproblem solution and the overall solution may be small, and adjustments (A.35) and (A.36) lose their effectiveness, requiring several iterations to reach consensus.

Let $f^{\overline{\tau}s\nu}$ be the fixed cost of bin $b \in \mathscr{B}^{\overline{\tau}s}$ of type $overline\tau \in \overline{\mathscr{T}}$ for scenario $s \in \mathscr{S}$ at iteration ν. At the beginning of the algorithm ($\nu = 0$), we impose $f^{\overline{\tau}s0} = f^{\tau}$. Then, when at least $\sigma_{\%}$ of the variables have reached consensus, we perturb every subproblem by changing $f^{\overline{\tau}s\nu}$ as follows:

$$f^{\overline{\tau}s\nu} = \begin{cases} f^{\overline{\tau}s(\nu-1)} \cdot M & \text{if } \delta^{\overline{\tau}s(\nu-1)} > \bar{\delta}^{\overline{\tau}(\nu-1)} \\ f^{\overline{\tau}s(\nu-1)} \cdot \frac{1}{M} & \text{if } \delta^{\overline{\tau}s(\nu-1)} < \bar{\delta}^{\overline{\tau}(\nu-1)} \\ f^{\overline{\tau}s(\nu-1)} & otherwise. \end{cases} \tag{A.37}$$

Here M is a constant greater than 1, while $\sigma_{\%}$ is a constant such that $0.5 \leq \sigma_{\%} \leq 1$. The current implementation of this heuristic strategy uses $\sigma_{\%} = 0.75$ and $M = 1.1$. The rationale for (A.37) is the following: if $\delta^{\overline{\tau}s(\nu-1)} > \bar{\delta}^{\overline{\tau}(\nu-1)}$, this means that in the previous iteration the number of bins of a given bin type $\overline{\tau}$ in scenario s was larger than the number of bins in the reference solution $\bar{\delta}^{\overline{\tau}(\nu-1)}$. Thus, the use of bins of type $\overline{\tau}$ is penalized by increasing the fixed cost by M. On the other hand, if $\delta^{\overline{\tau}s(\nu-1)} < \bar{\delta}^{\overline{\tau}(\nu-1)}$, we promote bins of type $\overline{\tau}$ by reducing the fixed cost by $1/M$.

A.2.4 Bundle fixing

To guide the search process, we introduce a variable-fixing strategy called bundle fixing.

We restrict the number of bins of each type that can be used, specifying lower and upper bounds. It should be noticed that it is equivalent to fix single bin-selection variables, since all bins of a certain type $\overline{\tau}$ are ordered and constraint A.28 ensures that the selection of bins follows this order.

Let $\bar{\delta}_m^{\overline{\tau}\nu}$ and $\bar{\delta}_M^{\overline{\tau}\nu}$ be the minimum and maximum number of bins of type $\overline{\tau}$ involved in the overall solution at iteration v:

$$\bar{\delta}_m^{\bar{\tau}v} \leftarrow \min_{s\in\mathscr{S}} \delta^{\bar{\tau}sv}, \tag{A.38}$$

$$\bar{\delta}_M^{\bar{\tau}v} \leftarrow \max_{s\in\mathscr{S}} \delta^{\bar{\tau}sv}. \tag{A.39}$$

At each iteration, the bundle strategy applies two bounds as follows. The lower bound $\bar{\delta}_m^{\bar{\tau}v}$ determines a set of compulsory bins that must be used in each subproblem; to implement this we set the decision variables $y_b^{\bar{\tau}s(v+1)}$ to one for $b = 1,...,\bar{\delta}_m^{\bar{\tau}v}$. The upper bound $\bar{\delta}_M^{\bar{\tau}v}$ is an estimate of the maximum number of bins of type $\bar{\tau}$ available in the next iteration; this reduces the number of decision variables in the subproblems. To implement this we remove decision variables $y_b^{\bar{\tau}s(v+1)}$ for $b = \bar{\delta}_M^{\bar{\tau}v} + 1,..., \|\mathscr{B}^{\bar{\tau}}\|$.

A.2.5 Termination criteria

There are to date no theoretical results on the convergence of the PH algorithm for integer problems. Thus, we implement three stopping criteria for the search phase of the proposed meta-heuristic, based on the level of consensus reached and the number of iterations.

The level of consensus is measured through equations A.38 and A.39, as consensus is reached when $\bar{\delta}_m^{\bar{\tau}v} = \bar{\delta}_M^{\bar{\tau}v}, \forall \bar{\tau} \in \overline{\mathscr{T}}$. To speed up the algorithm, we actually stop the search, and proceed to Phase 2, as soon as consensus has been reached for all the bin types except one, type $\bar{\tau}'$, for which $\bar{\delta}_m^{\bar{\tau}'} < \bar{\delta}_M^{\bar{\tau}'}$.

When neither of the preceding conditions has been reached within a maximum number of iterations (200 in our experiments), the search is stopped and the meta-heuristic proceeds to the Phase 2.

A.3 Phase 2 of the meta-heuristic

Phase 2 is thus invoked either when consensus is not achieved within a given maximum number of iterations, or the search was stopped when all but one bin type were in consensus.

In the first case, there is only one bin type $\bar{\tau}'$ with $\bar{\delta}_m^{\bar{\tau}'} < \bar{\delta}_M^{\bar{\tau}'}$, that is, not in consensus. Given the efficiency of the item-to-bin heuristic, Phase 2 computes the final solution by iteratively examining the possible number of bins for $\bar{\tau}'$ (a consensus solution is always possible because $\bar{\delta}_M^{\bar{\tau}'}$ is feasible in all scenarios):

- **For all** $\delta \in \left[\bar{\delta}_m^{\bar{\tau}'}, \bar{\delta}_M^{\bar{\tau}'}\right]$ **do**
  - Set the number of bins of type $\bar{\tau}'$ to δ;
  - Solve all the scenario subproblems with the heuristic;

- Check the feasibility of the solutions;
- Update the overall solution if a better solution has been found;

Produce the consensus solution.

When the maximum number of iterations is reached, consensus is less close. Phase 2 of the meta-heuristic then builds a restricted version of the formulation (A.1)–(A.10) by fixing the bin-selection first-stage variables for which consensus has been achieved, together with the associated item-to-bin assignment variables. The range of the bin types not in consensus is reduced through bundle fixing, and the resulting MIP is solved exactly.

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