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Operations Research for Planning and Managing City Logistics Systems

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Abstract. The chapter presents the Operations Research models and methods to plan and manage City Logistics systems, in particular their supply components. It presents the main planning issues and challenges, and reviews the proposed methodologies. The chapter concludes with a discussion on perspectives for City Logistics and decision-support methodological developments.

Keywords: City logistics systems; planning and management; decision-support methods; operations research; system design; service design; routing, last and first-mile pickup and delivery.

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1 Introduction

Urban freight transport encompasses the movement of freight vehicles whose primary purpose is to carry goods into, out of, and within urban areas (OECD, 2003). These movements are part of the logistics activities performed in the city regarding, mainly, the transport, storage, and handling of goods, to answer the demand raised by most economic and social activities taking place in urban areas. For the city inhabitants, it supplies stores and places of work and leisure, delivers goods at home, provides the means to get rid of refuse, etc. It forms a vital link for firms with suppliers and customers situated both within the city limits and elsewhere in the world. There are indeed few activities in a city that do not require at least some commodities being moved. Thus, efficient urban freight transport and logistics is a major enabling factor for city life and development. However, it is also a major disturbing factor to urban life in terms of congestion, pollution, safety, and security (OECD 2003).

The new organization and business models known as *City Logistics (CL)* have emerged to address these issues, aiming to conciliate, to jointly “optimize” the economic and social goals of sustainable urban transportation and logistics activities. While CL definitions vary (e.g., Crainic, 2008; Taniguchi, 2014; Gonzalez-Feliu, 2018c), a consensus seems to emerge of City Logistics as an *integrated logistics system*, based on cooperation among stakeholders, resource sharing, consolidation, synchronization of operations, multi and intermodality, and the separation of commercial transactions generating goods movements from the planning and execution of the corresponding activities. Each element’s degree and way of inclusion define problem variants and applications, as described in this chapter.

City Logistics are complex transportation and logistics systems (Benjelloun and Crainic, 2009; Taniguchi and Thompson, 2014; Bektaş et al., 2017). This follows, on the one hand, from the inherent interactions between the *supply* of infrastructure, resources, and service networks put up to answer the *demand* to move and, eventually, store freight on its way from origins to destinations. Complexity also follows from the fact that CL is part of the more extensive urban transportation system, where people and goods flow, objectives, and requirements meet and often conflict and are part of regional, national, and international networks. Finally, CL involves multiple actors, stakeholders, and decision-makers, from public authorities and various citizen associations regulating or pressuring the regulation processes to entities generating or receiving freight flows, from private or public firms operating vehicle fleets, warehousing capacity, and integrated services over large parts of the city to firms focusing on specific neighborhoods or the very last kilometer of the chain, often operating new-technology vehicles (e.g., drones and robots) and continually innovating in terms of delivery services.

Therefore, advanced decision-support methods are required to account for this complexity, address the associated challenges, and reach the CL goals of service, economic, and environmental efficiency. *Operations Research (OR)* provides the necessary methodology to design and deploy such advanced planning and management decision-support systems. The CL-dedicated OR research and development efforts started with the millennium and have yielded a broad and rich portfolio of methods for most planning and management issues. Reviewing this field is the scope of the chapter.

Given the various categories of stakeholders and the classical view of transportation analysis as the result of the balance of demand and supply, one may classify the planning and management methods as targeting *demand*, aiming to forecast the types and quantities of goods required to be moved and stored, or *supply*, which aim to design and optimize the transport and logistics systems that will serve that demand. Both approaches are complementary and necessary. Yet, given the complexity of the topic, the extensive coverage of demand aspects in the rest of the book, and the length restrictions, the focus of the chapter is on the supply side of CL systems and the Operations Research approaches to design and manage them. For modeling and methodological details in this area, as well as views on the other aspects of City Logistics, planning, and execution, the interested reader may consult the papers listed in the following sections, the extended version of this chapter (Crainic et al., 2021a), as well as several books and chapters (Bektaş et al., 2017; Crainic, 2008; Crainic et al., 2021b; Ehmke, 2012; Gonzalez-Feliu, 2018c; Taniguchi et al., 2001; Thompson and Taniguchi, 2001) and the compendiums of papers out of the City Logistics International Conferences (<http://citylogistics.org/>).

City Logistics and urban freight transportation and logistics share many elements and complexity-inducing factors and, thus, an extensive set of planning and management issues. The issues and methods presented in this chapter for the former may therefore be applied in the larger context of the latter. However, we focus exclusively on City Logistics systems as we view CL as paradigm-changing for cities and the avenue towards digitally-intelligent urban transportation and logistics systems.

The chapter first presents, Section 2, a systemic view of City Logistics and the main supply-side planning issues, which are detailed in the next three sections addressing, respectively, strategic planning (Section 3) mostly based on *Location* methodology, tactical-operational planning (Section 4) and the *Service Network Design (SND)* and *Vehicle Routing Problem (VRP)* methodologies, and dynamic management (Section 5)). Conclusions and perspectives, Section 6, bring the chapter to an end.

2 City Logistics Systems

This section introduces the main *City Logistics* (CL) concepts and definitions necessary to present the Operations Research methods proposed to support the smart, optimized CL-system planning and operations.

City Logistics *supply* infrastructure, resources, and service networks to answer the *demand* to move and, eventually, store freight on its way from origins to destinations. Demand is addressed in Section 2.1 together with the freight flows it generates, which circulate within the CL-supplied network. Section 2.2 introduces the supply side of the CL system, in particular, the facilities involved, the layout of the CL network made up of these facilities, and the demand origins and destinations, as well as the transport resources and services connecting them all. CL operations, that is, how demand flows are moved through the supply network, are briefly described in Section 2.3. Freight transportation and logistics involve many interested parties in providing service, using the service, or being impacted by the resulting operations. CL is no exception, and it may involve a relatively large pallet of stakeholders as evoked in Section 2.4. Section 2.5 finally describes the main issues related to planning CL systems in long, medium, and short terms, as well as to implementing, updating, and executing the plans and activities. The following section then presents the main Operations Research methods proposed to support decision-making at all these levels of planning and execution.

2.1 Demand and flows

Demand is the reason transport and logistics systems are designed and operated. When freight is concerned, demand means the quantities of particular products which need to be handled and delivered from their respective origins to their specific destinations in the network. These origins and destinations are usually defined by the *customers* of the system, which, in all generality, are all the firms, organizations, institutions, and private citizens that ship or receive freight through the system. The freight-demand production (“generation”) and consumption (“attraction”) take place both within and outside the city, even though most CL studies have so far focused on the external-production-internal-consumption case typical of consumer-goods distribution.

For planning purposes, the many possible external origins and destinations of CL demand are aggregated into several *external zones* (the “large” disks outside the hexagonal city limits in Figure 1), connected to the city by various transportation modes (see Section 2.2.3), schematically illustrated through dotted arrows in the figure. Similarly, locations within the city are aggregated into customer-demand zones, referred to as *customer zones* in the following, and represented by circular disks within the city limits of Figure 1. The granularity of the aggregation depends on the level of planning considered, e.g., the shorter the horizon, the higher the granularity, i.e., the more disaggregated data is required.

The demand side of the system thus consists of a set of freight loads that need to be moved between particular pairs of customer and external zones. Three types of demand may be identified (Crainic et al., 2012, 2021b). *Inbound demand* is to be delivered from external-zone origins to

customers in the city, while *outbound demand* is to be picked up at customers in the city and then be shipped to specified external-zone destinations. *Local demand* is to be picked up from a customer within the city and delivered to another customer within the city.

Each individual origin-destination (*OD*) demand is characterized by a volume to be moved and time-related features, e.g., its *availability* time representing when the demand would enter the system and could start to be handled, as well as delivery and pick-up *time windows* at customers within the city. The attributes of the physical *product* and the possible rules and restrictions in terms of vehicle and storage utilization may also be of interest (Crainic et al., 2009), particularly when a varied set of heterogeneous products needs to be handled. The use of smart containers (Montreuil, 2011, π -*containers*), which can be loaded together in the same vehicles irrespective of their content, could help address this challenge and facilitate CL operations. To simplify the presentation of Sections 3 - 5, but without loss of generality, we assume the use of smart containers in this chapter. In modeling terms, this yields single product problems, the loading container, but multicommodity in the OD demand treated.

Flows then represent the movements of these freight loads throughout the CL system, together with those of the vehicles carrying them, as well as for their handling in the facilities of the system. In the OR methods of the following sections, flows result from the decisions on how to satisfy demand with the provided supply to achieve the objectives of the CL system and its stakeholders.

2.2 Supply - Infrastructure, resources, and service networks

The supply side of a City Logistics network consists of one, two, or more layers of terminals, called *facilities* in the following, and the transportation means and infrastructures linking them and the customer and external zones. We briefly present the former in Sections 2.2.1 and 2.2.2, while the latter is the topic of Section 2.2.3. Figure 1 schematically illustrates two major CL network layouts and components, which are used to illustrate the concepts described in the chapter and the OR models of the following sections.

2.2.1 Facilities

Flows between external and customer zones pass through one or more facilities, playing various roles in the CL logistics chain, ranging from freight consolidation hubs for distribution within the city or long-haul transportation towards external destinations to transfer and re-consolidation points between modes of transport, to temporary storage locations. Facilities are essential components of CL systems to consolidate flows, coordinate transport, transshipment, and storage activities, and synchronize freight and vehicle movements. The various facilities found in CL applications (Meza-Peralta et al., 2020) may be classified as either city distribution centers or satellites. Notice that storage facilities may be customers for planning purposes when they are the destination of particular demand flows. We use this classification in this chapter.

The primary purpose of *City Distribution Centers* (*CDCs*) is to receive inbound freight for operations, e.g., storage, sorting, and consolidation, facilitating a coordinated and efficient city

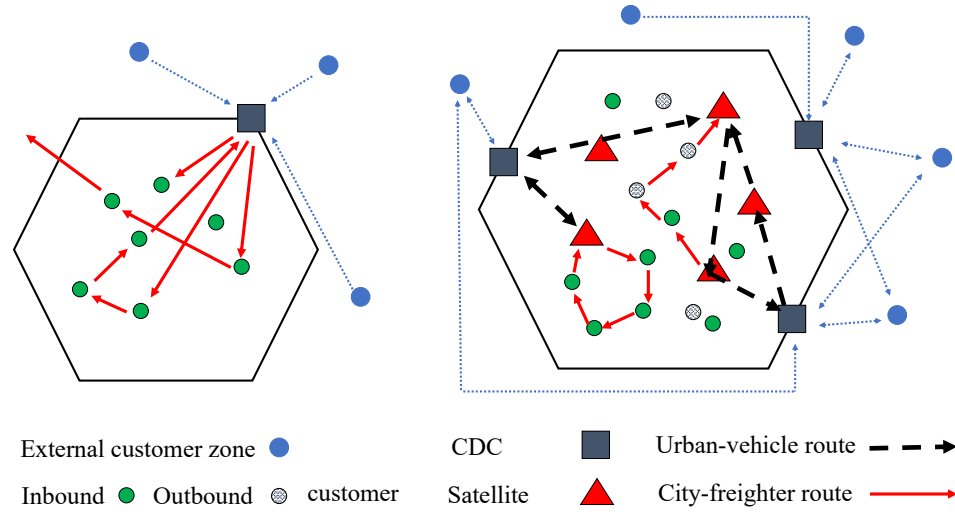


Figure 1: Single & two-tier CL system layouts and components

delivery. Outbound loads picked up within the city may also be delivered, sorted, and consolidated at CDCs for long-haul transportation to external-zone destinations. CDCs are defined here by their physical and functional role, not by institutional or collaborative issues. Thus, e.g., a wholesaler platform, an urban consolidation center, a regional distribution center, and an intermodal terminal may play a CDC role in a CL system. CDCs are often located at the border of the city, close to main interurban transportation infrastructures, and are illustrated by filled-up squares in Figure 1.

Satellites are part of multi-tier CL Systems. Satellites are located close to or within the city areas where traffic is controlled and certain vehicle types, e.g., large trucks, are not allowed to penetrate. It is at satellites, illustrated through triangles in Figure 1, that the junction is made between the CDCs, part of the first-tier of the system, and the customers within the CL-controlled area where loads are to be delivered or picked up from, freight being generally transferred between synchronized vehicles according to transshipment and/or cross-docking principles, with little or no temporary storage (Crainic et al., 2004). Vehicles operating on different tiers and carrying inbound or outbound cargo may thus be present simultaneously at a satellite, competing for the capacity it offers for vehicle docking, parking, and cargo transfer.

Satellites may thus be any type of (attended or unattended) “rendez-vous” location or facility, including dedicated terminals, parking lots, bus or rail stations, lockers, mobile depots, and locations within the city which may be used for short-time secure vehicle-to-vehicle transshipment (Verlinde et al., 2012). The type of satellites used in a particular CL system depends on the urban setting considered (dimensions, organization, etc.), the number of tiers involved (Section 2.2.2), and the type of transport service being implemented (Section 2.2.3). In all cases, satellites are “small” facilities (on either a public or private space), where CL logistics operations are carried out, efficiently connecting external and customer zones.

2.2.2 Layout

The network layout describes the form of that network, i.e., the definition and organization of the facilities and the connections between the facilities and the external and customer zones. The two basic layout configurations observed in City Logistics and urban freight networks are the single- and multi-tier networks, illustrated in Figure 1. *Tier* in the CL vocabulary stands for a set of facilities of similar nature and role, together with the transportation means and services connecting these facilities to those of the next “lower” tier. Notice that the first tier generally includes connections with the external zones, while the last tier also includes customer zones. Notice also that the vehicle-routing and logistics literature refers to tiers as *echelons*. We use the term “tier” in this chapter, with exceptions in Sections 3.2 and 4.2 to reflect routing-literature usage.

Single-tier CL Systems were proposed initially (for inbound demand) and are currently operating in many cities, particularly of small to medium dimensions. Illustrated on the left of Figure 1, single-tier CL systems operate CDC-type of facilities, customers being serviced directly from the CDCs, vehicle routes starting at a CDC to deliver or pick up loads at customers (initial deployments involved one CDC and one vehicle type only).

More advanced *multi-tier* system systems are emerging to personalize service and resources to the each particular neighbourhood, take advantage of new vehicular technologies that naturally lead to the design of multi-modal transportation chains (e.g., cargo bikes, drones, and robots), and to handle the complexity of large cities. Multi-tier systems are based on consolidation and involve the management of multiple interacting facilities and transportation resources. The right part of Figure 1 illustrates two-tier CL systems, which received the most attention in both the scientific literature and actual applications, involving CDCs on the first tier and satellites of a similar nature on the second. Several tier-specific types of satellites are involved when more than two tiers are considered. The size and range of activities at satellites are generally decreasing as the tier is further away from the first one, the focus of the activity of each satellite being a more local neighborhood. Notice that, even though the size of the formulations may grow significantly, the fundamental Operations Research methodological concepts are the same for two or more tiers. Therefore, the OR models described in this chapter are based on a two-tier system canvas, reflecting the majority of contributions in the literature.

2.2.3 Transportation

Transportation services in a CL system are provided by carriers operating vehicle fleets of various modes and characteristics adapted to the particular tier of activity.

Historically, road-based motor vehicles were the only ones considered in most literature and applications. The “multi modality” and environmentally-conscious characteristics of CL were addressed through new motorization types, e.g., electric, hydrogen, and hybrid, for smaller vans used in lower tiers. However, the field is continuously evolving towards true multi-modality and a broad range of vehicle types adapted to the particular tier and neighborhood they are expected to service.

First-tier transportation between CDCs and second-tier satellites illustrates this trend. Indeed,

one observes the increased involvement of people-oriented mass-transportation modes and vehicles, e.g., regular and light rail, and bus (e.g., Trentini and Mahl  n  , 2010; Freemark, 2011; Masson et al., 2017; De Langhe, 2017; Gonzalez-Feliu, 2018a; Riemann, 2019, see also <http://www.citylogistics.info/tag/cargo-tram>), as well as alternate freight-carrying modes, e.g., rail and canal or river barges (e.g. Lendjel and Fischman, 2014; Diziain et al., 2014; Van Duin, 2014). Combined with motor vehicles, these modes and services greatly enlarge the spectrum of transportation possibilities on the first tier in traditional and environmentally conscious motorization.

It is noteworthy that the utilization of dedicated light-rail services, e.g., tramways, belongs to the concept of *mobile depots*. It was initially introduced for service in historic city centers in Europe, and based on road modes only. It involves two tiers. Dedicated first-tier vehicles (or convoys of small trailers or tramway cars) stop at several strategic locations. They become satellites and meet second-tier vehicles for the transfer of inbound or outbound loads. Notice that the same principle may be used on lower tiers as well. Mobile facilities clearly illustrate that “location” decisions in the context of city logistics may be considered as strategic-planning issues and within the scope of short and medium-term planning.

Following Crainic et al. (2021b), we distinguish between *line-based* and *no-line* transportation modes and services. The latter include the various trucks and barges for which one may define services along any path within their admissible networks, such as a city trucking or canal network. Line-based modes are often captive of particular infrastructures, such as passenger buses, which are “captive” of their predefined lines, regular and light rail captive of their tracks, and trolley-buses captive of their aerial power lines. Two main approaches for line-based services are being contemplated within City Logistics projects around the world. On the one hand, regular vehicles may be equipped with special compartments for the transportation of goods. On the other hand, freight-dedicated vehicles may be operated on the same infrastructure, either independently or as parts of regular convoys.

Second, and lower-tier transportation is also increasingly multi-modal. The traditional small vans (Melo et al., 2014; Anderluh et al., 2021) are still encountered, but one also notices the utilization of eco-friendly electric or hydrogen small vans (Van Duin et al., 2013; Melo et al., 2014), traditional or cargo bikes (Gruber et al., 2014), drones and sidewalk robots (Savelsbergh and Van Woensel, 2016), automated light vehicles, well as individuals using their own cars (Durand and Gonzalez-Feliu, 2012; Carbone et al., 2017).

2.3 CL Operations

To simplify the presentation and to be consistent with the literature, first-tier vehicles are called *urban vehicles* in this chapter, irrespective of the mode. Similarly, vehicles used in single-tier CL systems, as well as the vehicles performing service on the lower tiers of multi-tier networks, are called *city freighters*.

Operations within single-tier CL systems are relatively straightforward as customer service is performed directly out of a CDC. Inbound loads from external zones received at a CDC are thus first sorted and consolidated into city freighters and distributed to customers. City freighters may also

pick up outbound and local freight at customers delivering it to a CDC and destination customers, respectively. The outbound loads brought to a CDC at the "same" time by several city freighters are sorted, consolidated, and loaded for the long-haul part of their journeys to their final external-zone destinations. The passage through a CDC notwithstanding, the itinerary of an OD demand in a single-tier CL system corresponds simply to part of a vehicle route.

Multi-tier CL systems involve a richer set of activities. To illustrate two-tier systems, inbound loads from external zones are first received at a CDC, to be sorted and consolidated into *urban vehicles*, which will bring them to satellites. A urban vehicle work starts from a CDC (after leaving its garage or a waiting station), travels to one or more satellites assigned to the service it performs, and returns to a CDC, possibly different from the one from which it started, to repeat the service, initiate a new one, or exit the system until called again.

Inbound loads arriving at a satellite are transshipped and consolidated (a second time) into *city freighters*, which deliver them to customers. City freighters also pick up outbound and local freight at customers delivering it to satellites and destination customers, respectively. The outbound loads brought to a satellite at the "same" time by several city freighters are loaded and consolidated into urban vehicles to be moved to the appropriate CDC, from where the goods are shipped to their final external zones. City-freighters thus also operate multi-tour routes among satellites and customers, with returns to the garage or waiting stations when consecutive tours are too far apart in time.

Demand in two-tier CL systems is thus moved from origins to destinations via itineraries that include the facilities and the transportation services on all relevant tiers. Inbound-demand itineraries are made up of the movement from the external zone to a CDC, an urban-vehicle activity, a transshipment operation at a satellite, and the final distribution by a city-freighter. Outbound-demand itineraries involve the same operations in reverse order. Local-demand itineraries correspond to pick-up and delivery routes (possibly passing at satellites to service the other types of demands) among customer zones.

Determining the mode and tier-specific services to offer, the routes to be performed by the vehicles, the synchronized schedules governing this execution, and the itineraries used to move the demand flows from origins to destinations make up an essential set of planning decisions and are part of most OR models presented in the following sections.

2.4 Stakeholders and decision makers

Identifying interested parties, together with their characteristics, objectives, limitations, and behavior, is generally considered part of the social, economic, and behavioral analysis of complex systems, including transportation and logistics. The CL aspect of these topics is amply analysed in the rest of the book. We, therefore, briefly identify the main classes of CL stakeholders by following the CL system structure described earlier in this section and briefly discussing the CL decision-making structure and its implication for the planning issues of Section 2.5.

As already described, CL systems are made up of a demand and a supply component, interacting

within the regulatory and fiscal environment set up by authorities and within the cultural and social environment of the city and country they belong to. We thus identify the stakeholder classes of customers, carriers, and authorities, with a brief mention of the indirect stakeholders involved.

Customers generate the CL system demand and are all the firms, organizations, institutions, and private citizens which ship, have shipped (i.e., they place orders generating demand for transportation), or receive freight through the system. It is from the customers who decide to be part of (served by) a CL system that identifies the products to be handled, together with their characteristics, as well as the temporal and economic characteristics of demand and, thus, of the looked-for service supplied. It is noteworthy that, in traditional systems, the organization of the transport-logistics chain is strongly linked to the transactional activities generating the demand. The latter is still in the scope of customer decision-making, together with possible transport and storage conditions requirements. However, the CL difference is to disconnect these two aspects on the city boundaries (at a CDC), the urban component being taken care of to achieve the customers and the city (and CL system) objectives. Two observations are necessary to be made in this respect.

First, customers desire high-quality, on-time service at the lowest price possible. These objectives must be accounted for in planning CL services, particularly since passing through terminals implies additional delays and costs. Optimizing the consolidation of flows, the resources shared, and the resulting supply network and services aims to answer these challenges. Second, one witnesses the constant increase in e-commerce scope and volume, accelerated by the confinement measures authorities imposed as a partial answer to the worldwide covid-19 pandemic. This results in higher demand heterogeneity, higher volumes of “small” packages sent to individuals’ homes, and a quest for rapid, even instant, deliveries (Durand and Gonzalez-Feliu, 2012; Dablanc et al., 2017). Integrating this increasing role of individuals as flow generators is a challenge both for the CL concept and organization and for the OR methods designed to plan and manage them.

Carriers provide the transport and warehousing resources and services making up the supply side of the CL system (or have the responsibility for those activities). We use the generic term “carrier” to cover actual owners and managers of freight-transport fleets of all possible modes or of facilities where CL activities may be carried on, or both, public or private owners and managers of people-transport fleets involved in carrying CL freight, and last-mile and logistics service providers, the so-called xPL (with $x = 2, 3$ or 4) depending on the range of services provided, which already coordinate transport for several customers. Carriers may involve all or only part of their resources in the activities of the CL system, sharing those resources with the system and the other stakeholders. The models described in the following sections address the planning and management of the CL resources made up of the shared resources. On the other side, Carriers have their own planning activities, not covered herein, with respect to how many resource to share and according to what conditions, as well as how best to manage the resources not shared with the CL system.

Orchestrators. Borrowing an IT term, the orchestrator provides the OR-based digital intelligence to integrate, plan and manage the (shared) resources and supplied services of the CL system to address the demand to achieve the stakeholder, system, and city objectives. In exploring the early literature, one may notice that IT and, especially, OR have been rather slow to penetrate the application field. This is changing, CL being increasingly viewed as part of an intelligent city.

The orchestrator is thus the *CL decision-maker*. From an institutional point of view, the orches-

trator could be a public entity, one of the carriers, or a neutral system manager. The latter option has the advantage of an arm-length distance from all parties involved, enforcing the confidentiality of the information provided by the stakeholders involved, and coordinating, managing, and globally optimizing the system according to the collaboration principles and conventions agreed among the participants. Notice that, while the neutral manager could be implemented as a distributed information and decision structure, the global scope of its decisions is the main issue here.

We complete this section with short mentions of the public authorities and the *indirect stakeholders*. The latter include citizens, lobbying groups, real estate actors, and professional associations. While enjoying the benefits of goods delivered and moved away, they may suffer and complain from the nuisances of freight-related traffic and activities. These impacted parties are not acting directly on CL systems but may have an essential influence through pressure on public authorities and changes to the “social acceptance” of freight-related activities. The fundamental concepts of City Logistics aim to address such issues. The impact costs included in many OR models and described in the following sections contribute to alleviating the negative impacts. Still, more social (with the public) and methodological (to represent these fears) integrated concepts are needed.

The *public policy and regulatory* authorities are crucial for making CL Systems viable and respected (Dablanc, 2007). According to the local culture and politics, they may get more (e.g., Western Europe) or less (e.g., North America) involved in the organization and management of CL. Still, they offer the necessary regulatory, fiscal, and operational environment, from the supra-national (e.g., the European Union) and national (budgetary and environmental laws and regulations) to the city (access, traffic, parking, environment, etc.) level regulation. These are essential issues beyond the scope of this chapter. We refer the interested reader to the relevant chapters of the book.

2.5 Planning and executing operations

City Logistics are complex consolidation-based transportation and logistics systems. They involve a broad set of customers and carriers, products, facilities, transportation modes, vehicles, and services, interacting in their spatial, temporal, and operational characteristics. They need to be collectively and simultaneously considered when deciding on the management and operations of the system. This translates into the need to design and plan the system, its services resources, and operations and, then, execute those plans. We introduce the central planning and execution issues in Section 2.5.1. We then briefly discuss two important characteristics of CL systems, time in Section 2.5.2 and uncertainty in Section 2.5.3, which are to be found in many of the decision-support models presented in the following sections.

2.5.1 Planning levels

The three planning levels found in most transportation and logistics settings, strategic, tactical, and operational (Crainic and Laporte, 1997), are also found in City Logistics planning and management.

Strategic planning (Section 3 addresses long-term design and deployment horizons, with impacts

usually valid for years, and rather high-level public or private management. Two sets of issues, decisions, and methods may be qualified as “strategic”. Setting up a CL system is undoubtedly a strategic decision. Thus, the first is at the level of public authorities, hopefully with the collaboration of the major stakeholders possibly involved in the CL system. They have to decide on deployment within the city or neighborhood and on design, partnerships, network layout, service type, policies, rules, legal and financial frameworks, etc., given each alternative’s expected behavior and performance. These evaluations should be part of more integrated approaches for urban planning and the corresponding people and freight transportation networks. Much more work is required in this field, particularly on the inclusion of freight transport issues into city urban and transportation planning methods. Discussion of these issues and methods (see Bektaş et al., 2017, for an introduction to the field) is beyond the scope of this chapter, as most of them are generally not of an Operations Research type. They may be and hopefully are, supported by Operations Research models providing quantitative evaluations and analyses of contemplated systems and policies. The second type of strategic planning methods, on the system design, and the tactical planning methods, on service design, provide such performance-evaluation tools for contemplated or existing CL systems and policy designs.

Deciding to set up a CL system of a given type for a particular city requires indeed designing the system. This means, in particular, to determine, e.g., the number, location, and characteristics of facilities, the main corridors allowed for each participating transportation mode, and the size and composition of fleets. Based on predictions of resource availability and user utilization needs, as well as on various criteria, e.g., economic, service-quality, resource utilization, and impact on the city, its inhabitants, and the environment, such models combine network design, location, and vehicle routing (*VRP*) methodologies. They are described in Section 3.

Tactical-operational planning targets the design of the CL services over a medium to short-term planning horizon. Recall that tactical planning for consolidation freight carriers (Crainic and Hewitt, 2021) aims to select and schedule services, together with the itineraries used to move freight flows from origins to destinations in the resulting service network. The goal is to satisfy the regular demand in the most cost- and resource-utilization efficient way possible while satisfying the service-quality levels set by the carrier to answer customer requirements. The tactical plan also yields activity profiles of terminals and the resources required to support the selected services. The service network and plan is determined for a relatively short period called *schedule length*, a day or a week, and it is then repeatedly applied over a particular medium-term planning horizon, the *season* (e.g., six months). The scheduling of particular resources, e.g., crews and terminal operations, may complete the process. It is assumed that the major elements of the plan, i.e., demand, selected scheduled services, and main resource assignments to services and terminals, will not be modified during regular operations for the length of the planning horizon. Adjustments of the plan to actual demand are then primarily performed through modifications to the terminal and fleet utilization, as well as to the routing of demand flows at operation time (see Section 5).

In City Logistics terms, the regularity of demand and selected services concerns the first-tier service operations of multi-tier CL systems, particularly the utilisation of terminal facilities and the customer-to-satellite assignment. This contrasts with the pick-up and delivery routes providing service on the lower tiers, which may vary from day to day according to the particular demand. The goal is to determine the most cost-effective plan to satisfy forecast demands with the available resources, where the generalized transportation costs account for operations-related costs and city-

impact considerations. With such a plan, material and human resources can be allocated for the duration of the planning horizon, which makes management easier and lowers costs (see Section 4).

Operational planning addresses the same issues but for a shorter planning horizon, generally equal to the schedule length. Planning is thus performed much closer to the activity time, e.g., the day before, rather than a number of weeks before, and with a better knowledge/estimation of the future demand and resource availability. The full range of decisions may be considered when the system environment is such that no long-term planning is possible (e.g., highly volatile demand and resource availability, combined to broad managerial capability to call upon and assign human resources). Alternatively, the short-term decisions may be guided by medium-term ones such as, for example, first-tier line-based services and schedules which cannot be altered. The fundamental methodology is the same in all cases. However, combining network design and vehicle routing and scheduling as appropriate to the particular application is considered. Section 4 presents the main methodological contributions to CL tactical planning.

Plans are put into practice through an *execution* phase. This chapter focuses on adjusting the plan, i.e., the re-organization and re-optimization of specific components (routes, itineraries, satellite activities), in real or quasi-real-time, following new or updated information. Indeed, many events may perturb operations and challenge the smooth execution of the plan, particularly in the highly constrained and congested urban context, even if uncertainty is explicitly accounted for in the planning process. These events may concern the demand, e.g., new orders or delayed ones and customers not ready to receive or load the planned freight, as well as the supply, e.g., incidents and accidents delaying or blocking planned routes and itineraries and larger-than-expected traffic delays. These issues and the dynamic adjustment and re-optimization OR methods proposed to address them for CL-system plans and operations are reviewed in Section 5.

2.5.2 Time representation

All problems and models discussed in this chapter exhibit important temporal, time, and timing defining characteristics. The *temporal* scope of refers to when decisions are taken (planned) concerning when and for how long they are implemented. In this respect, strategic and tactical-operational planning are *anticipatory-planning* processes and methods, generally performed based on estimated demand and resource levels. Operation optimizations and decisions are thus planned, without direct interaction with real-time events. In contrast, executing the plan and operations generally relies on dynamic, real-time decision processes and methods.

Anticipatory planning does not mean, however, that time-related (and uncertainty, see Section 2.5.3) issues are not considered. The *time* perspective refers to whether key data elements and decision variables are defined with respect to time, that is, whether their values are fixed for the duration of the schedule length and planning horizon, or are *time-dependent*. The passage of time is explicitly modeled in the latter case, time-dependent data and decision variables receiving one or several time attributes. Thus, for example, a particular demand may be defined by the moment (or time interval, also called *time window* in the following) it is expected to become available at the origin and a delivery time window at the destination. Similarly, the travel time along the same link of the CL network could be assumed fixed. Still, it could also receive specific time period-specific

values to reflect the estimated congestion effects. It is noteworthy that including time-dependent data in a problem definition and model implies that the corresponding decision variables are also time-dependent, and so is the model.

Timing refers to the case when several activities need to occur more or less simultaneously at the same particular point in time and space. In the City Logistics literature, this refers mostly to what Drexl (2012) defines as operation *synchronization* of different vehicles at the same or different locations concerning the moment in time when the vehicles perform their respective operation at those locations. The particular case of several first and second-tier vehicles meeting at the same satellite (Figure 1) to exchange freight is a major and challenging characteristic of multi-tier CL systems. The need for vehicle synchronization at satellites follows the simultaneous pressure of customer availability and delivery time windows, limited satellite capacity, and the goal of economically and environmentally efficient system operations. This raises significant challenges for planning activities and Operations Research-based methodology, as discussed in the following sections.

2.5.3 Accounting for uncertainty

Decision-making means evaluating alternatives and making decisions “now” by taking into account what may happen in the more or less distant future, that is, they mean the implicit or explicit inclusion of predicted/estimated data on demand and supply into today’s decision process and the OR methods designed to support them. Consequently, the quality of the plans and the system’s performance depend on the quality (accuracy) of the predictions and on how the uncertainty inherent to predictions is accounted for. Explicitly integrating uncertainty in planning methods aims to address these challenges.

In methodological terms, this translates into including a certain level and complexity of look-ahead capability into the problem definition and the mostly deterministic formulations presented in this chapter. Various sources and types of uncertainty may be identified (see, e.g., Klibi et al., 2010) from the ubiquitous, also called *random* or *business-as-usual*, variability in demand and travel and service times, to the rare but still predictable events, e.g., accidents and temporary modifications to infrastructure access, also called *hazards*, to the few and far between and difficult to predict but high-impact events, such as natural or man-made disasters, thus assigned the *deep uncertainty* label. Several main methodological approaches exist to explicitly model uncertainty and its consequences in optimization (see, e.g., Birge and Louveaux, 2011; King and Wallace, 2012; Bertsimas et al., 2011; Powell, 2021). The choice of methodology is related, on the one hand, to the problem addressed and the preferences of the decision-maker and, on the other hand, to the magnitude of the predicted variability and the confidence one puts in the forecasts. A series of problem settings and formulations follows from the combination of particular answers to these choices.

To illustrate, consider a tactical-planning problem where the daily variation of the volume of demand is considered. The tactical plan is built based on a prediction of this demand. When executed, the actual demand is “observed” a short time before the daily activities start, and the plan is adjusted by, e.g., calling on extra vehicles or modifying routes and schedules or both.

To reduce the impact of these variations on execution, one then aims for a tactical model that accounts for the variability of demand volumes by optimizing the cost of setting up the system and the expected cost to adjust the plan to the observed demand. The classical case of confidence in the prediction of (very) low variability leads to the choice of a *deterministic* model, such as most formulations presented in this chapter. Minor, accidental variations are then addressed during operations by, e.g., calling on extra vehicles or delaying some demand at a penalty cost.

At the other end of the spectrum, one finds the case of high variability combined with low confidence in the possibility to forecast it adequately. This case is characteristic of the (quasi) real-time operations of full-vehicle-load fleet-management problems, where resources (e.g., vehicles) are dispatched in reaction to incoming demands (e.g., Powell et al., 2007). *Approximate dynamic programming* (Powell, 2021) offers then the possibility to account for the impact of current decisions on the future state of the system (e.g., the availability of resources at specific locations at future time instants and the value of having a resource at the point in space and time), but no tactical plan may be built.

The various problem settings and methodological choices in between these extremes differ in the latitude left to the adjustment of the plan once the actual demand is observed. *Robust optimization* (Bertsimas et al., 2011) may be used to aim for plans which are valid under a broad range of demand variations, or when taking a longer horizon look at planning, under a set of extreme values which could significantly damage performance. *Chance-constrained* stochastic programming models replace constraints enforcing particular limits, e.g., deliver demand on time, by constraints requiring these limits to be obeyed with a certain probability, e.g., 90% on-time delivery. Intuitively, this approach appears attractive when time-related uncertainty is contemplated, particularly as probabilistic constraints may be combined with a multi-stage stochastic program. Most research in these areas has yet to be undertaken.

A priori, multi-stage stochastic programming (Birge and Louveaux, 2011; King and Wallace, 2012) appears appropriated to integrate uncertainty, particularly regarding demand, into tactical plans. The question then is what part of operations should be fixed within the plan, based on predictions, and what should be left to be decided on the day of operation execution, once new information becomes available (is “revealed”) and *recourse* actions may be taken to adjust the plan to these observations. Adjusting the plan involves costs, which vary according to the selected recourse, from doing nothing and paying penalties to muster extra resources and re-optimizing the operations. Put into stochastic-programming terms, “what decision goes into each stage?”, the first stage generally corresponding to building the plan, the second and following stages to the cascade of information-revelation and recourse actions occurring during operations. Two-stage formulations assume that new information becomes available and adjustments are performed only once at each occurrence of the plan application (e.g., each day). This is the methodology most often used in planning consolidation-based freight carriers (Hewitt et al., 2021), and it is the one we illustrate in this chapter (Section 4.4).

To sum up, the literature is very sparse regarding the explicit integration of uncertainty in planning models and methods for City Logistics, and most research is still to be undertaken. In particular, to the best of our knowledge, duration and cost uncertainty have not been addressed to any significant extent, a few contributions targeting business-as-usual demand uncertainty only.

3 Strategic Planning - Designing the System

Strategic planning generally addresses long-term decisions with long-term impacts. This section is dedicated to the system-design strategic decisions, focusing on the main methodologies proposed for the selection of facilities and their impact on the system performance. *Location*-based methodologies, Section 3.1, focus on where facilities should be, how large they should be, and what interconnections should be selected among these facilities as well as among them and the clients they serve. How the movements are to be performed, that is, the transportation activities with their spatial, temporal, and economic attributes, is less emphasized, the associated decisions and attributes being generally aggregated. More refined methodologies explicitly include the design and planning of the transportation network in the formulations. *Location-routing* addresses these issues combining location and vehicle routing (*LRP*; Section 3.2), while *Location-Design* combines location and (scheduled) service network design (Section 3.3).

3.1 Location

Since facilities are the starting point of supply, their location is a major issue in strategic planning. Therefore, most contributions in the literature addressing the design of CL systems focus on the location of facilities with varying levels of detail on the networks exploited and the activities performed. The problem has been developed and applied to many fields, mostly in regional and inter-urban transport (Crainic and Laporte, 1997), for single (Verter, 2011) or multi-tier systems (Ortiz-Astorquiza et al., 2018). In those surveys, the main principles of modelling, mathematical formulations and solution approaches can be found. However, in CL systems, the specific features of context, demand and supply need the development of specific modelling approaches. This first section describes then the two pioneering modeling approaches in designing CL systems.

Taniguchi et al. (1999) introduced probably the first model aiming to optimally select the locations and dimensions of facilities for a single-tier, single-mode CL distribution system. Proposed before the “City Logistics” term was adopted, the facilities are identified as “public logistics terminals” or “multi-company distribution centers”. They are seen as essential building blocks of cooperative freight systems, which could efficiently address the serious challenges cities face in terms of traffic congestion, environment, energy, and labor costs. The authors address a large-area transportation system. The network is made up of two parts, long-haul, for large vehicles bringing freight to the terminals (e.g., the expressway network), and pickup and delivery, for delivering freight from terminals to customers by a different fleet of small trucks. Origin to destination demand is identified for each part of the network. The terminals connecting the two parts are to be located to reduce the total generalized cost of the system, which includes the costs of terminal set up and utilization, transportation, pollution, and so on. The authors assume the facility-location decisions are taken by some authority, while the trucking companies or their drivers select the terminals to visit and the routes to perform. The authors propose a two-model approach, a high-level one to select and dimension facilities, and a nonlinear traffic-equilibrium-type model reflecting congestion and the choice behavior of the truck carriers at the lower level. Experimentation was carried on a small-scale application using a very aggregated representation of the road network in the Kyoto-Osaka region of Japan.

There are a few subsequent works based on this approach. Yang et al. (2005) adapts this framework to port areas, to interface maritime transport to city logistic, adding to (Taniguchi et al., 1999) warehousing components and an update of costs to include port issues. Authors propose a genetic algorithm to solve the problem in realistic cases and apply their work to the city of Dalian (China). Rao et al. (2015) go in-depth on the definition of sustainability evaluation criteria for locating such facilities, in a multi-criteria, fuzzy logic, perspective. This work remains theoretical, the numerical illustration is based on instances that do not belong to a real city but show the main interests of the approach. (Ruiz-Meza et al., 2021) propose a two-tier version of the system, i.e. mono-commodity and single mode, but adding a second layer of satellites to locate in parallel to CDCs. Authors propose a two-tier model that considers both size and location of terminals (1st tier) and satellites (2nd tier), and include synchronization issues at satellites via time constraints. The framework, solved using a commercial MIP software, is applied to the city of Barranquilla (Colombia). We believe it is worth examining, however, as it opens very interesting research avenues including the adaptation of recent results in bi-level programming, the modeling of various business and operational CL organizations, and solution methods able to address realistic-sized problem instances. Such developments could be used not only for designing the CL systems but also as components of urban planning methodologies.

Crainic et al. (2004) formally introduced the general two-tier CL system concept (see also Gragnani et al., 2004), which launched the continuously growing research stream on multi-tier CL systems. In this pioneering study, the CL consolidation and coordination activities are performed at facilities organized into a hierarchical, two-tiered structure (e.g., the right part of Figure 1 with major terminals sited at the city limits and cross-dock satellite facilities strategically located close to or within the CL area of the city. The authors consider inbound multi-product origin-to-destination demand and single motor-carrier modes and fleets for each of the two tiers of the system, the urban trucks, later generalized to urban vehicles, and city freighters, respectively. The authors address the strategic-decision issue of determining the satellite structure of the system, given aggregated, strategic-planning level representations of the city network and demand for transportation. They proposed a location-allocation methodology and performed a proof-of-concept study based on data from a large city with a very rich and dense web of activities, political, administrative, commercial, cultural, touristic, and multi-modal transport of people and freight, within a well-defined territory.

The network model includes nodes representing the potential satellite locations, the external zones (the CDCs), standing for the origin of the freight to be moved, the customer zones, i.e., the destinations of the demand, as well as the main intersections in the actual city ring-road and street network. The arcs of the network model represent possible movements between external zones and satellites, and between satellites and customer zones. Each such arc stands for the min-cost path in the respective part of the actual city network (arcs are uncapacitated, congestion factors being included in the travel costs).

The authors introduce the impact-on-the-city or *undesirability-factor* concept in defining the economic attributes of the network, in order to reflect the negative impact, or the perception thereof, of having a facility in a particular location or moving freight vehicles on certain streets or through certain neighborhoods of the city. Such a factor is included in the (fixed) cost to open a satellite in a given location, as well as in the travel costs associated with each arc for each product considered. Potential satellites are further characterized by location, product-specific unit handling costs, and capacities in terms of the maximum number of urban vehicles and city freight they can handle.

Several vehicle (fleet) types may operate at each tier. Each type is characterized by capacity and unit utilization cost, the latter being viewed as a “social” cost of the presence of a vehicle of that type in the corresponding part of the city.

The goal is to identify, among the candidate sites, a number of satellite locations where freight may be transshipped from urban vehicles to city freighters for distribution within the core of the city and, thus, satisfy demand. Selection decision variables are associated with each potential location. Path-flow decision variables are defined for each product and origin-to-destination demand to yield the quantity of that demand being moved from the external to the customer zone through each of the potential satellites. This structure leads to a location-allocation formulation, where the objective function minimizes the generalized cost of the system, accounting for the fixed cost of opening and operating the satellites, as well as the transportation costs to satisfy demand. Other than the flow-conservation (demand satisfaction) constraints, the model includes linking constraints enforcing the capacities of the selected satellites.

The model was presented as a means toward a proof-of-concept for the potential benefits of two-tiered CL, and actual data from the city of Rome was used to estimate the demand, the division of the city in external and customer zones, the identification of possible sites for the satellites, and the cost of moving within and impacting the city. The study area corresponds in its general lines to what is known as the *centro storico*, the historical center of Rome (the zone within the Aurelian walls as well as the neighborhoods around the Vatican City), an extremely important, sensitive, and busy area in Rome. The proof-of-concept experimentation produced very encouraging results, indicating that such a system may indeed contribute towards reaching the goals of a better city environment at a reasonable cost. This work was the seed for numerous research projects and contributions, including Baldi et al. (2012) addressing the same problem setting with stochastic costs for the flow paths.

3.2 Location-Routing

Location-routing formulations (Drexler and Schneider, 2014, 2015; Prodhon and Prins, 2014; Albareda-Sambola and Rodríguez-Pereira, 2019) aim to capture the intricacies and cost of using fleets of less-than-truckload vehicles to deliver and pick up goods using the facilities one desires to locate. The transportation part is therefore modeled on a network representing either the direct movements allowed among facilities and among those and the customer zones, or the actual infrastructure (e.g., street) network used to perform the routes. The former case corresponds to the representation generally used in the vehicle-routing field, the actual infrastructure network being used to compute the distance (cost) matrix and associate these to the network model (see Section 4.2). This is also the approach of most location-routing models, in particular those discussed in the following.

Guyon et al. (2012) proposed what may be the first location-routing model for CL. The authors addressed a single-tier, single-fleet, inbound traffic system, where vehicles deliver parcels from logistics facilities to customer zones inside the city. Each potential facility is characterized by a capacity, in number of bay doors for vehicles, which needs to be determined as well. Each customer zone must be serviced by a single vehicle route. The vehicles providing the service have limited loading capacity and the routes they may perform have limits on distance and duration, the latter including

service times at customers and travel times adjusted for congestion within each customer zone. The decision variables concern the selection of facilities and their corresponding capacities, together with the construction/selection of the vehicle routes needed to satisfy demand. The generalized objective function encompasses terms reflecting the economic cost and the environmental impact of the system, as well as the social acceptability of the facilities by the population. The integer programming formulation was solved using a commercial software. An application to the city of Marseilles, France, was used to showcase the performance of the methodology and the potential benefits of the proposed system.

Most LRP contributions to the planning of two-tier CL systems address location decisions on a single tier only (e.g., Hemmelmayr et al., 2012; Gianessi, 2014; Gianessi et al., 2016; Winkenbach et al., 2016; Boccia et al., 2018). A general formulation of a n -tier LRP (addressing location decisions at $n-1$ levels) can be found in Gonzalez-Feliu (2012). Given the limited chapter length, we focus on one of these contributions, which brings also forth an interesting variant of the CL architecture.

The CL system studied in Gianessi et al. (2016) is based on a ring of CDCs that collect the inbound and outbound flows of freight between the external and customer zones of the city. Freight between external zones and CDCs passes through specific points called gates, each gate giving access to a subset of potential and close by CDCs. Notice that, gates are not proper terminals, but play the role of first-tier facilities in directing traffic. Freight at a CDC may be either distributed directly to customers, or first moved to another CDC, closer to the respective customer zone, and distributed out of that facility. The inter-CDC movements are to be performed by a ring of transportation infrastructure or services, circling the city, while movements between CDCs and the customer zones they service are performed as pickup-and-delivery operations. A number of additional characteristics are considered, e.g., vehicle capacity and route length limits, open routes (i.e., not returning to the starting facility), extra vehicles available for hire, and fleet repositioning at the “end of the day”. Time aspects are not considered. The ring location-routing problem addressed by the authors then includes binary decision variables for the location of CDCs and the design decisions constructing the ring linking all the selected CDCs, continuous arc-flow variables on the superior network for the freight itineraries between the corresponding entry or exit gate to a first and, possibly, a second CDC, the latter on the ring, and binary pickup-and-delivery route-selection variables for the second tier customer visits. The authors propose a mixed-integer formulation, a number of valid inequalities to strengthen the formulation, and a matheuristic solution method that decomposes the problem into several main blocks: selection of facilities and demand assignment, ring construction, ring flow determination, and route generation. As expected, a commercial solver can solve tiny instances only. A hybrid heuristic, solving exactly the problem on a reduced set of routes gives good results as the size increases, but the matheuristic is needed for somewhat larger instances.

Boccia et al. (2011, 2010) are probably the first to address the integrated problem of simultaneously locating facilities on both echelons of two-tier CL systems, the transportation of freight on the resulting network being modelled through routing problems at each tier. The considered *Two-Tier Location-Routing Problem* (*2E-LRP* to use the usual “echelon” term found in the literature) setting considers the location of a set of capacitated CDC facilities on the first tier and of a set of capacitated satellites on the second tier. Urban vehicle move freight from CDCs to satellites, while city freighters deliver freight from the latter to customers. Vehicles on both tiers perform closed

routes, each ending at the same CDC or satellite it started from. Although pioneering, the problem setting is still very close to “classical” location-routing focusing on inbound demand for a single (subsuitable) product and a no-split-delivery policy within a static context (i.e., without time and synchronization considerations). Still, three sets of decisions make up this core 2E-LRP: 1) facility selection on each tier; 2) assignment of customers to selected satellites and of selected satellites to selected CDCs; and 3) vehicle routing on each tier.

Boccia et al. (2011) proposed several mixed-integer which follows classic modelling approaches for the Vehicle Routing Problem (VRP) (see Section 4.2): 1) a three-index model, inspired by the work of Ambrosino and Scutella (2005), with a detailed arc-based representation of the routing decisions; 2) a two-index model inspired by the multi-depot VRP of Dondo and Cerdá (2007); and a single-index path-based formulation with sets of routes (paths) being generated for each tier. The first formulation is very flexible. It may be adapted to address problem settings with either symmetric or asymmetric cost matrices, and it may be extended to take into account a large amount of features, e.g., multi-commodity (origin-to-destination) demands, customer and facility time windows, maximum route length restrictions, and heterogeneous fleets. It involves, however, a very large number of variables and constraints, which makes it harder to solve. The two-index formulation is less flexible, e.g., it is less suitable for asymmetric cost instances. Moreover, while it involves significantly less decision variables, it includes a larger number of difficult linking constraints. These differences were echoed in the results of an experimental comparison of the two formulations, performed using a commercial MIP software on a set of small problem instances. The three-index formulation yields better lower-bound values than the two-index one and, thus, appears to perform better as the problem size increases (in number of potential locations). Yet, the size of the instances that could be addressed is limited and the lower bounds are not sufficiently tight for efficient enumeration algorithms.

Two major research directions for this area thus appear promising. On the one hand, path-based (single index, also called set partitioning) formulations have proven successful for many VRP and a few location-routing settings (Albareda-Sambola and Rodríguez-Pereira, 2019). The need to dynamically generate routes on two or more tiers, and to route freight on itineraries combining pieces of these routes makes the problem extremely challenging, in particular when characteristics proper to CL systems are considered (e.g., several demand and traffic types, time-dependency of demand and routes, synchronization, and multiple tours). Most of the research in this area is still to be undertaken. Not surprisingly that, on the other hand, most developments are taking place in the second direction, efficient meta- and matheuristics being increasingly proposed.

Boccia et al. (2010) proposed a Tabu Search method for the basic 2E-LRP setting described above. The method is based on decomposing the problem by tier. This yields two tier-specific LRPs, each of which is further decomposed into a capacitated facility location problem and a multi-depot VRP. The meta-heuristic iterates on the LRP subproblems through a feedback loop, returning to the first tier when a new solution for the second tier either improves the best solution found so far, or violates the capacity of a selected CDC. Classic neighbourhoods make up the VRP part of the meta-heuristic. Compared to the results of the exact-solution method applied to the two formulations, the Tabu Search found the optimal solutions to all small instances and improved those the exact method could not solve to optimality.

Contardo et al. (2012) introduced a new two-index arc-based formulation for the same basic

2E-LRP setting where, besides the binary variables to select facility locations and the arcs used to move freight at each tier, 'new continuous variables stand for the amount of flow shipped to and from each satellite'. This formulation yields tight linear-relaxation lower bounds, shown to be much tighter than that what was offered in the literature. Moreover, most valid inequalities known to be efficient for the capacitated LRP (Belenguer et al., 2010; Contardo et al., 2013) are also valid for this new formulation. Contardo et al. (2012) use the satellite-flow variables to implement the idea of decomposing the 2E-LRP along tiers, yielding two tier-specific capacitated LRPs, into an exact solution method and a meta-heuristic. The Branch-and-Cut (B&C) algorithm makes use of the bounds and cuts mentioned previously, together with new valid inequalities particular to the problem setting. The Adaptive Large Neighbourhood Search meta-heuristic iterates on the two LRPs, addressing the first (CDC) tier LRP each time the new solution of the second (routing) tier LRP changes the satellite configuration. The ALNS meta-heuristic follows the structure of the ALNS proposed for the two-echelon vehicle routing problem (Hemmelmayr et al., 2012). Eight destroy and four repair operators are proposed. The former either explicitly open or close a satellite (three operators) or indirectly change the satellite configuration by removing sets of customers (the other five). Repair is performed according to insertion principles, all repair operators selecting an open satellite, a route, and an insertion position for every customer one needs to insert, but applying particular insertion criteria. Local search is used to improve the second-tier routes of promising solutions. An extensive experimental campaign highlighted the capabilities of the methodology proposed, the proposed exact and meta-heuristic solution methods being the best in their respective categories for the 2E-LRP.

We are aware of only one contribution targeting a multi-attribute 2E-LRP, which brings the LRP field closer to the general two-tier CL problem setting described in Section 2. Escobar-Vargas et al. (2021) addresses a rich 2E-LRP with time-dependent multicommodity inbound demand from external to customer zones, first and second-tier facilities, capacity restriction for the trans-dock satellites (i.e., a limited short-term warehousing capacity is available), tier-specific fleets with limited vehicle capacity, and synchronization. Two time attributes characterize each origin-destination demand: the availability time at the external zone (origin), which yields an availability time at each of the first-tier facilities which may service it, and the due time window for delivery to the customer zone (destination). The problem requires the selection of facilities on each tier, the assignment of each demand to a CDC and of each customer zone to a satellite, the timely delivery of that demand from its selected CDC through the selected satellite to its destination, the synchronized routing and scheduling of the vehicle fleets on each tier of the system. The vehicle schedules specify the departure times from the CDCs and satellites, synchronization taking place at satellites between the first-tier urban vehicles bringing the freight from the CDCs and the second-tier city freighters distributing the freight from satellites to the customer zones. The objective is to minimize the total cost of the system computed as the sum of the fixed costs of selecting facilities on both tiers and of the variable costs of operating vehicles on both tiers to transport the freight. Demand must be delivered on time and it must not be split (single itinerary and each customer visited by a single vehicle). The capacity limitations of the facilities and vehicles must be enforced.

Escobar-Vargas et al. (2021) propose two formulations for this problem setting, which differ in the representation of the time interval, also called *schedule length*, considered for planning and of how the system activities take place during that time. The first model is a three-index continuous-time formulation, which focuses on the timing of operations, i.e., the time instances when vehicles

arrive at and depart from CDCs, satellites, and customer zones. This representation of time leads to a compact formulation with a polynomial number of variables (relative to the arcs and nodes of the network). An allocation variable matches the vehicle and the commodity it picks up at the moment the operation takes place. Synchronization is then enforced by limiting the time difference between vehicles operating on different tiers when exchanging freight at satellites. The itinerary used for each demand may then be deduced by associating the vehicle flow (visits of vehicles to nodes), the allocations (what commodity is allocated to what vehicle), and the time variables (at what time a node is visited). The resulting MIP is then solved through a well-known commercial software.

The second model is a “classical” discretization approach, where the schedule length is partitioned into a number of time periods, each physical node being duplicated at each possible time period when an activity may take place (e.g., a customer zone is duplicated only at the periods within the relevant time window). This mechanism leads to a *time-space network*, where every node is a (physical node, time period) pair, physical arcs representing travel which may take place between two such nodes. In contrast to the continuous representation of time, this model explicitly encodes the timing decisions in the definition of the nodes and arcs in the network. Synchronization and other timing decisions and limits are consequently expressed as selection and routing decision variables and as constraints in the resulting time-space network MIP. It is well known that time-space network design formulations yield more precise results when the discretization is more refined (more time periods), but that they generally grow rapidly with this refinement. It is therefore noteworthy that Escobar-Vargas et al. (2021) develop the first Dynamic Discretization Discovery (DDD, Boland et al., 2017) solution method for location-routing. An extensive experimentation campaign evaluates the performance, in terms of computational efficiency and quality of the upper (feasible solutions) and lower bounds, of the two models and of the DDD solution method under various problem and parameter settings.

3.3 Location-Design

Section 4 presented Scheduled Service Network Design (SSND) models addressing tactical planning issues for CL systems. These SSND formulations yield “best”, optimal, when solved exactly, plans and multi-tier scheduled service networks in terms of the generalized cost of the system, given the forecast demand, the system layout, composition, and attributes, as well as current regulations and operation policies. The objective of this section is to emphasize that the SSND methodology may be used not only for drawing tactical plans and guiding operations, but also as a valuable analysis and evaluation tool for a broad range of longer-term issues. The study could be part of the cost-benefit analysis, in economic, social, and environmental terms, of possible CL system selection and deployment decisions. Similar studies may also be undertaken to evaluate potential impacts on the system performance of the evolution and modification of internal or external elements.

The SSND modeling framework with approximated second-tier routing (Section 4.3) appears appropriate to evaluate long-term strategic CL system selection, deployment, and modification scenarios, as the planning horizon implies a certain level of imprecision in the demand data. Such scenarios may be related to the design, structure, layout, environment, business models, and operating policies of the contemplated system, e.g., different 2T-CL layouts in terms of number,

location, and capacity of facilities, the design of freight-dedicated corridors throughout the city, particularly between CDCs and satellites, and the introduction of new or upgraded infrastructure and services. Solving the SSND formulation would provide the decision maker with an evaluation of the corresponding system performance in terms of the criteria and measures considered.

The SSND formulations of Sections 4.1 and 4.2 (as well as their variants integrating uncertainty, e.g., Section 4.4) may be used when more detailed system supply and demand elements are available and a more in-depth study is required. Such scenarios could concern, for example, changes in facility capacity, particularly in dense urban zones (e.g., new city traffic rules that restrict access and reduce satellite capacity, the assignment of customers to CDCs and satellites, the vehicle fleet deployment, including the number of modes and fleets, the fleet dimensions and corresponding vehicle characteristics, etc.

The SSND models may also be used to study different cooperation rules when several service providers (public and private carriers, terminals, etc.) share infrastructure and perform CL activities under joint planning and operations-management mechanisms (e.g., an intelligent, arm-length information-sharing and decision platform). Such rules may specify, for example, how to distribute costs, vehicle utilization, or both among the participating carriers and facility managers, in order to reflect their contractual commitments in terms of type and size of the fleet committed, territory covered, financial and risk share, etc. Not much research has been dedicated yet on how to extend SSND models to account for these issues.

To illustrate this problem setting (see, e.g., Crainic et al., 2020, for a limited foray into this field), consider a type of carriers operating at the first tier, each with a threshold value on its activity level, in terms of total ton-km performed or total cost of fleet usage. This threshold may be represented through an “acceptable range of variation” of the corresponding measure, and enforced by adding constraints to the formulation. These constraints would compare each carrier share with the total cost associated with the selection of services, and limit it to the corresponding range of variation. Penalties on exceeding the thresholds could be added to the objective function, instead of including constraints, to add flexibility to the solution methods. Integrated location-design formulations may also be built for a direct utilization as decision-support instruments for strategic decision-making concerning, e.g., number, locations, and characteristics of facilities, CDCs and satellites, to build or select, the construction of dedicated infrastructure or the connection of the CL facilities to public transport infrastructure and services, the types of vehicles to use and the dimensions of the fleets. Such integrated formulations generalize SSND models. Design (binary or non-negative integer) decision variables are added to represent the selection of the contemplated facilities or infrastructure structures, together with the corresponding commodity-flow decision variables. Then, one must add and the linking (also enforcing capacity limitations, of course) as constraints, connecting the various decision sets and enforcing, e.g., that only selected and paid for facilities may be used by selected services of commodity flows. A similar approach may be used to integrated fleet (vehicle) acquisition decisions or the addition or departure (selection-type of decision in both cases) of a stakeholder (e.g., carrier or facility management firm). Budget constraints, enforcing the total expenditure of selecting, operating, or both, may also be added to the formulations.

4 Short and Medium-term Planning - Designing the Service

We dedicate this section to four major classes of problem settings and models for the short (*operational*) to medium-term (*tactical*) planning of multi-tier CL systems. To simplify the presentation and to represent the literature adequately, we focus on the case of two-tier systems. Extending the methodology to multi-tier cases, particularly relevant for very large urban areas, implies moving from a routing component on the second tier to a multi-tier routing setting. This is a challenging and timely research area. Section 4.1 introduces a general methodology for CL tactical planning combining network design and vehicle routing. Section 4.2 examines models based exclusively on VRP principles for single and multi-tier settings. The issue of the representation of the lower-tier pick-up and delivery activities within tactical-planning models is addressed in Section 4.3, while uncertainty issues and tactical planning are illustrated in Section 4.4.

4.1 A general planning model for two-tier CL systems

We present a general modeling framework for two-tier CL systems, which accounts for time-dependent origin-destination demand, several line-based and no-line transportation modes and services, limited fleet sizes, various facility-capacity limitations, and synchronization requirements. The model addresses the main tactical-planning issues:

1. Select a subset of scheduled services out of the set of possible line-based and no-line multimodal services;
2. Build the multi-tour pick-up and delivery ($P\&D$) routes of the second-tier city freighters;
3. Determine the itineraries of each demand through the selected CL service network, including the assignment to a CDC and a satellite for inbound and outbound demands;
4. Manage resources, i.e., the terminals and the multimodal fleets of urban vehicles and city freighters, which connect and synchronize at satellites.

Scheduled service network design (SSND) formulations defined over time-space networks are generally used to model tactical planning problems for consolidation-based freight carriers and transportation systems. This is also the case for the first tier of this model, a multi-attribute P&D modeling approach being used for the second tier. The presentation follows Crainic et al. (2021b) and Crainic et al. (2009).

The tactical-planning optimization is performed for a given schedule length, CL infrastructure, potential first and second-tier services, and a deterministic estimation of demand, travel times, and activity times at facilities and customers. The goal of the model is to minimize a total generalized cost, reflecting both the economics of operating the system and the potential impact on the city while satisfying demand. The resulting service plan is supposed to be used repeatedly over a certain tactical-planning horizon.

As in most models discussed in this chapter, the problem is defined on a physical network. The nodes encompass the external zones, the customer zones, the CDCs, and the satellites. The external zones, which stand for the out-of-city origins and destinations, are linked by various transportation modes to the city and the CDCs. The CDC used by each demand is to be selected by the model and, thus, arcs representing the possible external zone - CDC connections are part of the physical network. The network also includes modal arcs representing the connection possibilities among CDCs and satellites and among satellites and customer zones.

Inbound, outbound and local requests for transportation make up the demand of the system. Each customer demand, with its volume, is defined between a pair of origin-destination physical nodes, which can be an external or a customer zone, and must move between these nodes. Time attributes specify when the volume is available at origin and when it must be delivered at the destination.

The SSND model is then built on a time-space network, corresponding to the discretization of the schedule length into an appropriate number of periods. The physical nodes are duplicated at all relevant time periods. A set of links representing the modal transportation and terminal-holding activities connecting these nodes completes the time-space network. Movements are performed by vehicles of different types and transportation modes.

The modeling framework does not impose limits to the volumes of a number of vehicles processed at CDCs, reflecting that most CDCs are large facilities, where capacity issues are not critical and sufficient space is available for vehicles to wait for loading and unloading activities. However, this is not the case for satellites, where the space available for transferring goods limits the number of urban vehicles and city freighters that can be present simultaneously. Furthermore, there is generally no space for storing goods at satellites or vehicles to wait. Several capacity limits are thus explicitly included for each satellite.

A potential first-tier urban-vehicle service is defined by the type of service, line-based or no-line, and mode. It starts from a CDC, travels to one or more satellites assigned to it, and returns to a CDC, possibly different from the one it started. The urban-vehicle route is thus composed of a series of legs, from the CDC to the first satellite, from the latter to the second one, until the last leg from the previous satellite to the destination CDC. The service schedule is given by the departure time from origin, as well as by the arrival and departure times at all the satellites on its route, which account for the travel time along the arcs of the specific mode and the loading and unloading times at satellites. A cost is defined for each service to capture both the monetary expenses of operating it and the city-infrastructure-utilization cost reflecting the “nuisance” factors related to the presence of the urban vehicle in the city at the particular time of the service.

The second-tier pick-up and delivery activities between satellites and customer zones are performed by city freighters operating multi-tour synchronized routes called work assignments. A city-freighter work assignment operates a city freighter of a given type (and mode or fleet) over a sequence of work segments, separated by returns to the garage, each segment being made up of visits to satellites to load and unload freight and one or several pick-ups (outbound demand), delivery (inbound demand), and pickup-and-delivery (local demand) activity phases. The schedule of a work segment starts in the period at the first satellite or customer on its route. It continues with the arrival and departure times at the visited satellites and customers. The cost of operating

city-freighter work assignments is composed of the costs of its segments and those associated with the garage (back and forth movements, idles time, etc.). Similar to the first-tier services, it includes the fixed operating cost and the city-infrastructure-utilization (“nuisance”) cost.

Demand is moved from origins to destinations via itineraries that include the facilities and the first and second-tier services. Inbound-demand itineraries are thus made up of the movement from the external zone to a CDC, an urban-vehicle movement, a transshipment operation at a satellite, and the final distribution by a city-freighter work segment. Outbound-demand itineraries involve the same operations in reverse order. Local-demand itineraries correspond to pick-up and delivery routes (possibly passing at satellites to service the other types of demands) among customer zones.

The path-based SSND formulation aims to minimize the number, cost, and impact of vehicles in the city while satisfying demand requirements and capacity limitations. Three sets of decision variables are defined to select urban-vehicle services, city-freighter work assignments, and demand itineraries, respectively. The objective function computes the total generalized cost of the system (operations and negative impact on the city) as the sum of the costs of the selected urban-vehicle services and city-freighter work assignments.

The constraints state that each demand must be satisfied by a single itinerary (split demands may be accommodated), enforce the urban-vehicle capacity restrictions for each leg of the vehicle route, and enforce city-freighter capacity restrictions at all times for each segment of a work assignment. These last two groups of relations are the classical linking constraints of network design formulations. Additional constraints enforce the satellite capacity restrictions regarding total numbers of urban vehicles (services), mode-specific urban vehicles, city freighters, and freight handled. Note that the coherence and synchronization of the respective numbers of urban vehicles and city freighters present simultaneously at satellites are provided by the flow of freight imposed by the demand itineraries. A final group of constraints limits the numbers of services and work assignments of each type operated to the size of the corresponding fleet.

4.2 Routing-based models

Routing vehicles, of any mode on the appropriate infrastructure, to provide transportation for the freight loads with origin or destination or both in the urban area studied is an intrinsic part of City Logistics. The issue is directly linked to the first/last mile/kilometer activities, particularly for single-tier systems, and most pick-up and delivery activities on the components of the second tier of more complex systems. It is also noteworthy that the generation of first-tier services may be addressed through routing principles. Not surprisingly, several models have been proposed where all transportation activities are represented through the vehicle routing perspective.

This subsection is dedicated to presenting a brief overview of these models. We start with the basics, namely, the last-mile/km delivery of inbound demands to customers, which is a core activity in all CL systems (Section 4.2.1). Demand delivery may take place out of CDCs, particularly in single-tier systems or satellites. We then turn to the case of the multi-type demand with combinations of inbound demand delivery, outbound demand pick-up, and local demand pick-up and delivery activities (Section 4.2.2). We conclude with models where routing is planned and possibly

synchronized, on several tiers (Section 4.2.3).

4.2.1 Last-mile delivery

City logistics customers are confronted with the final transportation operator, which provides the last-mile delivery service. Last-mile delivery is the final stage of the supply chain where products are sent from a facility, which can be a local warehouse, a CDC, or a satellite, to customers. Last-mile delivery is most often managed as a less-than-truckload service, where shipments for different customers are consolidated onto a vehicle. The vehicle then visits the customers in a sequence called a route. The determination of optimal routes is precisely the objective of what is called the *Vehicle Routing Problem (VRP)* in the operations research literature.

The VRP was introduced in the late 1950s by Dantzig and Ramser (1959). In its initial setting, the VRP is a “pure” combinatorial problem, far from the actual applications in City Logistics. The VRP is defined on a network. In CL terms, the nodes of this network represent the facility (the depot in VRP vocabulary) and the customers. These nodes are connected by uncapacitated edges (traffic may flow in both directions). A cost (distance, in pure VRP) is associated to each edge, to be incurred when a vehicle travels along it. Each customer has an inbound demand to be delivered from the facility-depot. A homogeneous fleet of capacitated vehicles is available at the facility-depot and provides the delivery service. The VRP aims at determining minimum cost routes, i.e., sequences of customers, such that each customer is visited once and the capacity of vehicles is not exceeded. This problem is now called the Capacitated Vehicle Routing Problem (CVRP), while the acronym VRP denotes the family of vehicle routing problems.

Over the last sixty years, there has been a steady increase in the variants considered, mainly motivated by applications. These variants are defined by considering a different type of input data, additional constraints, other objective functions. Several features have to be considered to tackle real-life applications such as those encountered in City Logistics. Such VRPs are called “rich VRPs”. Rich VRPs can be classified according to the scenario characteristics and the physical problem characteristics as proposed in Lahyani et al. (2015). The features of the scenario are defined by the type of input data, management decisions, number of depots, types of operation types, load splitting constraints, planning period, and vehicle utilization (single/multi-trip). The physical characteristics of the problem are related to the vehicles, the time-window structure and time constraints, the incompatibility constraints, and the objective function definition. These characteristics define variants of the VRP, which are generally addressed in a general setting but are relevant in City Logistics. We focus on some of them, starting with the variants based on the scenario characteristics. The input data can be dynamic (see Section 5). However, in short to medium-term planning, stochastic VRPs are of interest for capturing the variability of the environment. Stochasticity is usually considered in terms of demand, service times, and travel times (see Oyola et al., 2017a,b, for a survey).

The routing decisions can be made jointly with other management decisions in integrated routing problems. Among them are Location Routing Problems, which aim to simultaneously determine the location of depots and the routes rooted at those depots (Section 3.2). Inventory routing Problems consist in determining the routes and quantities to be delivered to avoid shortage at customers

(Coelho et al., 2014). This problem is related to the Vendor-Managed Inventory (VMI) policy, in which the supplier monitors the inventories of retailers and decides on replenishment policies. VMI is used in particular in food distribution in City Logistics (see, e.g., De Maio and Laganà, 2020).

The different types of operations considered in the VRP literature are encountered in City Logistics. We distinguish delivery/pick-up operations from/to a terminal, pick-up and delivery operations, and delivery-then-pickup operations. The first case corresponds to the classical VRP. The goods are loaded at the depot and then delivered to the customers or vice-versa. The second case is the general one known as the VRP with Pick-ups and Deliveries. Goods are picked up and delivered at any location. There are many variants of this problem. For example, pick-up and delivery sites can or cannot be different. A one-to-one relationship between the pick-up and delivery locations may be imposed, as in the courier industry, or not. In the last case, the operations are carried out in sequence: deliveries first, then pick-ups second. This problem is known as the VRP with Backhauls. For an overview of this class of problems, we refer to Battarra et al. (2014); Koç et al. (2020); Koç and Laporte (2018). In Section 4.2.2, we provide a brief overview of the VRP with Pick-ups and Deliveries in multi-tier CL.

Regarding the physical characteristics, we do not detail all constraints related to the vehicles, including their number, type, structure, capacities, loading policy, and driver regulations. Instead, we focus on the constraints related to time management. While a limit on the route duration is included in the basic definition of the VRP, the VRP with time windows (VRPTW) was among the first extensions considered. A hard time-window constraint at a node imposes that the node must be visited by a vehicle between a lower and upper time limit. A time window constraint is said to be soft when a penalty is applied for late arrival. Time windows can be unique or multiple and can be imposed at the depot. In the context of City Logistics, vehicles may visit facilities, CDCs or satellites, to be reloaded during the planning period. Time-windows are then defined at the satellites to model synchronization in a multi-level distribution systems (see Section 4.2.2; Nguyen et al., 2013). Desaulniers et al. (2014) propose a survey of models, exact methods, and heuristics for the VRPTW.

The last characteristic we would like to mention is related to the objective function. The classical variants of the VRP variants minimize cost-oriented functions such as the total distribution cost, total travel time, or total duration. However, other objective functions have been considered in the literature (see, e.g., Jozefowiez et al., 2008). In the context of City Logistics, the so-called sustainable VRP is particularly relevant. The sustainable VRP consists in taking into account social and environmental criteria in the design of routes. Social factors can be customer, driver, or society oriented depending on whether there are related to customer satisfaction, such as on-time delivery or the freshness of the products, related to job satisfaction, such as workload balance or delivery consistency, or associated with the density of population, the people utilization of the streets making up the route, or the cultural, social, or touristic interest of those same streets. Such social aspects have not yet been addressed, unfortunately, except for a few environmental issues. VRPs addressing the latter are called green VRPs in the literature. The environmental factors are related to gas emissions and the use of electric vehicles or hybrid vehicles, taking into account energy consumption. These alternative objectives have been classified by Vidal et al. (2020), and a review of the sustainable VRP in City Logistics is proposed by Dündar et al. (2021).

The VRP solution methods cover the whole spectrum of integer programming optimization

algorithms. They cover exact methods based on mathematical programming approaches as well as approximate procedures. Such methods are presented in the book by Toth and Vigo (2014). During the last ten years, algorithms have been designed to tackle specific variants of the VRPs, including many of the characteristics mentioned above. Nowadays, approximate methods are frequently based on metaheuristics. The most popular ones are tabu search, variable neighborhood search, genetic algorithms, and ant colony optimization (see, e.g., Elshaer and Awad, 2020). As for the exact approaches, they are based on the branch-and-price or branch-and-price-and-cut frameworks (see, e.g., Costa et al., 2019). A significant methodological advance is the development of algorithms able to identify high-quality/optimal solutions for different variants of the VRP. Two essential works in this line of research are the articles of Vidal et al. (2014) and Pessoa et al. (2020). Vidal et al. (2014) have developed a genetic algorithm hybridized with local search procedures, which is problem independent. Operators related to the specificities of the considered variant are selected automatically. They correspond to the assignment, sequencing, and evaluation of routes. The authors assessed 29 classical variants of the VRP on which they could match or outperform the state-of-the-art tailored methods. Considering exact methods, Pessoa et al. (2020) propose a generic framework to model VRP problems and a Branch-and-Cut-and-Price algorithm to solve them. This algorithm includes most of the advanced features, which were introduced to solve various VRP variants. New concepts are also introduced related to the modeling part, such as the concept of mapping between the route variables and the constraints of the master problem or to the solution method such as the concept of packing and elementarity sets, which lead to extend some advanced components such as the consideration of non-elementary routes (i.e., routes that serve more than once a customer). The authors were able to solve instances of 6 classical variants of the VRP to optimality. Their approach outperforms the state-of-the-art for five of them, while it is dominated on a specific class of instances of the VRP with pick-ups and deliveries.

To conclude this section, we should point out that several variants have appeared in the VRP literature that are directly related to the specifics of City Logistics in recent years. Thus, many articles consider the various types of last mile delivery services: 1) home delivery; 2) pick-up points such as dedicated lockers or stores; 3) trunk/in-car delivery, also called roaming delivery. In the latter case, customers' packages can be delivered to the trunks of cars. In-car delivery is different from home delivery and pick-up points delivery since a car moves and may be in different locations during different periods. These delivery services can be combined and proposed to customers who benefit from greater flexibility according to their convenience. Moreover it contribute to increase the rate of successful first-time deliveries and decrease delivery costs (e.g., Reyes et al., 2017; Yuan et al., 2021; Dumez et al., 2021).

The management of the vehicle fleet has specific characteristics in City Logistics. Very often, the route durations are shorter than the possible planning horizon. This means that the courier is going to make more than one route during his shift, but rather a sequence of routes. The multi-trip VRP addressed this additional assignment decision. We refer the interested reader to Cattaruzza et al. (2016) for a survey. Collaboration between carriers through city incentives has also been considered. Montoya-Torres et al. (2016) have shown that substantial gains in distance could be achieved for the city of Bogota with a horizontal collaborative system. Finally, large retailers can complement their delivery service by offering to deliver online orders to their in-store customers on their way home. This strategy is called crowd shipping and the related optimization problem has been addressed as the vehicle routing problem with occasional drivers (Archetti et al., 2016;

Dayarian and Savelsbergh, 2020).

When VRPs are addressed in the context of City Logistics, space and time issues naturally arise. A recurring concern is related to synchronization related to the load, to a resource, or locations. We refer the reader Sections 2.5, 4.1, and 4.2.3 where they are discussed in more detail. As mentioned above, the routing part can be considered too schematic in the VRP as a path between two places to visit is reduced to its distance and duration. Recently, authors have considered a more detailed approach by including information related to the real road network in the problem definition (see Ben Ticha et al., 2018, for a survey). Finally, to be even more realistic, many authors have considered the time-dependent VRP. In this case, time or speed functions are associated with the arcs of the underlying graph. In most models (see Gendreau et al., 2015, for a survey) arcs are associated with the pairs of locations to be visited. Recent works (see, e.g., Huang et al., 2017) have, however, defined them at the level of the real-road network.

4.2.2 Pickup & delivery Operations in Multi-Tier City Logistics

Most CL projects and research developments address inbound movements only, reflecting the dominant position the traffic proceeding from the exterior of the urban area towards its center occupies within the travel patterns observed in most cities. Yet, the volumes of freight produced within the city and shipped to locations within or outside it may be significant, particularly as the dimensions and density of the city increase. The situation is gradually changing, however, an increasing number of projects and contributions to the CL literature addressing the simultaneous satisfaction of several demand types with the same resources, facilities, and multimodal fleets (Crainic et al., 2021b). As a result, *Pickup-and-Delivery* vehicle routing (*P&D*) formulations are increasingly proposed to address the corresponding planning and management problems. This section focuses on challenges and recent contributions targeting these issues in the context of multi-tier CL systems.

To our best knowledge, Crainic et al. (2012) were the first to investigate this issue within the context of two-tiered CL systems. The authors did not formulate models or algorithms. They instead examined various integration strategies of inbound, outbound, and local (at the second tier) traffic and discussed the potential impact on operations and management of strategies where facilities and vehicle fleets are more or less integrated. Thus, for example, the problem is much simplified when the deliveries to customers (last-mile part of inbound demand) and the collection of goods at origins within the area (first-mile part of outbound demand) may be separated by, for example, performing them at different periods during the day. The same resources may then be used sequentially, within the constraints of the working hours of the facility employees and vehicle operators, for each type of operation. The total resource-related costs are then expected to be low. The models and methods described in Section 4.2.1 and the surveys mentioned above may be used for each operation.

Combining several demand and traffic types within the same operations procedures and, therefore, within the same optimization models is more complex, however, both from a managerial point of view and from a modeling and algorithmic-development perspective. Let us illustrate such potential complexity within the routing of vehicles on a second tier of the CL system. Figure 2 illustrates part of a potential city-freighter P&D route when the three demand types may be serviced within

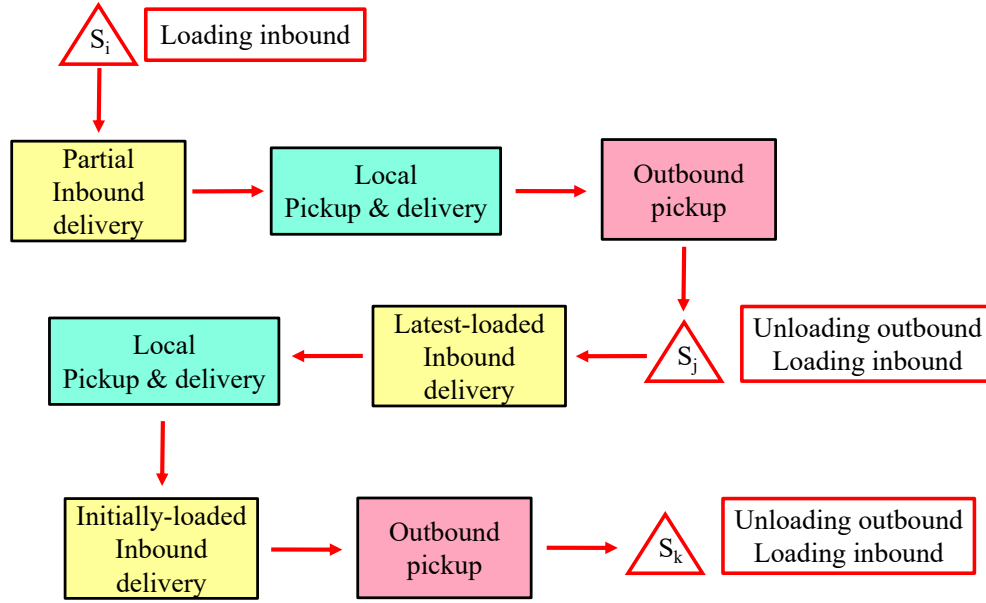


Figure 2: Pickup & delivery city-freighter route for multi-type demand

the same vehicle. We assume that an optimization module has built this route to minimize the generalized CL costs within the constraints of satellite and customers time windows, operating rules regarding the driver and the vehicle, and the vehicle loading and unloading operation policies, given the urban-area location and the time period. The latter is important for all P&D routing problems but are particularly stringent in the CL context. Indeed, mixing pick-up and delivery operations means that one has easy access to loads within the vehicle when a delivery needs to be performed. Thus, either the vehicle is so equipped that any load may be reached at any time, or sufficient time, and pace, is available at all relevant locations to unload what is needed to achieve a specific load which is to be delivered and to reload everything back into the vehicle, such situations are implausible to occur in CL contexts, or freight is to be loaded in an appropriate order for easy unloading and delivery. The *Last-In-First-Out (LIFO)* loading policy implements such an order, as well as the VRP-with-Backhauls operating strategy. According to the latter, a vehicle operating a P&D route first visits linehaul customers, which require deliveries, and then backhaul customers, which require pick-ups (see the P&D surveys referred to above, and Koç and Laporte, 2018, for a detailed review of model formulations and solution methods).

The city-freighter multi-tour route of Figure 2 was generated according to the LIFO policy. Still, the operation strategy provides quite a high flexibility in using resources and servicing customers. The vehicle loads inbound freight at satellite S_i and starts a sequence of visits to customers until all inbound traffic has been delivered. This sequence is followed by a series of P&D activities servicing local demand, followed by a sequence of collections of outbound loads, which are delivered to satellite S_j for transfer to a first-tier service bringing them to the appropriate CDC (and, from there, to their final destinations outside the city). The city freighter loads a new set of inbound loads, delivers some of them, continues with a series of P&D operations, completes the delivery of inbound demand, collects outbound demands, delivers them to a satellite, and continues its planned

route.

More complex strategies, still abiding by the LIFO rule, may be defined, as described in Crainic et al. (2012). The authors also emphasize that the efficiency of the routing problem, in terms of the number of vehicles, total cost, and time, will increase with the degree of integration of operations. Yet, on the other hand, the managerial and operational (particularly for the driver performing the loading and unloading operations) complexity would increase as well. The authors thus generalize the VRP-with-Backhauls idea and propose a *Pseudo-Backhaul* strategy, where several delivery, pick-up, and P&D sequences may be combined, provided each sequence is completely finished before a different type of operations is undertaken (the partition of the second inbound-delivery sequence in Figure 2 contradicts this definition). Figure 3 illustrates a city-freighter route implementing a Pseudo-Backhaul policy while servicing inbound, outbound, and local demand customers between two satellite visits.



Figure 3: Pseudo-Backhaul Pickup & delivery city-freighter route

Fontaine et al. (2021) applied such a policy to the utilization of first-tier vehicle compartments within a two-tier CL SSND tactical-planning model with approximated second-tier routing. Nguyen et al. (2017); Crainic et al. (2016b) adopted the same strategy in their studies of multi-zone, multi-trip VRP with P&D and time windows, where the vehicle routes visited a series of satellites (supply points in the articles) and inbound, outbound, and local demand customers, in such a way as to synchronize the hard time windows of the satellites and customers. The authors extended the tabu search algorithm proposed by Nguyen et al. (2013) to address the increased complexity and challenges of integrating the three demand types within the same model and algorithm. Bettinelli et al. (2019) proposed a Branch-and-Cut-and-Price algorithm for the same multi-trip problem with separated pick-up and delivery operations.

4.2.3 Integrated Freight and Vehicle Routing in Multi-tier City Logistics

Generalizing the definitions of Gonzalez-Feliu (2013) and Cuda et al. (2015), *Multi-echelon Vehicle Routing Problems* (*nE-VRP for a generic number of n echelons*) address the issue of optimally routing freight from origin to destination through the terminals of a multi-echelon/tier system, while simultaneously optimizing the routes of the vehicles providing transport services at each tier. The nE-VRP methodology is thus appropriate for the short to medium-term planning of multi-tier CL systems, mainly when no line-based transportation services are considered on the first tier and the vehicle routes of the no-line modes have to be determined. Cuda et al. (2015) present a general survey of the 2E-VRP historical development, models, and solution methods. Additional

information may be found in Cattaruzza et al. (2017), which describes the various freight flows and vehicle movements within urban areas and the implications in terms of models and solution methods. Guastaroba et al. (2016) also briefly touch on nE-VRP while focusing on intermediate facilities in service network design and routing.

The surveys referred to above, as well as in Sections 4.2.2 and 3.2, indicate that 1) the study of multi-echelon location-routing problems (Section 3.2) was initiated quite some time before that of nE-VRP; 2) the literature in both cases addresses almost exclusively two-echelon problem settings; we consequently focus this section on *2E-VRPs* applied to 2T-CL systems; 3) City Logistics is the application field which motivated the introduction of 2E-VRP problems, the paper by Crainic et al. (2009) introducing the first formal definition of the problem (Cuda et al., 2015); most papers in the literature focus on the basic version of the problem settings, the *Capacitated 2E-VRP (2E-CVRP)*.

Like the CVRP, the 2E-CVRP is defined on a network with nodes representing a single CDC (the depot), a set of satellites, and customers. Two sets of undirected edges link these nodes without capacity limits. The first set connects the first-tier nodes, CDC and satellites, and pairs of the latter, while the second performs the same role for the second tier, each satellite to customers and pairs of customers. Each customer has an inbound demand, all demand being available at the CDC. Two tier-specific homogeneous and capacitated fleets of vehicles provide the delivery services. A single itinerary must deliver each customer demand, a first-tier urban-vehicle route, a transfer at a satellite, and a second-tier city-freighter route. A cost is associated with each edge of the network, incurred wherever included in a vehicle route. A unit handling cost is associated with each satellite for unloading freight from the urban vehicle, transferring and loading it into the appropriate city freighter. The number of city freighters that may load freight at a satellite, i.e., the number of routes initiated at the satellite, is limited by a satellite capacity.

It is noteworthy, given this definition, that the application of 2E-CVRP methodology to City Logistics is restricted to cases with a single first-tier facility. Arc and path-based models may be defined for the 2E-CVRP, and exact and meta-heuristic solution methods have been proposed for both model types.

The 2E-CVRP name is introduced in Gonzalez-Feliu et al. (2008), including also a formal definition as well as a three-index, mixed-integer arc-based formulation (based on multi-commodity network design with arc flow decision variables). From that formulation, Perboli et al. (2011) (see also Perboli et al., 2010) introduce a set of families of valid inequalities to strengthen the formulation, two matheuristics, as well as a Branch-and-Cut algorithm with an initial heuristic solution. Jepsen et al. (2013) notice that, when the assignment of customers to satellites is given, the problem decomposes into a split-delivery CVRP on the first tier and a set of CVRPs, one for each satellite. The authors then propose a three-index edge-flow formulation, which provides upper bounds even for cases with more than three satellites. They derive a relaxation based on the previous observation, which provides a lower bound. These elements are then integrated into a Branch-and-Cut algorithm that outperformed the other exact algorithms present in the literature.

Sets of first and second-tier feasible routes are defined for path-based 2E-CVRP formulations, the cost of each route being computed as the sum of the costs of its arcs. Binary selection decision variables are associated to each route. A flow variable is also associated with each pair of first-tier vehicles and satellites representing the freight loaded on the vehicle at the CDC to be delivered

to the satellite. The path-based model then minimizes the total cost of the system, computed as the sum of the costs of the selected routes on the first and second tiers, plus the total freight handling cost at satellites. The constraints of the model enforce the capacity restrictions of the satellites, first and second-tier vehicles, the delivery to each customer by a single itinerary (no-split delivery, Archetti and Speranza, 2008), the flow balance at satellites (total flow brought in by urban vehicles must equal the total flow taken out by the city freighters), and the number of routes used at each tier to the number of vehicles in the associated fleet. Baldacci et al. (2013) proposed such a path-based formulation. The authors derive continuous and integer relaxations, a bounding procedure based on dynamic programming, a lagrangian heuristic, and a problem reformulation based on an enumeration of collections of first-tier routes yielding a set of multi-depot CVRPs with side constraints (Baldacci and Mingozzi, 2009). The exact solution method built on these elements outperformed the other exact solution methods present in the literature at that time. Yet, the current best exact algorithm for the 2E-VRP is a Branch-and-Cut-and-Price algorithm proposed by (Marques et al., 2020) for a new route-based formulation. Using several advanced CVRP model enhancements, the proposed route-based formulation does not include CDC-to-satellite flow variables but rather an exponential number of constraints (enforcing flow conservation), which can be separated in polynomial time. The authors also proposed new families of inequalities strengthening the linear relaxation of the model and a new branching strategy tailored for the two-echelon problem setting. The authors report optimal solutions to the instances in the literature (with up to 200 customers and ten satellites) and a set of new instances with 300 customers and 15 satellites.

The 2E-CVRP is NP-Hard (see, e.g., Cuda et al., 2015) and it is thus not surprising that heuristic solution methods are proposed. Large neighborhood-search-based meta- and matheuristics (Gendreau and Potvin, 2019) currently offer the best performances for this class of problems, including Hemmelmayr et al. (2012), which proposes an *Adaptive Large Neighbourhood Search* with destroy (removing part of the current solution, customers or satellites) and repair (to build a new feasible solution by re-inserting the removed customers or satellites in different positions) operators tailored for each tier of the problem; Breunig et al. (2016) improved most of the best solutions through a Large Neighbourhood Search (LNS) meta-heuristic, which focuses on the second tier through new route destroy and repair operators combined with a local-search route-improving phase, the first tier routes being reconstructed at each iteration; Wang et al. (2017) enhanced the problem setting with time-dependent travel times on congested second-tier arcs and fuel-consumption and emission cost considerations and proposed a matheuristic combining a *Variable Neighbourhood Search* meta-heuristic to construct a set of second-tier routes and an exact integer programming method over the set of generated routes. The currently best-performing meta-heuristic for the 2E-CVRD is proposed by Mühlbauer and Fontaine (2021) for a CL application involving cargo-bicycles on the second tier, containers being transferred at satellites from first-tier vans to cargo-bikes. The authors also acknowledge that travel times are not generally symmetric in urban areas and propose a new formulation addressing the issue. The synchronous parallel meta-heuristic (Crainic, 2019) starts with several different initial solutions, each being the starting point of a Large Neighbourhood Search thread (with particular parameter values). The threads are stopped and synchronized after a certain number of iterations, solutions are exchanged, and new initial solutions for the LNS threads are identified. A heuristic is used to update the first-tier routing when the demands at satellites are modified.

This rapid survey of the field (more references and in-depth surveys offered by Cuda et al., 2015;

Schiffer et al., 2019) illustrates that, on the one hand, most contributions address the fundamental problem setting but, on the other hand, urban transportation and CL characteristics start to appear in the 2E-CVRP literature. We already mentioned time-dependent travel times and environmental concerns (Soysal et al., 2015; Wang et al., 2017) and the utilization of cargo-bicycles on the second tier of a CL system with asymmetric travel times. As the variety and modes of vehicles used in City Logistics are continuously broadening, the introduction of electric vehicles in the 2E-CVRP problem setting is worthy of notice. (Breunig et al., 2019) address this problem and the particular challenges brought by the recharging constraints to second-tier vehicle routing, and propose an exact method based on the algorithm of Baldacci et al. (2013) and an LNS meta-heuristic inspired by ideas introduced by Breunig et al. (2016). Extensive comparison results showed the good performance of the proposed meta-heuristic and the value of integrated planning.

Also important is the explicit consideration of time considerations in 2E-CVRP settings. Grangier et al. (2015) integrate customer time windows, synchronization at satellites, and multi-trip second-tier routes in a new 2E-CVRP formulation. Customer time windows and no storage capacity at satellites imply *synchronization* requirements (Drexler, 2012), i.e., that first and second-tier vehicles must “meet” at satellites to ensure smooth freight transfers and on-time delivery at customers. The authors address this issue by explicitly defining decision variables for the time vehicles start service at the nodes, satellites, and customers, of the network, together with constraints enforcing the order of operations at satellites. An ALNS meta-heuristic is proposed, together with operators tailored to rebuild feasible solutions concerning time.

Yet, as this brief literature survey illustrates, 2E-CVRP contributions address very few of the system attributes and challenges of 2T-CL systems. Many of these attributes were introduced by Crainic et al. (2009) in the first formal definition of the two-echelon vehicle routing problem, presented within their study of tactical planning of two-tier CL systems. The authors proposed path and arc-based models for the 2E-VRPTW with multiple CDCs (depots), scheduled (i.e., time-dependent) multi-commodity non-substitutable inbound demand defined by origin-destination and by product type, customer time windows, heterogeneous and capacitated urban-vehicle and city-freighter fleets with particular product-to-vehicle restrictions, multi-tour city-freighter routes on the second tier, time-dependent travel times, capacitated satellites with no storage room, and synchronization requirements. The authors also defined the corresponding single-tier routing problem for the second tier of the system when the satellites handling each customer demand are known. The authors discuss solution-method avenues and introduce a meta-heuristic framework based on decomposing the problem along tiers. No implementation is, however, reported.

Research on this class of problems is still in its initial stages. We are not aware of any contribution addressing all the characteristics present in Crainic et al. (2009), which, moreover, does not include several important attributes, e.g., outbound and local demand, public and private high-capacity transportation modes (such as interurban rail connected to stations within the city and passenger light-rail, bus or trolleybus), “new” transport technologies, e.g., drones, robots, and autonomous vehicles, short-term storage, involvement of individuals in the last tier of the system, either to deliver or pick-up loads on their way out of or toward their destinations (e.g., crowd sharing) or to collect their own loads at near-by facilities (e.g., lockers), and uncertainty. Most of these recent delivery strategies have started to be addressed for one-tier systems (see section 4.2.1). Research in all these aspects is needed. In problem settings, it combines several of them, to problem definition, modeling, solution-method development, and case studies of applications in

cities in various social, political, economic, and cultural environments. We illustrate some of the first steps in this field in the rest of the section.

Zhou et al. (2018) address a 2E-VRP with inbound (e-commerce package) demand, multiple CDCs (depots), and shared resources. In this problem setting, each CDC belongs to a particular logistics operator. Hence, each customer is associated with a particular CDC, and the problem has multi-commodity (origin-to-destination) demand. The deliveries out of all CDCs are, however, performed through a set of shared satellites. Satellites have capacities restricting the amount of freight and the number of customers, which may be serviced. Homogeneous fleets of urban vehicles are associated to each CDC and are thus not shared. On the second tier, however, homogeneous fleets of city freighters are associated with each satellite and thus shared resources. All vehicles are capacitated, and each fleet is of a limited size. Duration limits are imposed on first-tier routes, while a maximum number of city freighters may be used globally. An additional type of facility is defined. Called *customer pick-up*, it stands for sites where customers may pick up their package close to one of their activity locations (e.g., home or work). A set of delivery preferences then characterizes each customer; either home, or a set of preferred pick-up facilities, or both. The goal is to design first and second-tier routes and the customer-demand itineraries given corresponding to-be-determined pick-up options to minimize costs while enforcing the usual facility, vehicle, and customer demands. A hybrid multi-population genetic meta-heuristic is proposed (based on Vidal et al., 2012), with very good results. The experimentation included a real-world instance, based on an application in China, and showed customers the benefits of offering pick-up options.

Dellaert et al. (2019) address a 2E-CVRP setting with multiple CDCs, a substitutable (may be satisfied from any CDC) inbound customer demand, hard customer time windows, and waiting allowed at all locations at no cost. Given the typical cost and capacity restrictions, the goal is to design sets of first and second-tier routes to satisfy customer demands within their time windows through single city-freighter visits. The authors propose a somewhat classical three-index arc formulation and discuss the additional complexity and challenges brought by the interconnectivity and coordination of first and second-tier tours at satellites, including arrival and departure times of the corresponding vehicle routes. The authors thus propose a second formulation based on *tour-trees*, a tour-tree being composed of an urban-vehicle tour and at least of city-freighter tour starting from each satellite visited by the urban vehicle. Considering the sets of feasible tour-trees, the one-path model takes the form of a set partitioning formulation, where the optimal set of tour-trees satisfying demand with a single visit to each customer is to be selected. A Branch-and-Price solution method is proposed. The authors also proposed a decomposition of the tour-trees along the tiers, yielding a two-path formulation. The associated solution method enumerates the first-tier tours and adapts a Branch-and-Price algorithm to generate the associated second-tier tours dynamically. This last formulation and solution method outperformed the one-path model on instances with up to five satellites and 100 customers (optimal solutions obtained).

The explicit consideration of origin-to-destination multi-commodity (inbound) demand constitutes an important development in the field. Dellaert et al. (2020) extend their previous work in this direction, and introduce an arc-based formulation, based on single-commodity one (Dellaert et al., 2019), and a three-path model (Crainic et al., 2009, and Section 4.1). The authors acknowledge the limitations of the arc-based formulation in terms of instance size, which may be addressed, and discuss the challenges of synchronizing first and second-tier vehicles at satellites, in particular to the dynamic generation of first and second-tier tours and OD demand itineraries, built out of

those two. They, therefore, propose a third model, where the first-tier routing is arc-based, while a path-based formulation takes care of the second-tier routes. Customer-to-satellite assignment decision variables and inter-tier synchronization constraints (more straightforward to write due to the arc formulation on the first tier) connect the two models. The authors extend the solution methodology proposed in the earlier paper and report near-optimal solutions for instances with up to five satellites and 100 customers.

We complete this literature tour with what we believe to be the first multi-objective contribution to the 2E-VRP literature in a CL context. Anderluh et al. (2021) address a problem setting, where cargo-bicycles or small electric vehicles perform the second-tier tours delivering inbound freight to customers in the controlled inner-center of the city (Vienna is both the inspiration and the source of the instances used for the experiments). A fleet of urban vehicles both performs this service in the rest of the city and brings the freight to be delivered in the inner city to meeting points where the two fleets synchronize, and transfers take place. Synchronization takes place at satellites without storage capabilities. The problem setting acknowledges that there is no clear-cut frontier between the inner and the rest of the city. Instead, there is a “grey zone” between the two and the goals is to select how to service (regular urban vehicle or cargo-bicycle). The authors explicitly consider the CL planning problem’s multiple objectives, identifying three goals to minimize transportation cost, emission, and disturbance inconvenience for citizens. They propose a Large Neighbourhood Search meta-heuristic and perform an extensive computational study of the impact of the different problem elements on the tactical plan proposed and on the city.

4.3 Multi-tier planning with approximated lower-tier activities and costs

The SSND model of Section 4.1, combining network design and vehicle routing methodologies, may be applied both to medium-term tactical and to short-term operational planning processes, with the appropriate definition of external and customer zones (more aggregated for tactical planning than for operational decisions) and estimation of demand and resources. It is indeed noteworthy that Crainic et al. (2009) introduced the *day-before* planning problem, together with path and arc-based versions of the SSND formulation (and the two-echelon VRPTW described in Section 4.2, Crainic et al., 2009), for the inbound-demand case.

However, the authors also noticed that including the detailed customer demand and the precise routing of second-tier vehicles when building the tactical plan some time before repeatedly applying it appears less appropriate than for the day-before situation. One certainly cannot neglect, however, lower-tier activities and costs. Their impact on first-tier decisions and the global performance of the CL system may be indeed significant, as they are a determining factor in building and selecting freight itineraries and ensuring the synchronization of vehicles at satellites. Approximating these activities and costs and embedding the approximations into the SSND formulation (similar development may be performed for the multi-tier routing models) appears as a promising research and utilization avenue. The model proposed by Fontaine et al. (2021) for the tactical planning of two-tier CL systems follows up on this observation.

The problem setting is similar to that of Section 4.1, in particular regarding the definition and attributes of first and second-tier facilities, the inbound and outbound multi-commodity demand,

the set of potential first-tier line-based and no-line multimodal urban-vehicle services. With respect to transportation modes and vehicles, the authors enrich the problem setting and formulation by introducing the notion of the compartment. This addresses the observation that several vehicle types have more than one cargo-holding space, e.g., river and canal barges with multiple cargo bays, most proposed cargo tramways, as well as any vehicle, by whatever mode, with vertical or horizontal separators of the cargo-holding space yielding a partition where each component may be accessed independently of the others. Compartments are introduced into the tactical-planning model by defining the set of its compartment services (of cardinality 1 when no compartments are present). Loads are thus assigned to a specific service compartment while all compartment services are selected when the corresponding service is selected.

As indicated above, the second tier is represented through an approximated cost of servicing each customer zone out of each satellite. It may be connected (delivery out of satellites to receiving customer zones and pick up at shipping customer zones to deliver at satellites then CDCs). The authors propose a compact network representation by adding this cost to the cost of the services which may carry the flow of the particular demand into or out of the satellite in time. Similar to all other costs described in this chapter, the assignment costs represent not only the transport, unloading, and loading costs, but also city-disturbance factors related to these activities.

Freight itineraries may then be defined straightforwardly based on the service used. An inbound-demand itinerary thus starts at the external-zone of origin, bringing the demand to the selected CDC, where the goods are loaded into an urban vehicle (and compartment) of the selected service, which transports them to the selected satellite (with possibly intermediary stops but no work on the goods considered), from where they are delivered to the final customer zone paying the approximated assignment-routing cost. An outbound-demand itinerary follows the same definition in reverse order. Notice that this definition is directly provided by the selection of a service and compartment, which fixes the CDC, satellite, and relevant time stamps which then, implicitly, takes care of the synchronization.

The formulation selects the first-tier scheduled services, determines the satellites which service each customer zone, selects the itineraries of each inbound and outbound demand, and provides an estimation of the dimensions of the urban-vehicle and city-freighter fleets required to satisfy demand, as well as of the utilization of the facilities and multimodal fleets.

It is an arc-based formulation of the SSND problem with resource management based on two sets of binary (yes or no) decision variables: 1) service selection and 2) assignment of given origin-destination demand to a specific service and compartment to be delivered to a particular satellited visited by the service.

The objective function minimizes the total generalized cost of the system. Constraints then ensure that each item is assigned precisely to one compartment and that outbound demand is assigned to a compartment only after the inbound demand is unloaded and the compartment is empty. Linking constraints enforce the capacity restrictions on each compartment and service. Capacity constraints limit 1) the number of vehicles of each fleet assigned to a city distribution center; 2) the number of urban vehicles, in total and per fleet (mode), present at a satellite at each time period; and 3) the total amount of cargo which can be unloaded or loaded at a satellite at each period. An innovative solution method based on Benders decomposition is proposed and shown to

be very effective through an extensive experimental campaign.

4.4 Illustration of demand uncertainty in CL tactical planning

The literature addressing uncertainty in the context of City Logistics is very sparse. We use these contributions to illustrate the business-as-usual demand uncertainty type of problem and the associated modeling challenges.

Crainic et al. (2016a) study the issue of uncertain demand in the two-tier CL context introduced in Crainic et al. (2009) (Section 4.1). Recall that such stochastic formulations are required when major human and material resources must be allocated and their utilization must be planned for the length of the planning horizon, before the actual operations take place, while simultaneously acknowledging the strategies and costs that are involved during operations to adjust the plan to the observed demand. The tactical plan, which is built prior to the beginning of the season, then aims to determine the main structure of the service network and associated resource allocation, which will be executed regularly at each period of the planning horizon, but without fixing the operational details that will be addressed at execution time. The goal is to optimize the overall cost (operations and environmental impact) of the system in terms of service selection and resource allocation, plus an estimation of the costs involved in adjusting the plan and operating accordingly over the contemplated planning horizon. One thus expects that the explicit *flexibility* thus introduced into the tactical plan makes it more robust, that is, increases the capability of the selected service network to accommodate a certain forecast range of demand variability with no or little modification to the activities of the major resources involved.

Crainic et al. (2016a) propose a two-stage stochastic-programming formulation, the first stage corresponding to the selection of the first-tier services and the determination of partial demand itineraries up to the selected satellites together with customer-to-satellite assignments. These results guide and constrain the second-stage recourse strategies, which address the selection of ad-hoc (additional) city freighters and the global city-freighter routing and, eventually, slightly modify the service network to deliver the revealed demand. The definition of first-tier services, second-tier city freight work assignments, and demand itineraries do not fundamentally change from the deterministic setting; the same may be said for most problem parameters. Indeed, definitions are adjusted according to the stage they occur (e.g., in the first stage, demand itineraries stop at satellites with customer-to-satellite assignments). Additional costs, decisions variables, and constraints are also added to account for the recourse strategies, e.g., the cost of ad-hoc freighters and their limited capacity enforcement, but they are of the same nature as the initial model.

The significant change in problem components is that, instead of a single figure assumed certain, customer-demand volumes are represented by some probability distribution of the possible realizations when the plan will be applied repeatedly. A set of scenarios then represents the future, each corresponding to a possible realization of the customer demands, that is, to a possible “day” when the CL system operates according to the plan, adjusting the latter to the revealed demand. This yields an extensive mixed-integer program composed of the decision variables and constraints of the first stage and of as many blocks of scenario-specific (decision variables and) constraints as the scenarios generate to represent the future. The objective value of the two-stage SSND formu-

lation links all the pieces together by minimizing the expected generalized cost of the system. It is composed of the objective function of the first-stage and the sum of the objective functions of each scenario in the second-stage, weighted by the corresponding probability of the scenario being met in the future.

Three recourse strategies are studied, all targeting the routing of regular and ad-hoc city freighters but differing in the degree of freedom relative to the first-stage customer-to-satellite assignments and whether or not slight adjustments are allowed to the service network selected in the first stage. The first strategy aims to modify the plan as little as possible and, thus, the sets of selected services and the associated customer-to-satellite assignments are not modified. Ad-hoc city freighters are added if needed, and the global routing is determined. The second recourse strategy adds flexibility to the system management by relaxing the customer-to-satellite assignments, which allows the re-optimization of the demand flows on the selected services and additional freedom in determining city-freighter work assignments. The third recourse strategy increases the managerial flexibility even more. It does not modify the first-stage service selection but introduces the possibility of slightly changing the departure times to fit the revealed demand better. The authors used the meta-heuristic of Crainic et al. (2009) as the basis of a Monte-Carlo evaluation procedure of these recourse strategies. Not surprisingly, the increased flexibility in resource allocation (satellite and city-freighter utilization) and system management displayed the best performances.

5 Real-time execution

At the execution phase, when CL systems operate, the plans prepared previously (at tactical-operational planning level, mainly the day before) are examined, updated, and executed. This is of particular importance since, in a highly constrained and congested context, small unexpected events can have huge consequences in realizing the plans. For instance, new orders arriving either little before routes start or during the time vehicles are delivering or picking up goods, customers not being home at the vehicle arrival time (failure to deliver), and traffic congestion or other unexpected events en-route (e.g., accidents) leading to not meeting time windows. As indicated in Section 2.5, we focus on the plan re-adjustment, i.e., the re-organization and re-optimization of various components (routes, itineraries, satellite activities), in real or quasi-real-time, following new or updated information, due to unexpected events or demand/capacity updates. We include the re-adjustment of vehicle routes and demand itineraries.

In the last decades, dynamic problems have attracted increasing attention from the research community (Psaraftis et al., 2016). These problems are characterized by the property that the problem inputs are partially known in advance and dynamically change during the operation period. This reflects the real demand from the current logistics and transportation industry. Dynamism is an intrinsic property of many real-world applications. The exact information related to request arrivals, customer locations, time windows, etc., is not always fully available when the routes are planned. On the other hand, the applications are boosted by the recent advances in communication and information technologies, which allow decision-makers to receive updated information in real-time and dynamically adapt the ongoing route plans to the changing environment.

Section 5.1 introduces the context, the main decisions to be addressed related to the adjustment of operational plans, as well as the main decision problems to tackle at the execution level. The main areas that impact route performance are on demands since they can change the entire route plan and need to be addressed on a more global, systemic level. Therefore, Section 5.2 describes optimization problems related to the adjustment of route sets (or itineraries) due to demand dynamics. Other areas that affect single routes and need a route, path, or itinerary adjustments, mainly done at local levels, are examined in Section 5.3, as well as the related optimization problems to deal with them. Finally, the crucial question of path (or trip) computation, resulting in the well-known family of the Shortest Path Problem (SPP), is examined in Section 5.4. The SPP is also used to estimate travel distances and times to feed strategic, tactical, and operational planning models. Still, it is at the execution phase that they need to be robust and reliable due to the needs of real-time computation.

5.1 Background, context, and problem statement

The real-time CL operations are subject to many unexpected events due to the urban context in which they are executed. Indeed, CL systems are included in a set of complex systems: the Urban Freight Distribution system, which is also part of the Urban Dynamics system (Gonzalez-Feliu, 2018b). These unexpected events during execution are a source of uncertainty. They can also be considered in tactical or operational planning (see Section 4.4). However, and although planners

do their best in anticipating those uncertainties and hazards setting their initial plan, they mainly materialize at the execution phase, imperatively necessitating a real-time action to modify these initial plans. Those main sources of uncertainty in a City Logistics context are:

- Demand and its characteristics. It involves the quantity to deliver, origin location, destination location and/or a time slot where the freight can be delivered. This impacts the entire route plan, since new demands, if accepted, need to be placed in the planned vehicles, possibly resulting in re-planning.
- Travel times and delays. This involves infrastructural issues such as congestion, traffic incidents or modifications in network accessibility related to works, manifestations, or other incidents that can limit the circulation or access to some arcs in the network. This leads to local re-optimizations at the level of every single route, either the re-scheduling of customers' visit orders or the re-calculation of the O-D path.
- Parking or accessibility issues at the destination. They can lead to a non-visit of the customer, which will induce a return, or the reintroduction of the customer in the remaining set of customers to visit, i.e., a re-scheduling of its visit.
- Vehicle availability. This can lead to a vehicle replacement, a partial fleet re-optimization, re-assignment, or a global re-routing of the entire fleet.

The main issue involves dealing with real-time changes due to uncertainties and dynamics during execution. Note that routes (or stops within the line) are pre-established, and the main changes in the plans involve demand loading/unloading needs (that can in some cases exceed capacities), re-scheduling of transit/stop times (due to different delay causes) or eventually trip or stop cancellations. Unexpected events can also lead to changes inside one route (route adjustments or re-configuration of the customer visiting order) or on a group of demands. At the optimization level, those modifications result in the following decision problems:

- The re-configuration of entire sets of routes (in a more systemic viewpoint) in a real-time vision, leading to the well-known families of Dynamic Vehicle Routing and Pick-up and Delivery Problems (DVRP and DPDP).
- The re-configuration of routes, re-scheduling of the customer's order, and adjustment of one route, leading to dynamic and time-dependent online versions of the Travelling Salesman Problem (DTSP).
- The calculation and re-calculation of itineraries and paths, for which online Shortest Paths Problems (SPP) are deployed.

Each of these three families of decision problems are examined in the next sections. Section 5.2 presents the main problems and solution methods related to dynamic re-configuration of entire sets of routes. Section 5.3 explains the main issues and events that impact the respect of each single route schedule, as well as the methods for adjusting and re-scheduling its customers' order and consequently re-configuring the route, totally or partially. Finally, Section 5.4 introduces the main issues of path calculation, starting from the SPP leading to their dynamic considerations.

5.2 Dynamic route optimization

Imperfect demand knowledge is the primary motivation of demand-driven, agile and responsive approaches to managing logistics and freight transport at both operational and execution levels (Christopher, 2016). Demand can be anticipated (see previous sections), but fast response to demand changes is necessary during the execution phase. Demand dynamics strongly impact the entire route set performance. Changes in demand can lead to unfeasible routes in terms of capacity requirements or time constraints.

Demand dynamics can take two forms: (1) unexpected events altering demand (errors in declaring volumes to transport, changes in time constraints, shipping issues and mistakes that change the availability of shipments, etc.), or (2) in some CL systems accepting real-time requests, the inclusion of online demand into already planned and partly operated routes.

In a dynamic context, requests are arriving either before or during the transport service time and can be accepted or refused by the company (Cattaruzza et al., 2017). These events are modeled as modifications in the demand, similar to online requests. The decisions in a real-time adjustment vision start by examining such requests to evaluate the feasibility of accepting them (i.e., processing them to deliver them). It is important to note that a fast decision needs to be made concerning a request's acceptance or refusal (Barkaoui and Gendreau, 2013) since customers are willing to wait for an answer for only a short amount of time. After a request is accepted, it needs to be assigned to a vehicle. If the vehicle is en route, it may need to return to the depot to pick up the parcel, or this parcel needs to be included in the next route of the vehicle. If the vehicle has not started its route, the assignment and the consequent route configuration can be made using a static algorithm.

We distinguish two main dynamic routing problems: the dynamic vehicle routing problem (DVRP) and the dynamic pick-up and delivery problem (DPDP). Although the basic formulations of such problems differ by their nature (Sections 4.2 and 4.2.2), the way dynamics is included in optimization, as well as the family of the solution algorithms, are similar. In the literature, the sources of demand dynamics in vehicle routing can be represented as follows (Pillac et al., 2013; Ritzinger et al., 2016):

- Stochastic Vehicle Routing Problems (SVRP) are defined when one or more parameters are uncertain when the routing is planned, i.e. their exact value is unknown but can be anticipated (mainly via random variables following known probability distributions). However, once routes are planned, they execute them without any new re-optimization or systematic re-organization (stochastic problems are used to anticipate those sources of uncertainty better but in advance and via static approaches).
- Dynamic (and deterministic) problems. In those problems, demand (and sometimes other constraint or cost elements) is revealed (totally or partially) during the execution of the transport plan. The optimization is then made in a real-time context, and although initial routes can be anticipated, they are re-optimized in a real-time context. In such problems, demand is deterministic, i.e., demands arriving in real time are known and sure, so the planning is made iteratively but has a deterministic nature.
- Dynamic and stochastic problems combine one or more uncertain parameters (not only de-

mand) with a dynamic optimization context (mainly related to demands arriving during the execution plans). They aim to handle real-world applications more accurately, considering the recent advances in information and communication technologies. The main idea of dynamic-stochastic problems is to simultaneously take dynamic events and stochastic knowledge from the revealed data. The problem is then dynamic and stochastic.

In the OR literature, Static and Stochastic problems are related to the two categories presented above. However, since static problems correspond to a (in general tactical or operational) planning phase, they occur in the pre-execution planning phase and not in online or real-time execution. Therefore, they have been addressed in Section 4.4. For further analyses of methods and problems related to dynamic adjustment of route sets, see Ritzinger et al. (2016); Oyola et al. (2017a,b) for DVRP and Berbeglia et al. (2010); Ulmer et al. (2020) for DPDP.

According to Kucharska (2019), DVRP problems can involve different types of dynamics: the nature and importance of customers (including the dynamic nature of demand), travel times, service times, or vehicle availability, among others. However, the literature agrees on defining a dynamic VRP only when at least the nature of the demand is dynamic. As on DVRP, in DPDP, the main dynamics issue is demand, i.e., the users' requests. Not all requests to be delivered are loaded at the route's starting point in pick-up and delivery routes. Consequently, the vehicle is, during its service, collecting and delivering parcels (Savelsbergh and Sol, 1995). In dynamic PDPs, some of the input data (the origin and destination of each demand, its volume, its eventual time constraints, travel times, and other operational issues, among others) are revealed or updated during the time period operations take place. For all those reasons, a solution to a dynamic problem (either for only delivery or for pick-up and delivery routes) cannot be a static, deterministic output, but rather a solution strategy specifying, given the revealed information, the main actions to be performed in a real-time context (Berbeglia et al., 2010; Ritzinger et al., 2016).

The dynamic (re) optimization of route sets can be defined as a mono-objective (Ritzinger et al., 2016) or multi-objective (Nahum and Hadas, 2016) problem. Taking into account the dynamic nature of demand, classical linear programming approaches, which are suitable for static cases, are not adapted, and new ways of solving such problems, mainly heuristics, were developed (Pillac et al., 2013; Ritzinger et al., 2016).

Berbeglia et al. (2010) propose the most general formalization of the DPDP, briefly concluding on the need to address the problem via heuristic algorithms and on the unsuitability of MIP and LP approaches, due to the dynamic nature of the problem, that will exponentially increase the complexity of such models. Ritzinger et al. (2016) shows the impacts of forecasting, pre-processing, and managing only online actions on the improvement of route performance, based on a meta-analysis of published CVRP works, some of them of CL nature. The authors do not propose a formal model and show the need to solve the problem using heuristics. In general, the literature on DVRP and DPDP (Berbeglia et al., 2010; Pillac et al., 2013) does not formally define such models for those reasons. Indeed, because of the dynamic nature of the problem, its solving needs to be interactive, so classical LP methods are not adapted.

In practice, the dynamic problem is in general transformed into a set of static problems (by discretizing time, for example) that are consecutively solved (Flatberg et al., 2007). An initial stage

is defined starting from a first set of static demands that, forming an initial static problem, can feed a classical, static VRP and then give the first set of routes. Then, each time a new request appears, a new static problem is defined. When new requests can be rejected, insertion procedures are used to determine whether the request should be accepted or discarded (in this case, the customer could know in real-time if his request is accepted or not), then re-optimization procedures could be used to determine the new routes. Those procedures can re-configure routes of vehicles not already running (in which case higher flexibility and re-configuration potential are allowed) or to routes in progress (in that case, the problem will compulsory include pick-ups and deliveries). In case all requests need to be accepted, insertion and re-optimization become compulsory. Such procedures find the most suitable route for the request, leading to a feasible solution that minimizes the overall cost increase of such action.

Since the speed of response in real-time optimization is crucial, most algorithms are based on local search or quick insertion procedures that allow a short computational time. An alternative to them is to launch more complex algorithms in the time between two events occur. A third solution would be to find a first, quick solution, pre-selecting a vehicle and scheduling its pick-up, and search for a better solution in the time left between a first solution is found and the pre-selected vehicle leaves its last destination before picking up that request. For deterministic problems, most frameworks propose insertion procedures mainly derived from the well-known savings algorithm (Clarke and Wright, 1964), the Push-Forward insertion method (Solomon, 1986) or popular local-search such as 2-Opt, 3-Opt, K-Opt or Or-Opt, among others (Du et al., 2005; Ritzinger et al., 2016). Those algorithms are also used to improve solutions, mainly because, being quick, they can be run in a real-time context. However, in recent years, the use of meta-heuristic has increased, with the Tabu Search (Gendreau et al., 1999) and the Genetic Algorithms (Hanshar and Ombuki-Berman, 2007) being the most widely used to solve, at each step, the static VRP obtained once a set of new requests is identified. Moreover, hybrid and evolutionary algorithms and adaptations of ALNS (Ropke, S. and Pisinger, D., 2006), very popular for static problems, are starting to be generalized.

Concerning stochastic and dynamic VRPs, the stochastic nature of demand is in general modeled as a Markov Decision Processes or with Stochastic Programming (Du et al., 2005). Because their ability to handle large-scale problems is limited, heuristics such as Simulated Annealing Algorithm or the Noising Method can be used (Du et al., 2005). However, all those approaches remain limited because of their high computation times, so local search heuristics, although less performing in reaching near-optimal solutions, appear to be more robust to handle real-time issues. In both cases (deterministic and stochastic dynamic problems), it is essential to note that classical metaheuristics used for static problems (see Section 4) are able to be adapted for their dynamic versions, knowing that they need to be combined to insertion heuristics and be run in few seconds (or minutes) to produce fast but robust solutions and support online decision making.

In City Logistics, few works addressed explicitly dynamic optimization, but the work of Taniguchi and Shimamoto (2004) is a pioneer in the field and merits to be cited. The authors propose a DSVRP for a single tier, mono-commodity, mono-modal CL system that considers dynamic travel time. This work is an extension of the stochastic VRP defined in Taniguchi et al. (2000) and Taniguchi and Yamada (2003) in an execution phase, where ICT reports the status of traffic dynamically. Vehicles can be tracked (via GPS or other devices) to re-schedule the entire sets of routes iteratively and dynamically during each execution phase. The authors propose a forecast

of routes via a stochastic VRP formulation that is solved using a genetic algorithm. A dynamic optimization procedure based on the definition of subsets of groups, the evaluation, at each time interval, of the feasibility of each set, then routes are moved from one set to another to improve the overall transport plans (knowing that some of the routes are already being executed) and the remaining customers to deliver are rearranged systemically (i.e., via the adjustment of route sets composition) using the same genetic algorithm. To test the model, a set of CL instances and a discrete event traffic simulation are used. In the same line, Van Woensel et al. (2008) propose to model traffic via a queueing model. The problem is similar, and mainly addresses travel time dynamics. The proposed model is solved via a heuristic method combining a constructive heuristic (that gives an initial set of routes) with a combination of local search and tabu search.

Other works presenting preliminary works on dynamic fleet management and optimization propose a conceptual model of dynamic management of demands and travel times for urban last-mile routes (for single-tier CL systems or city-freighter routes in 2-tier schemes), including the decision of accepting or not requests and re-routing vehicles (Zeimpekis et al., 2005), or focus on cooperation and information exchange related to the traffic to operate re-routing and adjustment, in a DSVRP where both demands and travel times are dynamic (Köster et al., 2015).

To summarize, in dynamic problems, a first, systemic solution, with a set of static demands is made (but can be done in a deterministic or stochastic demand context), then the dynamic demand arrival is managed by re-optimization and re-insertion procedures, whose goal is to find the suitable vehicles that can manage the requests (with a minimum cost increasing) then assigning them.

5.3 Unexpected events

The second family of optimization problems is related to the re-arrangement of a route due to unexpected events, locally, without the need for a global re-optimization or re-adjustment. This is usually made when unexpected events, like traffic, parking issues, road incidents, customer availability issues or other unexpected events change, during the route, ongoing travel times, service times, or the possibility to deliver or pick up a request at a customer's location. Indeed, traffic reliability can be the main issue in making urban deliveries more robust, regular, and efficient (Cedillo-Campos et al., 2014) and the non-respect of time constraints, either for access cities (Quak and De Koster, 2009; Munuzuri et al., 2013; Munuzuri and van Duin, 2014) or for servicing a customer (Deflorio et al., 2012) have a substantial impact on the feasibility of the remaining set of customers of a route.

When executing a route and the driver faces an unexpected event, rearranging the remaining composition of the route can be (sometimes) easier than making a global route set re-optimization, since the first action can be executed locally. Nowadays, trucks and delivery vehicles have terminals able to give the required computational efforts for a local route re-optimization. For those reasons, a series of decision problems can be related to re-arrangement and re-optimization of single routes or itineraries, including:

- Online calculation of a new path between two points, with or without impacting the route composition: in case of a traffic or infrastructure problem, the first action is, in general, to

re-calculate the path to reach the next destination (Ran and Boyce, 1996). This is done via shortest path problems which are addressed in the next section.

- Route re-organization due to unexpected events: in case of significant delays because of road accessibility or traffic during a journey, the visit of some customers can be compromised, and the route needs online re-organization. Since, in general, only one route is affected each time, the dynamic problem is a DTSP (Eyckelhof and Snoek, 2002), as discussed below.
- Dynamic search of best parking slot/delivery bay location: in some cases, since a set of neighbor customers are defined, the truck driver can, using ITS, find the closest delivery area free to optimize its parking searching time and avoid double lines (Magniol et al., 2018). To identify such locations, online matching and assignment problems can be used. This can have an impact on the total travel time of a route and might need route re-optimization.
- Customer prioritization: prioritization techniques can support the choice of customers to keep in the route and those that will not be served and whose demand needs to return to the depot (Senkel et al., 2013). This does not change the customers' order in a route (and would not affect the execution of the remaining plan) but needs to account for non-delivered requests to be processed once the route is finished at the depot.

Those issues motivate and promote the development of dynamic traveling salesman problems (DTSP), i.e., dynamic optimization and re-optimization of a route taking into account the modifications of arrival and/or departure times (Ravassi, 2011). Indeed, in DTSP, the primary sources of dynamics are travel times between customers, which are continuously subject to change. Dynamics in this family of problems arise then mainly on travel and service times (Eyckelhof and Snoek, 2002), although in some variants, not all customers need to be visited (those unvisited imply penalties for the deliverer instead). To handle those dynamics (i.e., on arrival and departure times at customers, and then on the capability to respect all time constraints), various methods are proposed, evolutionary algorithms being the most popular (Zhou et al., 2003; Liu and Kang, 2003; Osaba et al., 2012). Also, ant colonies optimization shows a high number of works, learning procedures being used to handle real-time optimization to reduce computation times (Strak et al., 2019). However, since the TSP can be solved by dynamic programming, this technique can also be adapted to solve its dynamic variants.

To the best of our knowledge, the first work dealing explicitly with dynamic re-arrangement of routes in CL systems is that of Ehmke (2012). The author considers various types of problems (also dynamic versions of VRP). Still, one of the main contributions of this work arises from the interactions and influences between traffic information and the robustness of route optimization, with an in-depth focus on single route optimization and time-dependent TSP (TDTSP). Travel times are calculated from traffic conditions via ICT as on Ehmke et al. (2012b). The author shows that reliable mastering information improves single-route optimization substantially. An extension of this work can be seen in Ehmke et al. (2012a), where the authors propose a set of heuristics for solving a dynamic TSP, mainly classical construction heuristics, adapted to a dynamics context, like Nearest Neighbor, Dynamic Programming Nearest Neighbor, Insertion procedures, the Savings Algorithm and combinations of them. This framework presents the advantage of being reliable, quick of execution, and adaptable to real situations.

5.4 Computation of Shortest Paths

Beyond the complex problems described above, CL operators face a more basic but challenging problem: shortest path computation. Indeed, from an operational point of view, operators need to compute shortest paths repeatedly to determine routes on a short-term horizon or adjust them in real-time. The shortest path can be calculated based on distance or duration. We consider the latter in what follows. In city logistics, this fundamental problem turns to be difficult for several reasons: 1) it must be determined on a road network, i.e., on a large-scale network; 2) the computation time must be extremely short, typically less than one second; 3) in real-time, the travel information is updated frequently, i.e., typically every two minutes.

Several strategies have been developed to address these concerns. We describe below the main ones, first for the static case and then for the real-time problem. To cope with the size of the network and the need for short computation times, a common strategy in the static case is to implement a duration oracle. It consists of a pre-processing step during which precomputations are performed and stored in ad-hoc structures and a query step which, in the best case, is performed in constant time. In road networks, a relevant approach is to build a *Highway Hierarchy* in the pre-processing step (see Sanders and Schultes (2005)). Notice that computation time is not an issue for this step since it is performed in advance. When we turn to dynamic shortest path problems, the first issue is collecting and fusing traffic information. Several sources of real-time traffic data exist. For example, a municipality can install a network of cameras to measure traffic by image processing. Sensors can be installed within the pavement. On toll road networks, electronic tags provide an additional source of information. Due to their widespread use, cell phones equipped with GPS can also be used to monitor traffic. Finally, connected cars are a rich source of traffic data as they provide a set of parameters related to the behavior car in its environment. Initially, limited fleets of such vehicles, also called probe vehicles, were considered: taxi fleets, police cars, etc. Nowadays, more and more vehicles have onboard devices which allow detailed data collection.

The dynamic single-source shortest path problem is an online problem based on the traffic data, which are typically updated every two minutes. The algorithms (Fakcharoenphol et al. (2004)) include two main steps: the graph update phase, which consists in deleting, adding arcs, or in modifying their characteristics, and the computation of the shortest path from an origin to a destination. The algorithms able to proceed to add and remove operations are called fully dynamic algorithms. When only deletion operations are considered, they are called decremental algorithms and incremental for add operations only. A naive approach, which consists in computing the shortest path from scratch after each graph update, would lead to an algorithmic complexity that is too high given the dynamic nature of the problem. From a theoretical point of view, Roditty and Zwick (2004) showed that the algorithmic complexity of the update phase for decremental algorithms is unlikely to be better than the number of arcs multiplied by the number of nodes. Therefore, from a theoretical point of view, researchers have mainly considered epsilon approximation algorithms, see, e.g., Bernstein and Roditty (2011), Henzinger et al. (2014). From a practical point of view, the algorithms (see Nannicini et al. (2010)) frequently consider a time-discretization approach. This is because the data update is not performed continuously but according to a time step. Moreover, data updates do not include all network arcs but only a subset of them. Researchers (see Nannicini et al. (2010)) have proposed propagation techniques to enlarge the set of impacted arcs.

Solution algorithms are mainly based on the Dijkstra and A* algorithms, which are speed-up by implementing additional procedures. First, a Highway Hierarchy of the road network can be considered (see above). Then, a bidirectional search (from the origin and from the destination) can be invoked. A lower bound on the remaining time from the current point to the destination can also be considered (A* algorithm). Goldberg and Harrelson (2005) introduced a subset of nodes called landmarks from and to which shortest paths are computed to all other vertices in a pre-processing step. From these durations, we can easily define a lower bound. Impressive results are obtained by Nannicini et al. (2010) who implemented a bidirectional Dijkstra algorithm using a Highway Hierarchy. On the French road network (more than seven million nodes and 17 million arcs), they could identify near-optimal paths in less than 0.1 seconds. This approach dominates other algorithms based on landmarks which require a time-consuming update phase.

One exciting work relating SPPs to City Logistics is found in Nakamura et al. (2010). The authors propose a path calculation method inside dynamic vehicle routing approaches for single-tier CL systems. They adapt the adaptive least-expected path algorithms presented by Miller-Hooks (2001), the Fu and Rilett (1998)'s continuous-time, traffic-related, shortest path method, and the well-known Dijkstra et al. (1959)'s algorithm based on average travel times. The authors show that all the path calculation algorithms result in similar overall route performance, so the final costs do not differ significantly, proving the importance of estimating shortest paths when dynamically re-calculating routes.

6 Conclusions and Perspectives

In this chapter, we reviewed the various Operations Research approaches to design and efficiently manage advanced City Logistics systems, efficiency being measured in economic terms for the involved parties, and the impact on the environment and life of the city and its citizens.

We view City Logistics as paradigm-changing for cities and one of the main avenues, echoing and interacting with other similar developments in new business and organizational models such as Physical Internet and synchromodality towards digitally-intelligent freight transportation and logistics systems. The issues and methods presented in this chapter for City Logistics may therefore be applied in the larger context of the latter. Operation Research and analytics accompany and sometimes precede this evolution by providing decision-support methods and software tools for analyzing, planning, and managing transportation and logistics systems. The impact is a two-way street as changes in social and industrial behavior and technology challenge the field and spur modeling and algorithmic development. We reflected on this symbiosis in this chapter.

Given the chapter-length restrictions, the complexity of the topic, and the extensive coverage of the demand and socio-economic aspects in the rest of the book, we focused on the supply side of City Logistics systems. We first presented a systemic view of City Logistics and the main supply-side planning issues. We then detailed the main model and method Operations Research frameworks dedicated to strategic planning, tactical-operational planning, and dynamic management, identifying several challenges and emerging topics which we sum up in the following.

Modeling, methodological, and application issues and challenges are many and of the utmost interest, both for City Logistics and Operations Research. On a general level, it is noteworthy that the particular political, social, and entrepreneurial characteristics of each city and country impact directly how technology is accepted and used, what and how information is exchanged, how traffic is ruled, and how people and institutions can behave. A continuous scientific challenge is how these application characteristics are adequately represented in quantitative decision-support methods, together with the study of the impacts of such characteristics on methodological efficiency. New technology and changing social behavior also strongly influence the field and science. The former includes a vast range of issues, from the Internet of Things, the Smart City concepts, and the automated vehicles and terminals, to the drones, robots, lockers, and crowd-based logistics, which are increasingly part of local delivery and pickup activities. The latter is also extensive, from the movement towards an automated, digitally intelligent transportation and logistics 4.0 industry, to the continuously stronger trend of online shopping combined with customer requirements for very fast and very cheap service, the increasing variety of time and cost-defined customer-service classes, and the revenue management strategies. How these issues are represented individually and when several are jointly present in the problem setting makes for particularly challenging issues. The challenge is increased considering that one needs coherent representations at all planning and management levels and aims for an objective function and constraint formulations that are amenable to efficient solving.

We already mentioned in previous sections several important and challenging research directions not only for City Logistics but also for location, service network design, and vehicle routing in general. One of these major research directions is to extend these model classes to the multi-tier

cases, which also integrate inbound, outbound, and local demand into comprehensive formulations. Worthy of notice in this context is the modeling and algorithmic challenges of integrating and synchronizing time- and OD-dependent service network design, location, and multi-tour heterogeneous pickup and delivery routing. On the one hand, this raises the issue of the adequate modeling of routing into tactic and strategic formulations and the related efficient and representative approximations of costs and times. On the other hand, one notices the need for significant research efforts to model time dependencies and synchronization, particularly in multi-tier routing settings.

Most methods described in the chapter assume that some entity plans and manages shared resources and services of the system to answer the global demand. Research on the various mechanisms for information exchange, collaboration, resource/capacity sharing, and jointly-satisfying decision making for multiple cases of stakeholder consortia, operating a unified system of private and public resources under various profit-cost-risk-resource utilization sharing rules, is seriously lacking, however. More efforts are needed to define and analyze such mechanisms from both the individual entity and the system. Adequately representing such mechanisms in the Operations Research models and methods makes up the other facet of this research area.

We emphasized that the uncertainty characterizing City Logistics planning and operations is not yet, adequately addressed. Research is needed regarding both modeling and solution-method developments concerning the explicit representation and integration of the uncertainty, at all levels of planning and management, regarding the demand and travel and service times at facilities and customer locations. Resilience and recovery from various disturbing events make up a second important direction of research which, to our best knowledge, has not been addressed yet for CL systems. Uncertainty is also an essential element of revenue management mechanisms, which are also in dire need of research. Uncertainty, resilience, and revenue management are broad issues for transportation and logistics, and research in those directions promises to yield substantial results for both science and applications.

Regarding solution methods, one observes that there is not as yet any exact or meta-heuristic solution method consistently providing high-quality solutions to integrated formulations. Moreover, the algorithmic challenge increases significantly with the dimensions of the system in numbers of facilities, customers, fleets, time periods. It is further compounded when uncertainty is explicitly considered. Research is thus required on high-performance solution methods for deterministic and time-dependent stochastic location and network design models, with explicit or approximated routing, for City Logistics. Here are a few very promising avenues to be studied individually and, eventually, combined into efficient solution frameworks: 1) decomposition methods of path and arc-based formulations through, e.g., novel projections of the synchronization relations on tier-specific subproblems; 2) dynamic generation of first-tier services and lower-tier pickup and delivery routes, taking advantage of the similarities among network design and vehicle routing problems; 3) dynamic generation of the multi-tier time-space network; 4) exact parallel methods and collaborative-search matheuristics to efficiently address deterministic and stochastic formulations of realistic dimensions.

We complete the chapter with two integrative research directions, which challenge and may benefit the broader community. First, the integration of demand prediction, learning mechanisms, and optimization methods leads to comprehensive models, algorithms, and decision-making support instruments. Second, follows the observation that freight transport and logistics in general, and City Logistics in particular, are very poorly represented, if at all, in the methods for urban planning.

Working towards integrating City Logistics systems into the more general urban planning and land use management system will be highly beneficial for the city and its citizens.

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