City Logistics

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Abstract

This chapter provides an introductory overview of city logistics systems, highlighting the specific characteristics that make them different from general logistics problems. It analyzes the types of decisions involved in managing city logistics applications, from strategic, tactical, and operational, and identifies the key models to address them. This analysis identifies types of problems, location, location routing, and variants of routing problems with time windows, all those with ad hoc formulations, derived from the constraints imposed by policy and operational regulations, technological conditions, or other specificities of urban scenarios, which result in variants of the classical models that, for its size and complexity, become a fertile field for metaheuristic approaches to define algorithms to solve the problems. Some of the more relevant cases are studied in this chapter, and guidelines for further and deeper insights on other cases are provided to the reader through a rich set of bibliographical references.

Keywords

City Logistics · Decision Support Systems · Location Models · Metaheuristics · Vehicle Routing with Time Windows

Introductory Remarks on City Logistics: The Nature of the Problem

City logistics systems exhibit intrinsic characteristics that differentiate them from the general logistics systems, as part of the supply chain, in terms of the specificities of the scenarios where they occur (urban and large metropolitan areas), as well as for the economic relevance that they have as part of the freight distribution system. This section is aimed at explaining and highlighting these two crucial aspects.

Logistics and City Logistics

Logistics, as defined by the Council of Logistics Management CLM [13], is "that part of the supply chain process that plans, implements, and controls the efficient, effective flow and storage of goods, services, and related information from the point of origin to the point of consumption in order to meet customers' requirements." However, when logistics activities take place in urban areas, they show unique characteristics making them different from the general logistics activities. Thus, in order to differentiate the two phenomena and to highlight the special characteristics, the transport in urban areas, and specifically the freight flows associated with the supply of city centers with goods, is usually referred to as "city logistics," "urban freight distribution," or "last mile logistics."

Taniguchi et al. [51] define city logistics as "the process of totally optimizing the logistics and transport activities by private companies in urban areas while considering the traffic environment, traffic congestion and energy consumption within the framework of a market economy." This definition can be updated by adding to the concept of the energy consumption the contemporary concerns on the environmental impacts such as emissions, urban noise, vibration, etc., generated by logistic vehicles in urban areas. These impacts affect not only the economy but also the quality of life of the city residents.

An analysis of city logistics activities, and how they are performed, results with an immediate identification of their specific intrinsic characteristics. It allows for establishing substantial differences between logistics and city logistics justifying the entity of city logistics as an individual field with proper identity. Some of the main city logistics characteristics include:

- Spatial restrictions:
  - Urban microstructure determined by the urban network (e.g., one-way streets, dead-end streets, etc.) causes the paths between customers, or between the depot and the customers, to differ depending on the order of the visits.
  - Limited vehicle access. Most cities mandate limited access for some areas of the city for specific types of vehicles during specific time windows.
  - Small-quantity deliveries.
  - High density of delivery points.
- Traffic infrastructure: traffic schemes banning specific turnings, traffic lights and their associated traffic control plans, etc.
- Environmental concerns and sensitivities:
  - Growing role of small specialized urban vehicles (i.e., environmentally friendly vehicles commonly referred to as green vehicles) as a consequence of sustainable urban policies implying energy savings, reduction of emissions, noise, etc.
  - Low automation and critical human role when manual deliveries are necessary.
  - High operational and environmental costs, as a consequence of the human involvement among other reasons.

The Relevance of City Logistics

Urban logistics operations consist of the set of activities related with the distribution of goods and provision of services within an urban area. There is a wide range of examples of urban logistics that includes parcel delivery, material collection, goods storage, waste collection, home delivery services, or electrical appliance reparation services, among others. Current urban activities are far away from what they were a couple of decades ago. New challenges have emerged, new technologies have been developed, and urban population dynamics have changed.

The road system is the main transportation modality in most countries. In Europe, 68% of goods transportation is made by roads (BESTUFS report [6]). Countries with less developed rail networks tend to have higher road utilization. Moreover, a high proportion of all goods are delivered within the cities. Cities as London and

Dublin estimate this proportion in slightly more than 40% (BESTUFS report [6]), while almost 70% of the deliveries are concentrated in Tokyo (Taniguchi et al., [51]). In summary, road transportation is the **main** freight transportation mode, and **high proportion** of the **total** goods transportation happens in **cities**.

The significant impact of commercial vehicles in daily traffic is evident. According to the BESTUFS report [6], about a fifth of a city's traffic flow is made up of commercial trucks. In London, freight transport accounts for 20%–26% of the total traffic, while in Italy this proportion is estimated to be 18%. In the same study, it is reported that urban freight in French cities represents between 13% and 20% of the total traffic. Overall, the BESTUFS [6] estimates that between 15% and 20% of the average flow in cities during rush hours correspond to logistics fleets (i.e., light goods vehicles, heavy goods vehicles, etc.). Consequently, logistics fleets are a net contributor to traffic congestion in urban and metropolitan areas and have a relevant impact on energy consumption and on the quality of life in cities.

Although urban freight distribution represents a small fraction of the total transportation length, the Council of Supply Chain Management Professionals, Goodman [29] estimates that the last mile cost accounts for about 28% of the total transportation cost. In a study made by the European Logistics Association and AT Kearney [21], it is shown that transportation activities account for approximately 43% of the total logistics costs. Assuming that the cost of delivering within urban areas (i.e., the last mile cost) is 28%, we can then estimate that the cost of urban freight activities represents about 12% of the total logistics costs.

A Systems Approach to City Logistics

The complexity of city logistics systems should be addresses from a systemic perspective accounting for all of its components and, what is more important, their interactions determining the dynamics of the system and the way it behaves. Namely, it should be addressed in terms of the conditions, operational but also technological, which are imposed by the relationships among stakeholders, which are synthetically described in this section.

Any systemic approach to city logistics must look at the system as a whole, identify its components, and account for their mutual interactions. For example, consider the impacts that city logistics activities have on traffic congestion, and at the same time, consider how in return the city logistics activities are impacted by traffic congestion and operational constraints of the urban areas.

Thus, the *city logistics models must account for the two-way interaction*. They should include the effects of the city logistics deliveries and commercial activities on urban traffic congestion, and conversely they should include operational constraints in routing and logistics optimization models considering time-varying traffic congestion allowing defining how city logistics activities are impacted by traffic congestion.

Notwithstanding, a systemic approach should neither forget that urban freight distribution is mainly a private sector activity, designed to maximize the profits, which takes place in a public scenario under rules and constraints determined by public authorities. In the words of Boudoin et al. [10], "today, the city as a geographic and economical space is the centre of attention of decision makers of the private and public sectors, considering that the performance of the logistics system depends also greatly on the decisions taken by these two categories of actors. The urban logistics spaces are in the core of the goods distribution device, as they are interfaces between interurban and urban, private and public, producer and consumer." A systemic approach must also take into account that city logistics is a scenario with various stakeholders with possibly different and conflicting interests.

Public stakeholders will usually be interested in achieving social, economic, environmental, or energetic objectives, while private stakeholders, namely, private shippers and freight carriers, aim to reduce their freight costs and to optimize their traffic flows in accordance with their specific needs, which are not conforming to the objectives of an overall optimization. Therefore, a systemic approach to city logistics must:

1. Be supported by a holistic view in modeling approaches integrating urban and logistic planning which will allow innovative approaches to urban logistics solution.
2. Suitable to be applied in practice in terms of a framework enabling the understanding between stakeholders, fostering new ways of stakeholder collaboration, and providing policy frameworks allowing sustainable business models.
3. Become operational in terms of decision support tools to efficiently implement the desirable policies.

In other words, the conceptual approach to such systemic view must be able to appropriately account for the roles of the main stakeholders and the relationships between them as highlighted in the conceptual diagram in Fig. 1.

Freight operators supply their services under supply conditions and contracts with customers imposing constraints on:

- Fleet routing and scheduling.
- Service times and delivery conditions that could be determined by the characteristics of the delivery (i.e., loading and unloading) point.
- Service time windows imposed either by the customer requirements or by the regulatory conditions determined by local authorities.

The supply regulations established by the local government strongly determine the way in which logistics fleets operate. The restrictions to access inner city, namely, in cities with historical centers, reinforced in most cases by access control systems, usually impose time constraints that determine the routings and scheduling, which can also be affected by the existence, or not, of loading/unloading points and regulations on their use. Furthermore, the regulations on vehicle sizes authorized to operate in urban areas, or green logistics policies imposing thresholds on the acceptable levels of emissions, could determine the fleet compositions.

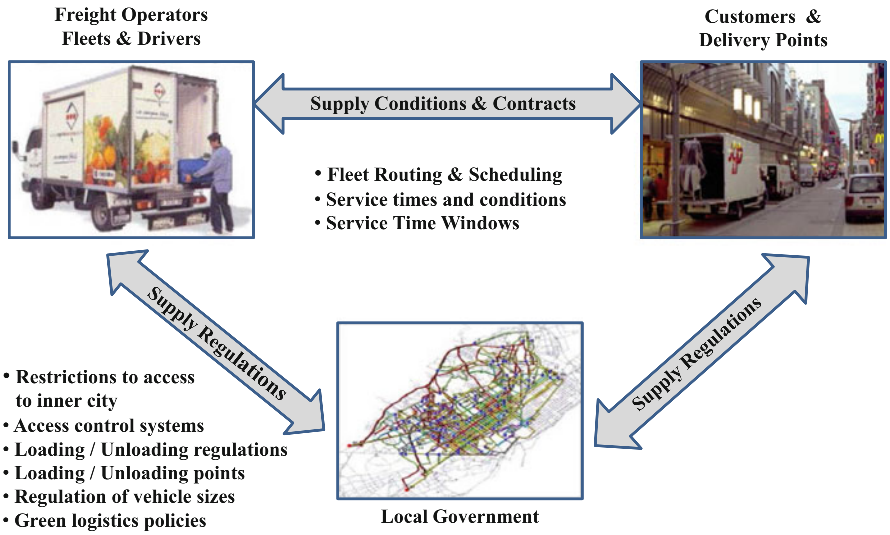

Fig. 1 Stakeholders' interaction in city logistics operations

Organizational Aspects and Decision-Making in City Logistics

The proposed systemic view must be translated in terms of a model, suitably representing the system, which, further than providing a deep understanding on how the system works, should provide support to any type of operational decisions on the system. Two key aspects in this process are, respectively, identify and understand the main logistics operations and identify and distinguish the decision levels in the management of the city logistics system. This view is neatly aligned with the key approach of Operations Research: acquire enough knowledge about a system to understand how the system works, and formulate the system's knowledge in terms of modeling hypothesis that can be subsequently translated in terms of a formal model (usually a mathematical model) which can be used to make decisions about the system. Therefore, understanding the nature of the decisions in city logistics, which of them depend on the nature of the system, and which are conditioned by the relationships among stakeholders is part of such knowledge acquisition to build models of city logistics. Decision levels for fleet management applications (Goel [28]) are primarily:

- **Strategic:**
  - Decisions that usually concern a large part of the organization, have major financial impact, and may have long-term effects: typically concern the design of the transportation system.
  - The **size and mix** of vehicle fleet and equipment.
  - The **type and mix** of transportation services offered.

  - The territory coverage including **terminal location**.
  - Strategic alliances and cooperation, including the integration of information systems.
- **Tactical:**
  - Concerns short- or medium-term activities: typically involve decisions about how to effectively and efficiently use the existing infrastructure and how to organize operations according to strategic objectives.
  - Equipment acquisition and replacement.
  - Capacity adjustments in response to demand forecasts.
  - Static pricing and pricing policies for contract and spot pricing.
  - Acquisition of regularly requested services, including pricing and provisional routing.
  - Long-term driver to vehicle assignments.
  - Cost and performance analysis.
- **Operational:**
  - Commercial vehicle operations underlay a variety of external influences which cannot be foreseen: real-time management decisions have to be made to appropriately react on discrepancies between planned and actual state of the transportation system.
  - Load acceptance.
  - Real-time dispatching considering the actual state of transportation system.
  - Instructing drivers about their tasks.
  - Monitoring the transportation processes, including tracking and tracing and arrival time estimations.
  - Incident management.
  - Observing the state of order processing.
- **Real Time:**
  - Concerns all activities needed to monitor, control, and plan transportation processes.
  - The required information that dispatchers must collect to manage the fleet include vehicle positions and traffic conditions.
  - The decisions that dispatchers must make to manage the fleet include diversion of vehicles from current route to new destinations and insertion of customers into predefined routes.
  - The most challenging task is the generation of dynamic schedules.
  - Determination of plans indicating which vehicle should visit, pick up, deliver, or service a customer and at what time.

As a consequence of the fact that the stakeholders can play different roles in the city logistics scenarios, they can adopt various organizational forms. These organizational forms can be individual with no self-coordination, individual but with different degrees of coordination in which the private stakeholders are the main actors, or super-coordinated where public organizations play the main role currently referred to as goods distribution centers. Each scenario implies different levels of decision from the long-term strategic decisions on the locations of warehouses or distribution centers to the operational decisions concerning fleets and routing and scheduling of fleet vehicles. Moreover, the real-time decisions on rerouting and rescheduling vehicles as far as traffic and operational conditions change become each time more relevant due to technological evolution. Efficiency in these scenarios may be achieved through better fleet management practices, rationalization of distribution activities, traffic control, freight consolidation/coordination, and deployment of intermediate facilities [36].

This last measure plays a fundamental role in most of the city logistics projects based on distribution system, where transportation to and from an urban area is performed through platforms. These platforms are called city distribution centers (CDC), goods distribution centers, or city terminals (CT) [42]. They are located far from city limits. Freights, directed to a city and arriving by different transportation modes and vehicles, are consolidated at platforms on trucks in charge of final distribution. According to Boccia et al. [8], "these platforms have had a great impact on effectiveness of freight distribution in urban areas, but their use is showing some deficiencies because of two main reasons: their position (often far from final customers) and the constrained structure of urban areas."

To overcome the limits of such single-echelon system, distribution systems have been proposed, where another intermediate level of facilities is added between platforms and final customers. These facilities, referred to as satellites or transit points (Fig. 2), perform no storage activities and are devoted to transfer and consolidate freights coming from platforms on trucks into smaller vehicles, more suitable for distribution in city centers (Crainic et al. [16, 17]). This two-echelon system could determine an increase of costs due to additional operations at satellites. However, these costs should be compensated by freight consolidation, decrement of empty trips, economy of scale, reduction of traffic congestion, and environmental safety.

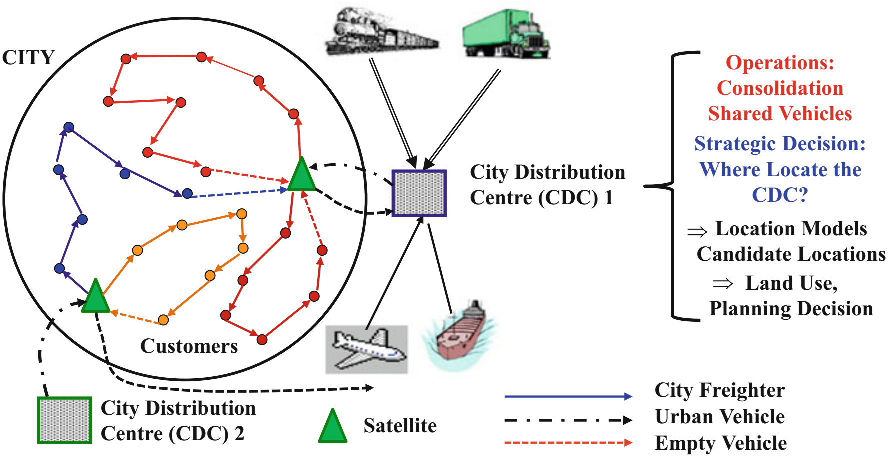

Fig. 2 Two-echelon freight distribution systems and implied decisions

The model simultaneously determines how many depots (CT or CDC) should be open, their locations at the first echelon, how many vehicles (urban vehicles) are needed to supply the satellites, how many satellites should be open at the second echelon, which vehicles (city freighters) should operate from which open satellites, and which customers each vehicle should service.

Most of these decisions must be supported appropriately and that implies the use of suitable models (Giani et al. [24]). Location models (Daskin and Owen [19]) become the key components of strategic decision-making concerning decisions on warehouse or CT locations. Vehicle routing models are at the core of operational and real-time fleet management decisions and processes. Therefore, they deserve a special attention and become the main operational tools to achieve the objectives of private stakeholders, shippers, and freight carriers. Routing problems in urban areas have specific characteristics that differentiate them from generic routing problems. Bodin et al. [9] have coined the term "street routing" to highlight these differences.

Fleet Management and ICT Applications

We have already highlighted the key role of decision-making in city logistics, and the role of models to support strategic decisions has been highlighted in the previous section. However, the tactical and operational decisions should not be forgotten, as they usually determine the quality of the service, which is highly appreciated by customers. Operational decisions in urban areas are changing very fast due to the impacts of the new telecommunication technologies. Further than enabling faster and more flexible operational modes, the new telecommunication technologies induce deep sociological changes in customers' uses, which in turn foster a quick evolution of management policies. The implications of the latter will be discussed in this section.

The growing importance of the real-time fleet management applications is mainly due to the recent significant evolution of pervasive automatic vehicle location (AVL) technologies (Goel [28]). Fleet management in urban areas has to explicitly account for the dynamics of traffic conditions leading to congestions and variability in travel times severely affecting the distribution of goods and the provision of services. An efficient management should be based on decisions accounting for all factors conditioning the problem: customers' demands and service conditions (i.e., time windows, service times, and others), fleet operational conditions (e.g., positions, states and availabilities of vehicles, etc.), and traffic conditions.

Instead of making decisions based on trial and error and operator's experience, a sounder procedure would be to base the decisions on the information provided by a decision support system (DSS). Regan et al. [47, 48] provide a conceptual framework for the evaluation of real-time fleet management systems which considers dynamic rerouting and scheduling decisions implied by operations with real-time information as new orders or updated traffic conditions. The recent advances in information and communications technologies (ICT) have prompted the research on dynamic routing and scheduling problems. At present, easy and fast acquisition and processing of the real-time information is feasible and affordable. The information, which becomes the input to dynamic models, captures the dynamic nature of the addressed problems allowing for more efficient dynamic fleet management decisions.

Barceló et al. [4, 5] propose and computationally explore a methodological proposal for a decision support system to assist in the decision-making concerning the real-time management of a city logistics fleet in dynamic environments when real-time information is available. Figure 3 depicts the architecture of such a DSS based on a dynamic router and scheduler. The feasibility of the proposed solutions depends on:

- The availability of the real-time information, which we assume will be provided by ICT applications, combined with the knowledge of the scheduled plan with the current fleet and customer status.
- The quality of the vehicle routing models and algorithms to efficiently tackle the available information to provided solutions.

Unlike the classic approach, where routes are planned with the known demand and they are unlikely to be changed throughout the planning period, the real-time fleet management approach assumes that real-time information is constantly

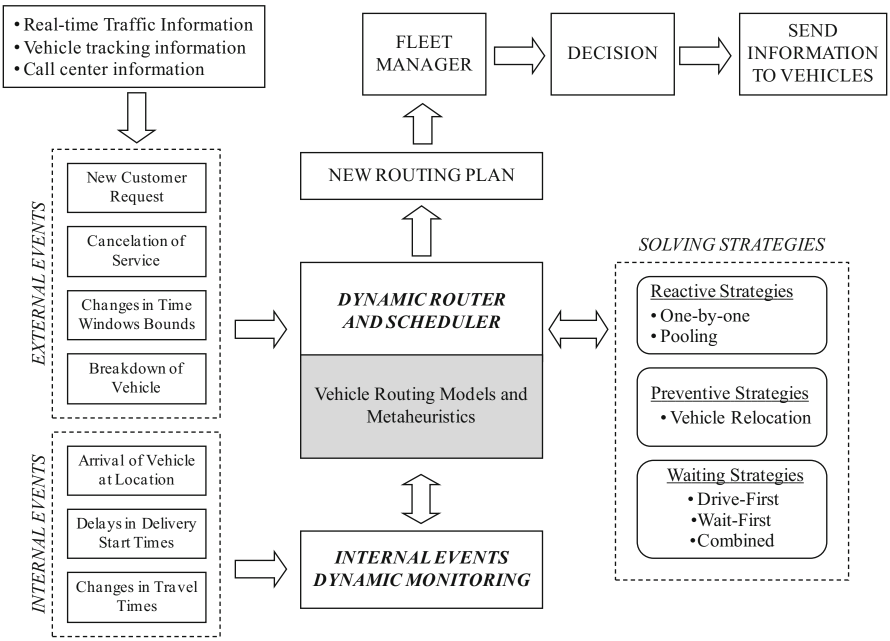

Fig. 3 Logical architecture of a decision support system for real-time fleet management based on a dynamic router and scheduler

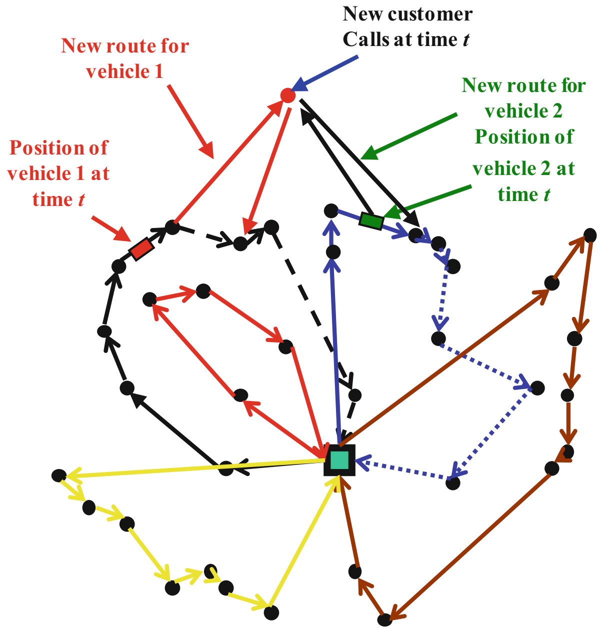

Fig. 4 Dynamic vehicle rerouting in a real-time fleet management system

revealed to the fleet manager who has to decide whether the current routing plan should be modified or not. The process assumes partial knowledge of the demand. At the beginning of the considered time period (i.e., one work day), an initial schedule for the available fleet to serve the known demand is proposed. This initial operational plan can be modified later on, when the operations are ongoing and new real-time information is available. The new information can concern new demands, unsatisfied demands, changes in the routes due to traffic conditions, changes in the fleet availability (i.e., vehicle breakdowns), etc. It constitutes an input to a dynamic router and scheduler (DRS) which provides a proposal of a new dynamic operational plan prepared on the basis of real-time information.

Figure 4 depicts an example of how the conceptual process described in Fig. 3 can be handled by a dynamic routing and scheduling system. The routes, initially assigned to a set of five vehicles, are identified with various colors. The arrows indicate the order in which customers are to be served according to the initial schedule. We assume that vehicles can be tracked in real time. At time t, after the fleet has started to perform its initial operational plan, a new customer calls requiring a service which has not been scheduled. If real-time information, such as positions and states of the vehicles and current and forecasted traffic conditions, is available to the fleet manager, he or she can use it to make a better decision on which vehicle to assign to the new customer and whether the new assignment results in a direct diversion from a route (vehicle 2) or a later scheduling (vehicle 1).

Vehicle routing problem (VRP) techniques constitute a fundament for the transportation, distribution, and city logistics systems modeling. The static version of the VRP has been widely studied in the literature. Among others, an extensive survey on VRP was provided by Fisher [22] and by Toth and Vigo [54]. The static approaches reckon with all the required information to be known a priori and constant throughout the time. However, in most of the real-life cases, a large part of the data is revealed to the decision-maker when the operations are already in progress. Thus, the dynamic VRP assumes partial knowledge of the demand and that new real-time information is revealed to the fleet manager throughout the operational period. A comprehensive review of the dynamic VRP can be found in Ghiani et al. [24]. Psaraftis [45, 46] and Powell et al. [44] contrast the two variants of the problem and clearly distinguish the dynamic VRP from its static version.

A wide variety of vehicle routing problems with time windows (VRPTW) becomes the engine of real-time decision-making processes to address situations where real-time information is revealed to the fleet manager, and he or she has to make decisions in order to modify an initial routing plan with respect to the new needs (Barceló and Orozco [1]). Real-time routing problems are mainly driven by events which are the cause of such modifications. Events take place in time, and their nature may differ according to the type of service provided by a motor carrier. The most common type of event is the arrival of a new order. When a new order is received from a customer, the fleet manager must decide which vehicle to assign to the new customer and what is the new schedule that this vehicle must follow.

A standard practice of introducing the dynamism into the definition of a routing problem is to determine specific features as *time-dependency*. The VRP with time-dependent travel times acknowledges the influence of traffic conditions on the routing planning. An introduction to the problem and a made heuristic development is provided in Malandraki and Daskin [37]. Further algorithm developments for the static VRP with time-dependent travel times can be found in Ichoua et al. [32], Fleishman et al. [23], and Tang [50]. The dynamic VRP with time-dependent information has also been addressed by Chen et al. [12] and Potvin et al. [43].

Thomas and White [53] addressed the problem by assuming that stochastic information was represented by the time of arrival of a new request. The objective of their approach was to find the best policy for selecting the next node to visit that minimizes the total travel time. They called this problem the *anticipatory routing problem* as vehicles anticipate the arrival of a new customer by changing their path if the request is received while they are in transit. The authors assumed that a new service may be delivered only if the reward or benefit is sufficiently high. The problem was modeled as a finite-horizon Markov decision process, and the authors used standard stochastic dynamic programming methods to solve each one of the proposed instances. Thomas [52] extended the results by incorporating waiting strategies with the objective of maximizing the expected number of new customers served. They also modeled the problem using a finite-horizon Markov decision process. The authors proposed heuristic algorithms for real-time decision-making.

In the approach proposed by Barcelo et al. [2, 3], time-dependent information is generated by means of traffic simulation of a real-world urban network, in order to emulate the role of a real-time traffic information system providing reliable real-time information on traffic conditions and short-term forecasts.

In order to test the management strategies and algorithms assuming the availability of the real-time information, the dynamic traffic simulation model emulates the current travel times estimated as a function of the prevailing traffic conditions and the short-term forecast of the expected evolution of travel times that an advanced traffic information system would provide. This is a basis for making more realistic decisions on the feasibility of providing the requested services within the specified time windows. Furthermore, simulation can also emulate real-time vehicle tracking giving access to positions and availabilities of the fleet vehicles, which is the information required by a DRS.

This example was inspired by the modeling framework proposed by Taniguchi et al. [51], including models needed by the authorities to support long-term planning decisions accounting for the already mentioned interactions between city logistics activities and urban congestion.

Strategic Decisions in City Logistics

The current evolution of city logistics systems has raised the interest in the variants of location models to support the concerned strategic decisions. In many cases they are induced by regulations imposing conditions on the location of the CTs or CDCs and restrictions on the vehicle types allowed to operate in the inner city, leading to organizational restructuring of the services from intermediate satellites. The potential scenarios illustrated in Fig. 2 can be generically addressed by two types of location models, described in this section, depending on whether the routings of the service vehicles are explicitly included in the model or not.

Two-Echelon Single-Source Location Problems

The increasing importance of the e-commerce results with interesting organizational decisions. For example, more and more people purchase products online, but are not usually at home at daytime and cannot accept the deliveries, return the unaccepted deliveries, or deliver the parcels to be sent to other customers. As a consequence, there are required alternative solutions for home deliveries.

An example of such alternative solution was described in BESTUFS II [7]: the Packstations used by Deutsche Post and DHL in Germany. Similar solutions were also deployed in other countries. Usually, they are locker facilities installed in specific locations, which provide automated booths, or locker boxes for self-service collection and delivery of parcels.

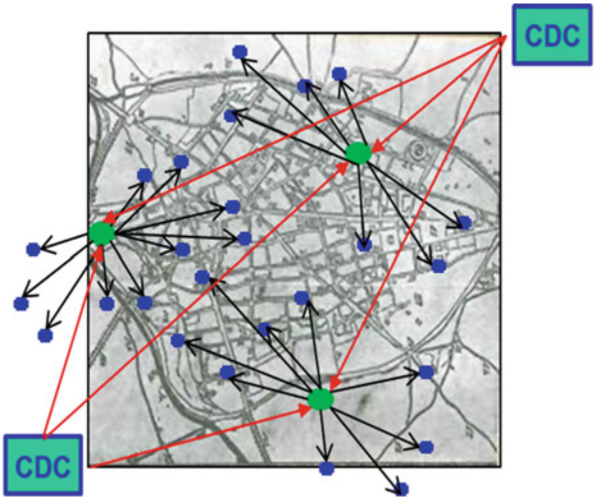

Fig. 5 Two-echelon single-source location problem

In this case, the logistics system can be considered as a particular case of a *two-echelon single-source location problem*, in which special fleet of vehicles service the satellite-automated booths (marked in green in Fig. 5); the special fleet can consist of urban vehicles, such as vans or trucks, fulfilling specific urban regulations regarding sizes and technologies, for example, special vehicles with less than 3.5 tonnes weight, with electrical engines, or propelled by biofuel or low emission fuels. Customers (marked in blue in Fig. 5) travel to the automated locker boxes for service.

In the pilots reported in BESTUFS II [7] the locker boxes have been installed in public spaces (e.g., main station, market place, petrol stations, etc.), and also at parking places of big companies. However, the search for systematic, general solutions can be formulated in terms of two-echelon single-source models. This is the problem arising in a two-stage distribution process, with deliveries being made from first-echelon facilities (e.g., city terminals) to second-echelon facilities (e.g., satellites) and from there to customers. The two-echelon, single-source, and capacitated facility location problem can be considered as an extension of the single-source capacitated facility location problem, dealing with the problem of simultaneously locating facilities in the first and second echelons where:

- Each facility in the second echelon has limited capacity and can be supplied by only one facility in the first echelon,
- Each customer is served by only one facility in the second echelon.

The model simultaneously determines how many depots (CTs or CDCs) should be open, what are their locations at the first echelon, how many vehicles (urban vehicles) are needed to supply the satellites, how many satellites should be open at the second echelon, which vehicles (city freighters) should operate from which open satellites, and which customers each vehicle should service.

Notation:

$I = \{1, 2, \ldots, m\}$: Set of potential facilities (satellites)
$J = \{1, 2, \ldots, n\}$: Set of customers
$K = \{1, 2, \ldots, nn\}$: Set of potential depots (CDCs)
a_j: demand of customer j, $\forall j \in J$
b_i: capacity of facility (satellite) i, $\forall i \in I$
f_{ik}: cost of assigning facility i to depot k, $\forall i \in I$, $\forall k \in K$
c_{ijk}: cost of facility i from depot k servicing customer j, $\forall i \in I$, $\forall j \in J$, $\forall k \in K$
g_k: cost of setting a depot at location k, $\forall k \in K$

Decision variables:

$$Y_{ik} = \begin{cases} 1 & \textit{if facility i is open and served from depot } k,\ \forall i \in I,\ \forall k \in K \\ 0 & otherwise \end{cases}$$

$$X_{ijk} = \begin{cases} 1 & \textit{if facility i served by depot k services customer} j, \forall i \in I, \forall j \in J, \forall k \in K \\ 0 & otherwise \end{cases}$$

$$Z_k = \begin{cases} 1 & \textit{if a depot is set a location } k,\ \forall k \in K \\ 0 & otherwise \end{cases}$$

The model:

$$p : \text{Min} \sum_{i \in I} \sum_{k \in K} \sum_{j \in J} c_{ijk} x_{ijk} + \sum_{i \in I} \sum_{k \in K} f_{ik}\ y_{ik} + \sum_{k \in k} g_k z_k \tag{1}$$

subject to

$$\sum_{j \in J} a_j x_{ijk} \leq b_i \quad \forall i \in I, \forall k \in K \tag{2}$$

$$\sum_{i \in I} \sum_{k \in K} x_{ijk} = 1 \quad \forall j \in J \tag{3}$$

$$\sum_{k \in k} y_{ik} \leq 1\ \forall i \in I \tag{4}$$

$$x_{ijk} \leq y_{ik}\ \forall i \in I, \forall j \in J, k \in K \tag{5}$$

$$y_{ik} \leq Z_k \quad \forall i \in I, k \in K \tag{6}$$

$$x_{ijk}, y_{ik}, z_k \in \{0, 1\} \quad \forall i \in I, \forall j \in J, k \in K \tag{7}$$

The objective function (1) includes the total cost of assigning customers to facilities, the cost of establishing facilities, and the cost of opening depots. The side constraint (2) ensures that the customer demand serviced by a facility does not exceed its capacity. The equation (3) ensures that each customer is assigned to exactly one facility. Each facility can be serviced by only one depot, as defined by constraint (4). The inequality (5) states that the assignments are made only to open facilities (i.e., customers are allocated only to open facilities). Lastly, the formulation (6) ensures that facilities are allocated only to open depots.

Tragantalerngsak et al. [55] propose a variety of Lagrangian heuristics for this problem. Taking into account the computational results achieved, one of the most performing Lagrangian decompositions analyzed is based on the possibility of strengthening the resulting subproblems as a consequence of the observation that at least one depot must be open. Therefore, without any loss of generality, there can be used the constraint:

$$\sum_{k \in K} z_k \geq 1 \tag{8}$$

Also, there may be included a constraint which forces to open sufficient facilities to supply all customer demands:

$$\sum_{i \in I} \sum_{k \in K} y_{ik} b_i \geq \sum_{j \in J} a_j \tag{9}$$

This will improve the lower bound provided by the relaxation.

By relaxing the constraints (3) and (6), with Lagrangian multipliers λ and ω, respectively, the problem can be separated into the two following Lagrangian subproblems LRxy and LRz:

$$LR_z : \min \sum_{k \in K} \left(g_k - \sum_{i \in I} \omega_{ik} \right) z_k \tag{10}$$

subject to

$$\sum_{k \in K} z_k \geq 1 \tag{11}$$

$$z_k \in \{0, 1\} \quad \forall k \in K \tag{12}$$

and

$$LR_{xy} : \min \sum_{i \in I} \sum_{k \in K} \sum_{j \in J} (c_{ijk} - \lambda_j) x_{ijk} + \sum_{i \in I} \sum_{k \in K} (f_{ik} + \omega_{ik}) \tag{13}$$

subject to

$$\sum_{j \in J} a_j x_{ijk} \le b_i \quad \forall i \in I, \forall k \in K \tag{14}$$

$$\sum_{k \in K} y_{ik} \le 1 \forall i \in I \tag{15}$$

$$\sum_{i \in I} \sum_{k \in K} b_i y_{ik} \ge \sum_{j \in J} a_j \tag{16}$$

$$x_{ijk} \le y_{ik} \quad \forall i \in I, \forall j \in J, k \in K \tag{17}$$

$$x_{ijk}, y_{ik} \in \{0, 1\} \quad \forall i \in I, \forall j \in J, k \in K \tag{18}$$

Let $g1_k = g_k - \sum_{i \in I} \omega_{ik}$; then problem LR_{xy} can be solved by inspection:

$$z_k = \begin{cases} 1 \text{ if } g1_k \le 0 \\ 0 \text{ Otherwise} \end{cases} \tag{19}$$

In the case where all $g1_k > 0$, set $z_{k'} = 1$, where $g1_{k'} = \min_k\{g1_k\}$ and $z_k = 0,\ k \ne k'$.

The problem can be reformulated as

$$\min \sum_{i \in I} \sum_{k \in K} v_{ik} y_{ik} \tag{20}$$

subject to

$$\sum_{k \in K} y_{ik} \le 1 \quad \forall i \in I \tag{21}$$

$$\sum_{i \in I} \sum_{k \in K} b_i y_{ik} \ge \sum_{j \in J} a_j \tag{22}$$

$$y_{ik} \in \{0, 1\} \quad \forall i \in I, k \in K \tag{23}$$

where $v_i k$ is the optimal solution of

$$\min \sum_{j \in J} (c_{ijk} - \lambda_j) x_{ijk} + (f_{ik} + \omega_{ik}) \tag{24}$$

subject to

$$\sum_{j \in J} a_j x_{ijk} \le b_i \quad \forall i \in I, \forall k \in K \tag{25}$$

$$x_{ijk} \in \{0, 1\} \quad \forall i \in I, \forall j \in J, k \in K \tag{26}$$

The problem of finding v_{ik} is now a 0-1 *knapsack problem* involving all facilities, but the fact that each facility can be served only from one depot enables to rewrite the problem as follows:

$$\text{Let } v_i = \min_k\{v_i k\} \tag{27}$$

Solve

$$\min \sum_{i \in I} v_i u_i \tag{28}$$

subject to

$$\sum_{i \in I} b_i u_i \geq \sum_{j \in J} a_j \tag{29}$$

$$u_i \in \{0, 1\} \quad \forall i \in I \tag{30}$$

This is a 0-1 knapsack problem with n variables. The lower bound for problem P is then given by $LBD = v(LR_{xy}) + v(LR_z)$. The upper bound *UBD* can be found from the solution of the problem LR_z as follows:

Let z_k^* be the solution to LR_z and $\tilde{K} = \{k|z_k^* = 1\}$. Solve LR_{xy} again but over the depots in $\tilde{K}$. The solution from this restricted set is then used to find a feasible solution. Let $\mathbf{u}^*$ be the solution to this problem, and denote $\tilde{I} = \{i|u_i^* = 1\}$.

Then

$$y_{ik}^* = \begin{cases} 1 \text{ if } i \in \tilde{I} \; and \; k \in \tilde{K} \\ 0 \text{ otherwise} \end{cases} \tag{31}$$

The corresponding solution $\boldsymbol{x}^*$ is obtained as the solution giving the v_{ik} coefficients if $i \in \tilde{I},\ k \in \tilde{K}, y_{ik}^* = 1$. Otherwise, $x_{ijk}^* = 0$.

Using these solutions no capacity constraints are violated, but there may be some customers j that were assigned to multiple open facilities or not assigned to any facilities. A *generalized assignment problem* is constructed from these customers, open facilities, and the remaining capacity of open facilities. The solution to these problems reassigns these customers and provides the expected upper bound.

Once the lower bound *LBD* and upper bound *UBD* of the optimal objective function have been calculated, the Lagrangian multipliers λ and ω are updated until a convergence criterion is met.

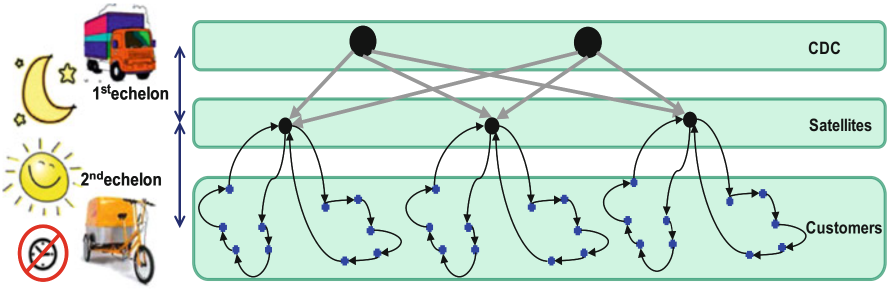

Fig. 6 An example of two-echelon location routing accounting for special urban regulations

Two-Echelon Location Routing

There are more variants of the location problems arising from a combination of organizational decisions and urban regulations on the characteristics and conditions of the logistics fleets, as discussed in section "Organizational Aspects and Decision-Making in City Logistics" and illustrated in Fig. 2. A more appealing version of the addressed location problem is the *two-echelon location routing*. In this case, in the first echelon, city freighters service satellites from city distribution centers. In the second echelon, special small urban vehicles serve customers from satellites in downtown regulated zones.

A special case of the two-echelon location routing, also prompted by the growth of e-commerce in urban areas, is the one depicted in Fig. 6. Here, the services to the satellites from the CDCs are provided by special fleets during the night. During the day, special city freighters (e.g., electrical vehicles, tricycles, etc.) serve the customers from the satellites.

Nagy and Salgy [38] elaborated a rather complete state-of-the-art report on this problem. They proposed a classification scheme and analyzed a number of variants as well as the exact and heuristic algorithmic approaches. Drexl and Scheinder [20] updated this state-of-the-art survey, providing an excellent panoramic overview of the current approaches. Metaheuristics dominate the panorama since they look more appropriate to deal with real instances of the problem. Perhaps one of the most appealing is that of Nguyen et al. [39] based on a GRASP approach combined with learning processes and path relinking. Another interesting heuristic, an approach to a relevant variant of the problem based on a Tabu Search accounting for time dependencies, can be found in Nguyen et al. [40]. The interested reader is directed to these references given that space limitations do not allow including them in this chapter.

Operational Decisions: Routing Problems

According to Taniguchi et al. [51], vehicle routing and scheduling models provide the core techniques for modeling city logistics operations. Once the facilities, or the city logistics centers, have been located, the next step is to decide on the efficient use of the fleet of vehicles that must service the customers or make a number of stops to pick up and/or deliver passengers or products. Vehicle routing problems constitute a whole world given the many operational variants using them. The book of Toth and Vigo [54] provides a comprehensive and exhaustive overview of routing problems. To illustrate their role in city logistics, we have selected the relevant case of pickup and delivery models with time dependencies, which play a key role in courier services, e-commerce, and other related applications.

Pickup and Delivery Vehicle Routing Problem with Time Windows

Pickup and delivery vehicle routing problem with time windows (PDVRPTW) is a suitable approach for modeling routes and service schedules for optimizing the performance of freight companies in the city logistics context (e.g., the couriers). It is also a good example to demonstrate the operational decisions in the routing problems.

In this problem, each individual request includes pickup and a corresponding delivery of specific demand. The relationships between customers are defined by pairing (also known as coupling) and precedence constraints. The first constraint links two particular customers in a pickup-delivery pair, while the second one specifies that each pickup must be performed before the corresponding delivery.

Therefore, the main objective of the PDVRPTW is to determine, for the smallest number of vehicles from a fleet, a set of routes with a corresponding schedule, to serve a collection of customers with determined pickup and delivery requests, in such a way that the total cost of all the trips is minimal and all side constraints are satisfied. In other words, it consists of determining a set of vehicle routes with assigned schedules such that:

- Each route starts and ends at a depot (a vehicle leaves and returns empty to the depot),
- Each customer is visited exactly once by exactly one vehicle,
- The capacity of each vehicle is never exceeded,
- A pair of associated pickup-delivery customers is served by the same vehicle (pairing constraint),
- Cargo sender (pickup) is always visited before its recipient (delivery) (precedence constraint),
- Service takes place within customers' time window intervals (time windows constraint),
- The entire routing cost is minimized.

In order to describe mathematically the demonstrated PDVRPTW, we define for each vehicle k a complete graph $G_k \subseteq G$, where $G_k = (N_k, A_k)$. The set N_k

contains the nodes representing the depot and the customers, which will be visited by the vehicle k. The set $A_k = \{(i, j) : i, j \in N_k, i \neq j\}$ comprises all the feasible arcs between them. Thus, the problem formulation takes the form

$$\min \sum_{k\in K} \sum_{(i,j)\in A_k} c_{ijk} x_{ijk} \tag{32}$$

subject to

$$\sum_{k\in K} \sum_{j\in N_k\cup\{n+1\}} x_{ijk} = 1 \qquad \forall i \in N^+, \tag{33}$$

$$\sum_{i\in N_k^+} \sum_{j\in N_k} x_{ijk} - \sum_{j\in N_k} \sum_{i\in N_k^-} x_{jik} = 0 \qquad \forall k \in K, \tag{34}$$

$$\sum_{i} \sum_{j\neq i} x_{jik} \leq |S| - 1 \qquad \forall S \subseteq N : |S| \geq 2, \forall k \in K \tag{35}$$

$$\sum_{j\in N_k^+\cup\{n+1\}} x_{0jk} = 1 \qquad \forall k \in K, \tag{36}$$

$$\sum_{i\in N_k\cup\{0\}} x_{ijk} - \sum_{i\in N_k\cup\{n+1\}} x_{jik} = 0 \qquad \forall k \in K,\ j \in N_k, \tag{37}$$

$$\sum_{i\in N_k^-\cup\{0\}} x_{i,n+1,k} = 1 \qquad \forall k \in K, \tag{38}$$

$$x_{ijk}(z_{ik} + s_i + c_{ijk} - z_{jk}) \leq 0 \qquad \forall k \in K,\ (i, j) \in A_k, \tag{39}$$

$$e_i \leq z_{ik} \leq l_i \qquad \forall k \in K, \quad i \in N_k \cup \{0\}, \tag{40}$$

$$z_{i,k} + c_{i,p(i),k} - z_{p(i),k} \leq 0 \qquad \forall k \in K, i \in N_k^+ \tag{41}$$

$$x_{ijk}(q_{ik} + d_j - q_{jk}) = 0 \qquad \forall k \in K, (i, j) \in A_k, \tag{42}$$

$$d_i \leq q_{i,k} \leq Q \qquad \forall k \in K, i \in N_k^+ \tag{43}$$

$$0 \leq q_{p(i),k} \leq Q - d_i \qquad \forall k \in K, i \in N_k^+ \tag{44}$$

$$q_{0k} = 0 \qquad \forall k \in K, \tag{45}$$

$$x_{ijk} \in \{0, 1\} \qquad \forall k \in K, (i, j) \in A_k, \tag{46}$$

where

N: set of customers, where $N = N^{+} \cup N^{-}, \left|N^{+}\right| = |N^{-}|$,
N^{+}: set of all customers that notify pickup request,
N^{-}: set of all customers that notify delivery request,
c_{ijk}: nonnegative cost of a direct travel between nodes i and j performed by vehicle k, assuming that $c_{ijk} = c_{jik} \forall i, j \in V$,
i: customer, where $i \in N_k^{+}$,
$p(i)$: pair partner of customer i, where $p(i) \in N_k^{-}$,
d_i: customer's demand that will be picked up/delivered at $i/p(i)$, respectively, where $d_i = d_{p(i)}$,
q_{ik}: vehicle's k capacity occupancy after visiting customer i,
a_i: arrival time at customer i,
w_i: waiting time at the customer i, where $w_i = max\{0, e_i - a_i\}$,
z_{ik}: start of service at customer i by vehicle k, where $z_i = a_i + w_i$.

The nonlinear formulation of the objective function (32) minimizes the total travel cost of the solution that assures its feasibility with respect to the specified constraints. Equation (33) assigns each customer to exactly one route, while formulation (34) is a pairing constraint, which ensures that the visit of each pickup-delivery pair of customers $(i^{+}, p(i^{+}))$ is performed by the same vehicle k. The inequality (35) eliminates the possibility of construction of potential sub-tours. The three following constraints secure the commodity flow. Equality (36) defines the depot as every route's source and states that the first visited customer is the one with a pickup request. Likewise, formulation (38) determines the depot as every route's sink, and the last visited customer is the one that demands a delivery service. The degree constraint (37) specifies that the vehicle may visit each customer only once. The schedule concordance is maintained by equations (39) and (40) according to which, in case that a vehicle arrives to a customer early, it is permitted to wait and start the service within the time window interval only. The precedence constraint (41) assures that for each pair of customers the pickup i is always visited before its delivery partner $p(i)$. The next three restrictions express the dependencies between the customers' demands and the vehicles' restrained current and total capacities. Equation (42) indicates that after visiting the customer j, the current occupancy of the carriage loading space of the vehicle k is equal to the sum of the load carried after visiting the preceding customer i and the demand collected at customer j. According to inequality (43), the dimension of current occupancy of the total capacity of the vehicle k after visiting a pickup customer i shall be neither smaller than its demand d_i nor bigger than the entire vehicle's capacity. Similarly, following formulation (44), the current capacity of the vehicle k after visiting a delivery customer $p(i)$ shall never be smaller than zero and bigger than the difference between the total vehicle capacity and the size of its delivery request $d_{p(i)}$. The capacity constraint that considers the depot (45) states that the vehicle does not provide it with any service. The last formulation (46) expresses the binary and nonnegative nature of the problem-involved variable.

The exact algorithms are able to solve to optimality only the VRP problems with small number of customers (Cordeau et al. [15]). The heuristics do not guarantee optimality, but since they are capable of providing, for large-sized problems, a feasible solution in a relatively short amount of time, they strongly dominate among all the methods. What is more, the heuristics are proven to be quite flexible in adaptation to different VRP problem variations, which is of special importance when considering the real-world applications.

Tabu Search (TS) has been applied by many researchers to solve VRP. It is known to be a very effective method providing good, near-optimal solutions to the difficult combinatorial problems. The TS term was firstly introduced by Glover [27], and the concepts on which TS is based on had been previously analyzed by the same author Glover [26]. The main intention for TS creation was the necessity to overcome the barriers, stopping the local search heuristics from reaching better solutions than the local optima and explore intelligently a wider space of the possible outcomes. In this context, TS might be seen as extension of the local search methods or as a combination of them and the specific memory structures. The adaptive memory is the main component of this approach. It permits to flexibly and efficiently search the neighborhood of the solution.

The input to TS constitutes an initial solution created beforehand by a different algorithm (Fig. 7). An initial solution construction heuristic determines tours according to certain, previously established rules, but does not have to improve them. Its characteristic feature is that a route is built successively and the parts already constructed remain unchanged throughout the process of the execution of the algorithm.

Sweep algorithm is a good example of a VRP initial solution construction heuristic. It was introduced by Gillett and Miller [25]. However, its beginnings might be noticed in earlier published work of other authors, e.g., Wren [57] and Wren and Holliday [58]. The name of the algorithm describes its basic idea very well. A route is created in the process of gradually adding customers to a route. The selection of customers to add resembles the process of sweeping by a virtual ray that takes its beginning in the depot. When the route length, capacity, or the other previously set constraints are met, the route is closed, and the construction of a new route is started. The whole procedure repeats until all the customers are "swept" in the routes. A graphic representation of the sweep algorithm is provided in Fig. 8.

The solution provided by the classic sweep algorithm for PDVRPTW most likely will violate precedence and pairing constraints. The initial solution does not have to be feasible since it will be improved later on by TS in the optimization step. However, a feasible initial solution for PDVRPTW can be provided by a modified sweep algorithm accounting for side constraints. As a result, when a customer is met by the sweeping ray, it is added to the currently built route together with its corresponding partner, respecting the precedence constraint. The details on sweep algorithm adapted to provide initial solution for PDVRPTW are presented in Algorithm 1.

Unified Tabu Search heuristic proposed by Cordeau et al. [14] can be used to optimize the initial solution. Originally, it was designed to solve a VRPTW.

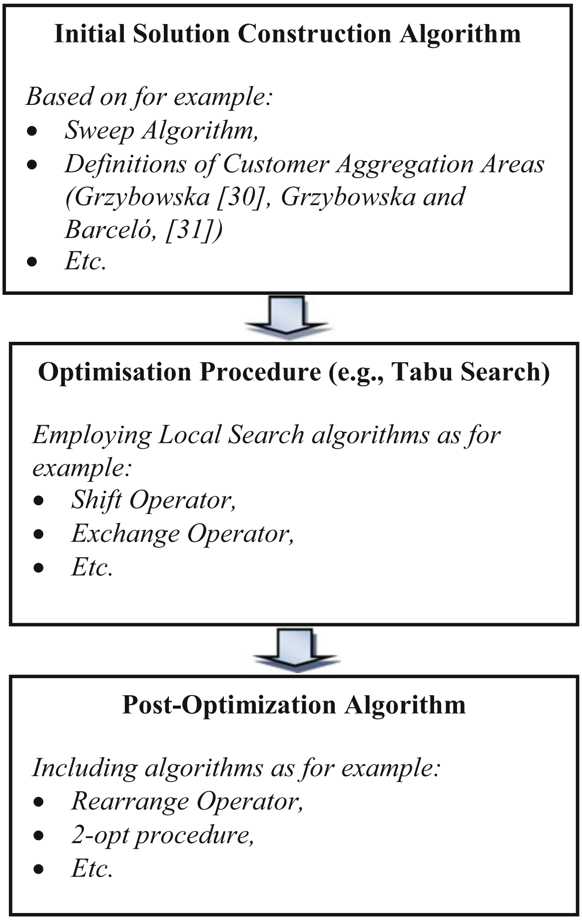

Fig. 7 Composite approach to solve a VRP

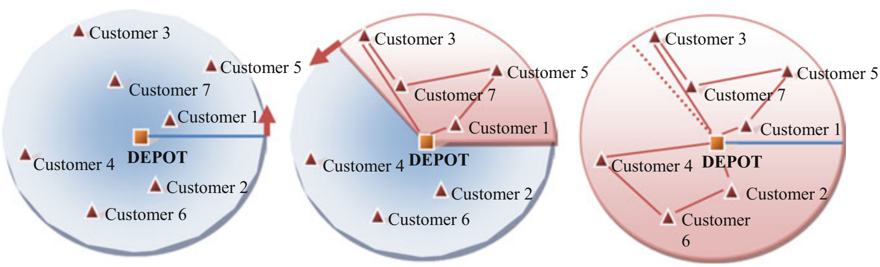

Fig. 8 Sweep algorithm

However, it can be adjusted to solve PDVRPTW. The main change regards the fact that each modification of a route concerns a pickup-delivery pair of customers instead of an individual customer. This affects the architecture and functioning of TS structures (e.g., adaptive memory). In addition, the local search algorithms used in TS need to consider the constraints of pairing and precedence.

TS starts with establishing the initial solution as best ($s^* = s_{\text{ini}}$). In each iteration, the employed local search algorithm defines a *neighborhood* $N(s^*)$ of the current best solution s^* by performing a collection of a priori designed *moves* modifying the original solution. The new solution s that upgrades the original solution, and characterizes with the best result of the objective function, is set as the best ($s* = s$). This repetitive routine (i.e., *intensification phase*) lasts until no further improvement can be found, which is interpreted as reaching the optimum. It uses the information stored in the short-term memory (i.e., *"recency" memory*) recording a number of consecutive iterations in which certain components of the best solution have been present. The short-time memory eliminates the possibility of cycling by prohibiting the moves leading back to the already known results, during certain number of iterations. The moves are labeled as *tabu* and placed at the last position in the *tabu list* – a short-term memory structure of length defined by a parameter called *tabu tenure*. The value of the tabu tenure might be fixed or regularly updated according to the preestablished rules, e.g., recurrently reinitialized at random from the interval limited by specific minimal and maximal value (Taillard [49]). The higher the value of the tabu tenure, the larger the search space to explore is.

Algorithm 1: Sweep algorithm for PDVRPTW

1. Let L be the list of all the customers $L = N \backslash \{0\}$
2. Sort all the customers by increasing angle $\angle A0S$, where S is the current customer, 0 is the depot, and A according to the chosen variant is either randomly chosen or fixed reference point.
3. Divide L into k sub-lists such that each sub-list l satisfies:

$$\angle A0S \in \left(\frac{2l-2-k}{k}\pi, \frac{2l-k}{k}\pi \right], \forall l \in K = \{1, \ldots, k\}$$

4. Sort all the customers in each sub-list l in decreasing order according to the travel cost between the depot and the customer.
5. **If** the sub-list l is not empty, **then** select the first customer, search for its partner, **and** insert both customers in a route in the least cost incrementing position. Respect the precedence constraint.
6. Delete the inserted customers from the sub-lists and go to step 5.
7. Repeat steps 5 and 6 for all the sub-lists.

The consequent choice of the next best solution is determined by the current neighborhood and defines the general direction of the search. The lack of broader perspective in most of the cases leads to finding a solution, which represents a local optimum instead of a global. It is also due to the decision on when to finish the whole procedure improvement (i.e., *stopping criterion*), which might be determined by a designated time limit for the complete performance or by a previously established number of repetitions, which do not bring any further improvement. In order to overcome this handicap, TS stops the local search algorithm and redirects the search in order to explore intelligently a wider space of the possible solutions (i.e., *diversification phase*). This includes permitting operations, which result in deterioration of the currently best solution. This phase requires access to the information accumulated during the whole search process and stored in the long-term memory structure (i.e., *frequency memory*). The success of the complete method depends on the balance established between these two phases, which complement each other instead of competing.

The functioning of the algorithm based on tabu bans is very efficient. However, oftentimes it may result in losing improvement opportunities by not accepting highly attractive moves, if they are prohibited. In such cases, the *aspiration criteria* should be activated. It is an algorithmic mechanism, which consists in canceling the tabu restrictions and permitting the move, if it results in construction of the new solution with the best yet value of the objective function. The implementation of TS is presented by Algorithm 2.

Algorithm 2: Tabu Search

1. Let η be the maximal number of permitted TS iterations.
2. Let α and β be the parameters of preestablished value equal to one.
3. Let Δ be the value of the objective function.
4. Let s be the initial solution.
5. Let s^* be the best solution and $s* = s$
6. Let $c(s^*)$ be the cost of the best solution.
7. **If** the solution s is feasible, **then** set $c(s^*) = c(s)$; **else** set $c(s^*) = \infty$
8. Let $B(s)$ be adaptive memory structure, whose arguments are initially set equal to zero.
9. **For** all the iterations $\kappa < \eta$, execute local search operator and create neighborhood $N(s)$
10. Select a solution from the neighborhood that minimizes the Δ function.
11. **If** solution s is feasible **and** $c(s) < c(s*)$, **then** set $s^* = s$ **and** $c(s^*) = c(s)$
12. Update $B(s)$ according to the performed move.
13. Update α and β

To define the neighborhood of a current solution, TS uses a local search algorithm. Local search algorithms are commonly used as intermediate routines performed during the main search process of more complex heuristics. However, they constitute individual algorithms. Some of them are referred to as *operators* with specified features (e.g., *shift operator*, *exchange operator*, *rearrange operator*, etc.), while the others possess their own denomination (e.g., the local optimization methods involving neighborhoods, which apply to the original solution a number of modifications equal to k, are known as the *k-opt* heuristics).

Algorithm 3: Pickup-delivery customer pair shift operator

Let s be the current solution containing a set of routes R
Calculate $c(s)$, $q(s)$, and $w(s)$
Let $s^* = s$ be the best solution with cost $c(s^*) = c(s)$
Let $f(s^*) = \infty$ be the value of the objective function of the best solution s^*
Let $\Delta^* = \infty$ be the best value of the objective function
Let $B(s)$ be the empty adaptive memory matrix
For each route $r_1 \in R$ **and for** each route $r_2 \in R$, **such that** $r_1 \neq r_2$
For each pickup-delivery customer pair $m \in r_1$
Remove pair m from route r_1
Set bool TABU = FALSE
If the value of the tabu status in $B(s)$ for r_2 **and** pair m is $\neq 0$, **then** TABU = TRUE
Find the best insertion of pair m in r_2 and obtain new solution s'
Calculate $c(s')$, $q(s')$, and $w(s')$
Let $f(s')$ be the value of the objective function of the new solution s'
Let $p(s')$ be the value of the penalty function of the new solution s'
Let $\Delta = 0$ be the value of the objective function
If $f(s') < f(s^*)$, **then** $\Delta = f(s')$; **else** $\Delta = f(s') + p(s')$
Check the feasibility of solution s'
Set bool AspirationCriteria = FALSE
If $c(s') < c(s^*)$ **and** solution s' is feasible, **then** AspirationCriteria = TRUE
If $\Delta < \Delta^*$ **and** (Tabu = TRUE **or** AspirationCriteria = TRUE), **then** $\Delta^* = \Delta$ **and** the best move was found

Shift operator is a good example of a local search algorithm in TS. Its objective is to remove a customer from its original route and feasibly insert it in another route of the current solution, in such a way that its total cost is minimized. When solving PDVRPTW the shift move includes a pickup-delivery customer pair instead of an individual customer. During the entire search process, all the pickup-delivery pairs are successively moved, and all the possible reinsertion locations in the existing routes are checked. Only the moves which are in accordance with all the side constraints shall be accepted. Algorithm 3 presents the functioning of shift operator in TS for solving PDVRPTW.

The algorithm uses the values of violations of the constraints for the calculation of the objective function, as well as for determining the rate of the penalties, which need to be imposed for not complying with initial restrictions. These values are calculated according to the following formulas:

$$\Delta = f(s) + p(s) \tag{47}$$

$$f(s) = c(s) + \alpha \cdot q(s) + \beta \cdot w(s) \tag{48}$$

$$p(s) = \lambda \cdot c(s) \cdot \sqrt{n \cdot k} \cdot \varphi(s) \tag{49}$$

$$\varphi(s) = \sum_{(m,r)\in B(s)} \rho_{m,r} \tag{50}$$

where

Δ: objective function,
$f(s)$: cost evaluating function for the solution s,
$p(s)$: penalties evaluating function for the solution s,
$c(s)$: cost of solution s,
$q(s)$: vehicle capacity constraint violation function for solution s,
w(s) : time windows constraint violation function for solution s,
α: parameter related to the violation of the vehicle capacity constraint,
β: parameter related to the violation of the time windows constraint,
λ: scaling factor,
n: total number of customers,
k: total number of vehicles
φ(s): parameter controlling the addition frequency,
$B(s)$: adaptive memory matrix,
$\rho_{m,r}$: number of times the pickup-delivery customer pair m has been introduced into route r.

It is a usual practice to complement the TS heuristic with a *post-optimization* step. Its objective is to further improve the solution provided by TS. It is important to note that the final result has to be obligatorily feasible. Local search heuristics are often used for post-optimization purposes and *2-opt heuristic* is a good example. The 2-opt procedure is the most common representative of the family of k*-opt heuristics*. It has been introduced by Croes [18] for solving a Travelling Salesman Problem. The main idea of the 2-opt method is valid for the other k-opt heuristics. In the main, it consists of removing two nonconsecutive arcs connecting the route in a whole and substituting them by another two arcs reconnecting the circuit in such a way that a new solution which fulfills the predefined objectives is obtained. This move is commonly called a *swap* since it consists of swapping two customers in the original sequence. The swap can be performed in accordance with one of the following strategies: (i) search until the first possible improvement is found, and perform the swap, and (ii) search through the entire tour and all possible improvements, and perform only the swap resulting in the best improvement. A graphic representation of 2-opt procedure is provided in Fig. 9.

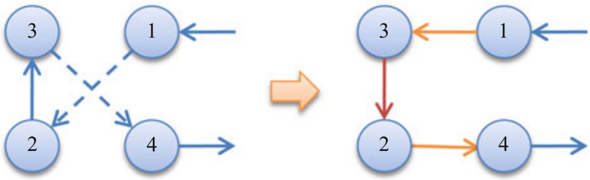

Fig. 9 2-opt algorithm

As in the case of the previously presented algorithms, the classic formulation of the 2-opt algorithm needs to be adapted to solve the PDVRPTW. The final solution needs to be strictly feasible; thus all the side constraints, including pairing and precedence, need to be respected. The PDVRPTW adapted 2-opt algorithm is presented by Algorithm 4.

Algorithm 4: 2-opt algorithm adapted to PDVRPTW

1. Let R be the set of routes defining the current solution s
2. **For** each route $r \in R$
3. Let $r*$ be the best route and $r^* = r$
4. Calculate $c(s^*)$, $q(s*)$, and $w(s*)$
5. **While** best move is not found
6. Let $pos(i)$ be the position of customer i in the sequence of customers of route r
7. Let $pos(j)$ be the position of customer j in the sequence of customers of route r
8. **For** each customer i and j in route r **such that** $pos(j) = pos(i) + 2$
9. Create new empty route r'
10. **For** each customer h in route r
11. **If** $pos\ (h) \leq pos$(i) **or if** $pos(h) \geq pos(j + 1)$, **then** append customer h to r'; **else** append customer h at position $pos(i) + pos(i) - pos(h) + 1$ to r'
12. Calculate $c(s$'), $q(s$'), and $w(s$') and check the feasibility of route r'
13. **If** $c(r$'$) < c(r^*)$ **and** route r' is feasible, **then** $c(s^*) = c(s$'$)$ **and** the best move was found

Real-Time Management

Under this category we cluster what are considered the most relevant city logistics services made available by the pervasive penetration of the ICT technologies. These technologies made it possible for the demand to occur anywhere and at any time. This entails a request for the system to provide the capability of suitably responding to the demand in real time, and in a way that at the time satisfies the quality requirements of the customers, and also provides the most suitable benefit to the company. This section describes the main characteristics highlighting the dynamic aspects of the problem, which must be addressed by efficient computational time-dependent versions of the ad hoc algorithms. This is an area of applications characterized by the synergies between technologies, decision-making, and sophisticated routing algorithms. The domain of application, however, has recently been expanded to account also for emerging versions of public transport services, special cases of demand-responsive transport services, which can be formally formulated in similar terms (just replacing freight or parcels by persons). This application will be considered in section "Extensions".

Let us suppose that an initial operational plan has been defined with k routes and that there is an *advanced traffic information system* providing real-time information that allows us to calculate current travel times for every pair of clients. Since most of real-world fleets are usually equipped with *automatic vehicle location* (AVL) technologies, it also assumed that the fleet manager is capable of knowing the exact location of the vehicles at every time and has a two-way communication with the fleet.

In our proposed *rerouting algorithm* (RRA), we compute the feasibility of the remaining services while we keep track of the current state and location of the vehicles. In order to simplify the tracking process, we consider two approaches: either to compute feasibility once a vehicle finishes a service and informs about its current situation to the fleet manager or in a periodical manner after updating the fleet's situation. In the first approach, the trigger for the computations is only the departure of the vehicle, but there might be risks when vehicles take longer times to complete the service. The second approach is computationally more intensive, but it may prevent future failures in the service when unexpected service times are present.

In the case of the vehicle routing with time windows, there are two critical factors that define the feasibility of a route: capacity and time windows. Assuming that no variations in demand are expected (e.g., more units to pick up), capacity can be neglected as the corresponding route (static or dynamic) is built taking into account this constraint. In such case, time windows constraints become more critical as there are many uncontrollable parameters (e.g., unexpected traffic conditions, delayed service, etc.) that may affect the feasibility of a service and, therefore, the performance of the route.

Figure 10 describes the full dynamic monitoring process. On one hand, we have the advanced traffic information system which provides current and forecasted travel times of the road network to the fleet manager. On the other hand, we have the fleet management center that is able to communicate with the vehicles and receive their position along with other data such as current available capacity and status.

These two sources are inputs to a dynamic tracking system which through a desired strategy (periodic, after service or both) computes the current feasibility of the routing plan. If an unfeasible service is detected, the RRA is triggered to find a feasible current plan. If a customer cannot be allocated to a vehicle that is on the road, the RRA tries to assign an idle vehicle housed at the depot. If no vehicles are available, a penalty is applied.

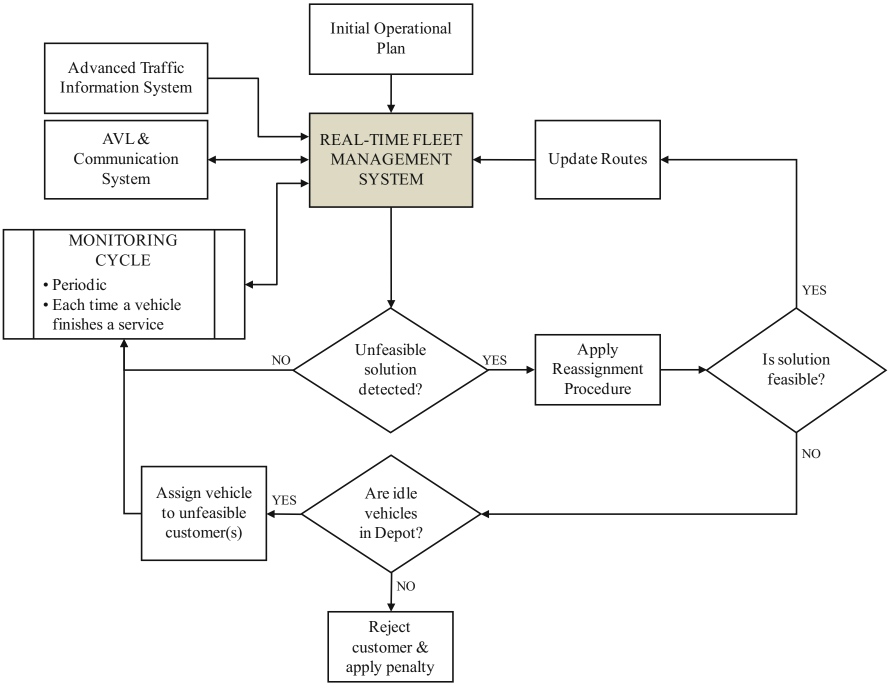

Fig. 10 Rerouting algorithm through dynamic tracking of the fleet

Computation of Feasibility

Computing the current feasibility of a route depends on the state of the vehicle at the time of evaluation. If a vehicle is traveling to the next scheduled customer or departing from a customer's location after service, the feasibility of the route is obtained by computing the expected arrival times to the next customers on the route. If at the time of evaluation, a vehicle has already started a service or waiting to start it, we must first estimate the departure time from the current location and then the arrival times in the rest of the route.

Under our approach, we assume that drivers send messages to the fleet management center when they arrive to and start or end a service with a customer. Therefore, at the time of evaluation, if a vehicle providing service has not finished under the estimated time lapse, the algorithm assumes that the remaining service time is the expected time used in the computation of the route. That is, if a service is assumed to take 10 min and, at the time of evaluation, the vehicle has 14 min without sending the end-of-service signal, the algorithm assumes, in a preventive way, that the vehicle needs another 10 min to complete the service.

Formally, the feasibility conditions can be computed as follows. Let $\hat{a}_i$ be the estimated arrival time of a vehicle at customer i, E_i the lower bound of the time window of customer i, e_i the estimated service start time at customer i, S_i the estimated service time at customer i, and $T_{ij}(t)$ the travel time between customer i and j when vehicle departs at time t. Let V_k be a dummy node in the network representing vehicle k which route is given by $\{1, 2, \ldots, i,\ i+1, \ldots, n-1,\ n\}$.

If at time t_e, the vehicle has just finished a service at customer i or it is traveling to customer $i+1$, the estimated arrival and service start times at the next scheduled customers can be computed as follows:

$$\hat{a}_i = \begin{cases} t_e + T_{V_k,h}(t_e) & \text{if } h = i+1 \\ e_{h-1} + S_{h-1} + T_{h-1,h}(e_{h-1} + S_{h-1}) & \text{if } h = i+2, i+3, \ldots, n \end{cases} \tag{51}$$

$$e_h = \max\{E_h, \hat{a}_h\}, \quad \text{for } h = i+1, i+2, \ldots, n \tag{52}$$

On the other hand, if at time t_e, the vehicle is waiting to start service or providing service to customer i, we first compute d_i, the expected departure time from customer i. Let a_i be the real arrival time of a vehicle at customer i's location. Therefore, d_i is computed as follows:

$$d_i = \begin{cases} t_e + S_i & \text{if } \max\{\mathrm{E_i}, a_i\} + S_i < t_e \\ \max\{E_i, a_i\} + S_i & \text{otherwise} \end{cases} \tag{53}$$

In this case, the expected arrival times in subsequent customers $h = i+1, i+2, \ldots, n$ are given by:

$$\hat{a}_h = \begin{cases} d_i + T_{i,i+1}(d_i) & \text{if } h = i+1 \\ e_{h-1} + S_{h-1} + T_{h-1,h}(e_{h-1} + S_{h-1}) & \text{if } h = i+2, i+3, \ldots, n \end{cases} \tag{54}$$

where e_h is computed as in (2). The service at customer h becomes then *unfeasible* if $\hat{a}_h > L_h$, where L_h is the upper bound of the required time window in customer h. Figure 11 depicts a situation when one of the services becomes unfeasible.

The proposed RRA consists of computing feasibility conditions every time a vehicle has finished a service and is ready to depart from its current location. If one or more customers are detected to be in an unfeasible sequence, they are withdrawn and reinserted in the route using a greedy *dynamic insertion* heuristic (DINS). A re-optimization procedure is then applied using a *Tabu Search*-based metaheuristic (DTS). The greedy insertion heuristic is described in the following subsection.

If DINS algorithm does not find a feasible assignment to the vehicles on route, it allocates the withdrawn order to an idle vehicle in the depot. If no vehicles are available, the algorithm rejects the customer. The pseudo-code of the RRA is the following:

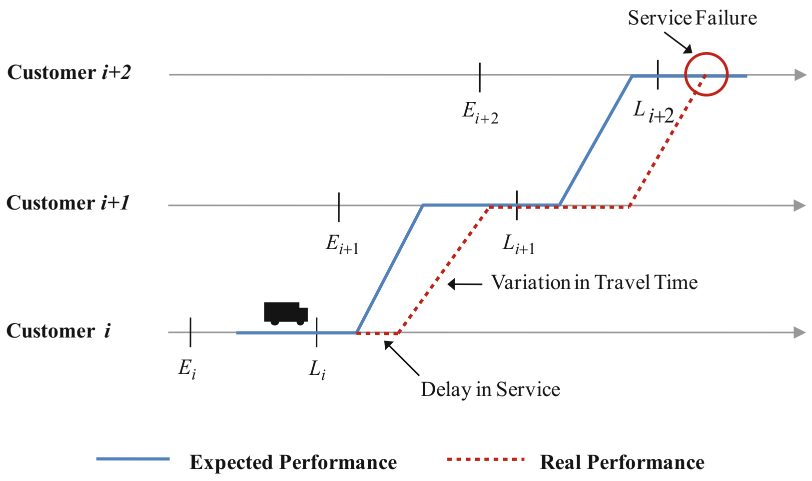

Fig. 11 Example of service failure due to delays [41]

Algorithm 5: Rerouting algorithm

After a vehicle k finishes a service:

1. Compute feasibility conditions for all unvisited customers in the route of vehicle k
2. Let U_k be the set of unvisited customers which are now unfeasible in current scheduling
3. **If** $U_k = \varnothing$, **then** STOP; **else** continue to step 4
4. **For** each customer $u \in U_k$, withdraw u from route applying operator DELETE(u)
5. **For** each customer $u \in U_k$, reinsert u in current routes applying DINS algorithm
6. **If** reinsertion is not possible for a customer, **then** create new route with available vehicle (if any)
7. Apply DTS algorithm to re-optimize routes.

The RRA assumes that all customers that are found to be unfeasible have the same importance, ranking, or priority. Therefore, if there is more than one unfeasible customer, step 5 selects randomly, with equal probability, the next customer to be inserted in the routes.

Heuristic Approach

The RRA is a two-phase methodology that first identifies customers that are likely to be not serviced on time and then reassigns them in order to optimize the service level of the fleet. After the identification of customers, the algorithm withdraws those customers from the routes and uses them to build a set of customers U_k to be reassigned. The reassignment algorithm works by first inserting customers in U_k with a greedy insertion heuristic, and then, routes are re-optimized using a Tabu Search metaheuristic.

Dynamic Insertion Heuristic (DINS)

The heuristic used in the DRS is derived from the basic insertion heuristic proposed in Campbell and Savelsbergh [11], where every unrouted customer is evaluated at every insertion point. The evaluation of this movement consists in checking the feasibility and profitability of every insertion, which is the negative of the amount of additional travel time added to the route. The customer with a feasible insertion having the maximum profitability is then selected and inserted in the route. We have adapted this heuristic by introducing some new elements to reflect the dynamics of the operations of a fleet in an urban environment.

The objective of DINS heuristic is to insert a new client into the current routing plan once the vehicles have started the services. The general idea of the algorithm is simple. When a new client arrives to the system, the algorithm checks the current state of the vehicles. Then, routes with insufficient time to visit the new client within their schedule are rejected. Finally, the algorithm searches for the least cost feasible insertion in the candidate routes. If no feasible insertion is possible and there are idle vehicles at the depot, a new route is created including the new customer.

We assume that there are n routed customers in R different routes at the beginning of the time planning horizon. We also suppose that there is a single depot with a homogeneous fleet of vehicles with capacity Q. We define the following notation:

$T_{i,j}(t)$: travel time between customers i and j when vehicle departs at time t,
V_r : vehicle assigned to route r, $r = 1, 2, .., R$,
q_r : total demand assigned to route r,
d_i : demand of customer i,
E_i : time window lower bound of customer i,
L_i : time window upper bound of customer i,
e_i : earliest service start time at customer i,
l_i : latest service start time at customer i,
S_i : service time at customer i.

The time window of a customer i is denoted by (E_i, L_i). The values e_i and l_i refer to the earliest and latest time a service can take place at customer i, and they must satisfy the following condition: $E_i \leq e_i \leq l_i \leq L_i$. If we wish to insert customer w at time instant $t > 0$, the vehicles of the fleet may have one of the following three states:

1. The vehicle is in service at some customer i (SER).
2. The vehicle is moving to the next planned customer on the route or waiting at the customer location to start service within the time window (MOV).
3. The vehicle is idle at the depot, without a previously assigned route (IDL).

The state of a vehicle will let us know when a vehicle should be diverted from its current route, be assigned to a new one if it is idle, or keep the planned trip. Whenever a new customer arrives, the status of each vehicle must be known to compute travel times from their current positions to the new customer.

The first iteration of the algorithm consists of rejecting those routes that are definitely infeasible. To do this, it is necessary to compute the total available time of the routes, i.e., the sum of the available time (if any) of a vehicle on the assigned route. We define the available time of a vehicle as those periods of time where (i) a vehicle is waiting to provide service to a customer or (ii) a vehicle has finished the scheduled route and is returning to the depot. This is, in fact, the maximum slack time a vehicle has available to travel and service customer w.

The calculation of the available route time can be done by estimating the arrival times at each of the scheduled customer locations that has not been served at the time of insertion of the customer w. The arrival time a_i at customer i is computed from the current position of the vehicle, and we assume that the vehicle will start service as soon as it arrives, if the customer's time window is already open; otherwise, the vehicle waits. The calculation of arrival times can be made as follows.

If, at instant t, the vehicle is moving toward the next customer i, then the estimated arrival time is given by $a_i = t + T_{Vr,i}(t)$. The arrival times at subsequent customers on the route are computed as follows:

$$a_i = \max\{E_{i-1}, a_{i-1}\} + S_{i-1} + T_{i-1,i}(\max\{E_{i-1}, a_{i-1}\} + S_{i-1}) \tag{55}$$

Hence, the available time of a vehicle in route r at some node i (including the depot) is the difference between the associated lower limit of the time window and the arrival time of the vehicle to that location. That is, $W_i^r = \max\{E_i - a_i, 0\}$. Therefore, the total available time of a route r is given by $AT_{v_r} = \sum_i W_i^r$.

From each route, we choose the unvisited node that is the closest to the new client. If the travel time from that node to the new customer is greater than the total available time AT_{Vr}, then we reject the route. If every route is rejected, a new route must be created for this new customer. The routes obtained, as a result of this previous iteration, are *possibly feasible* in the sense that vehicles serving those routes have enough time to travel to the new customer. This is a necessary condition, but not sufficient, because we have to check for time windows feasibility. The second major iteration of the algorithm consists, therefore, in checking the feasibility and profitability of an insertion in every arc of the possible feasible routes. The feasible insertion with the highest profitability is then selected, and the corresponding route must be updated.

Feasibility. In order to evaluate the feasibility of the insertion of customer w between nodes i and $i+1$, we must compute e_w and l_w, the expected earliest and latest service start times, respectively. The earliest service start time at the inserted customer w is given by:

$$e_w = \begin{cases} \max\{E_w, t + T_{V_r,w}(t)\} & \text{if } V_r = i \\ \max\{E_w, e_i + S_i + T_{i,w}(e_i + S_i)\} & \text{otherwise} \end{cases} \tag{56}$$

The latest service start time is calculated through a backward procedure starting with the depot (the last node to be visited by the vehicle) as follows:

$$l_w = \min\left\{L_w, \tilde{t}_w - S_w\right\} \tag{57}$$

where $\tilde{t}_i = \arg\max_t \{t + T_{i,i+1}(t) - l_{i+1}\}, \ \forall t \leq l_{i+1} - T_{i,i+1}(t)$ is the latest possible departure time that allows the vehicle to arrive to the next scheduled customer $i+1$ at time l_{i+1}. If $e_w \leq l_w$ and $D_w < Q - q_r$, the insertion is feasible.

Profitability. The profit of an insertion is defined as the negative of the additional travel time incurred from inserting a customer in a route. If customer w is to be inserted between nodes i and $i+1$, the profitability of this insertion is given by:

$$\begin{aligned} \text{Profit} = -\lfloor T_{i,w}\left(\max\{E_i, a_i\} + S_i\right) + T_{w,i+1}\left(\max\{E_w, a_w\} + S_w\right) \\ - T_{i,i+1}\left(\max\{E_i, a_i\} + S_i\right)\rfloor \end{aligned} \tag{58}$$

If no insertion is possible and there are available vehicles at the depot, then a new route that includes customer w is created. If the whole fleet of vehicles is already occupied, then the call is rejected, and a penalty may be applied. Given a customer w to be inserted at time t into a set R of routes, the pseudo-code of the DINS heuristic is as follows:

The solution obtained by DINS heuristic can be further optimized by applying DTS.

Dynamic Tabu Search (DTS)

DTS constitutes an adaption of the *Unified Tabu Search* (UTS) heuristic proposed by Cordeau et al. [14]. The modifications of the original method were made in order to include the dynamic aspects of the addressed problem. One of the most important modifications regards the engagement of the operators, which perform the local search only on the unvisited customers of the scheduled routes.

Similarly as UTS, DTS is an iterative process searching for the best solution $s*$. In each iteration, the algorithm searches for the best non-tabu solution s' in the neighborhood space $N(s)$ of current solution s, which minimizes the value of the

Algorithm 6: DINS heuristic

1. **For** each route r in R **do**:
Compute available time AT_{Vr}
Find travel time from w to closest neighbor
If available time is not enough, **then** reject route r
Else, add route r to R', the set of possible feasible routes
2. **For** each route r in R' **do**:
Check the status of the vehicle and set its position as the starting node of the route.
For each arc $(i, i+1)$ of the remaining route sequence **do**:
If insertion of w is feasible and profit is improved **then**:
Store current profit and insertion places
3. **If** insertion is possible **then:**
Insert w in least cost arc and update selected route.
4. **Else,** create a new route with an available idle vehicle (if any).

cost function $f_D(s)$ or satisfies the aspiration criteria. The solutions found in the search process are evaluated by the cost function:

$$\mathrm{f_D}(s) = c_D(s) + \alpha q(s) + \beta d_D(s) + \gamma w_D(s) \tag{59}$$

where

$c_D(s)$: estimated total travel time of the routes for the pending scheduled customers,
$q(s)$: total violation of the vehicles' capacity,
$d_D(s)$: total violation of the routes duration,
$w_D(\mathrm{s})$: total violation of the time windows constraint of the customers to be visited.

The adaptive memory matrix $B(s)$ denotes the attribute set of a solution s and is defined as follows: $B(s) = \{(i, k)$, where customer i (or a pair of customers in the case of PDVRPTW) is visited by vehicle $k\}$.

The penalty function $p(s)$ was added to the objective function in order to diversify the search of the solutions toward new or not thoroughly explored areas. For each solution s' such that $f_D(s') \geq f_D(s)$, the penalty is calculated as follows:

$$\mathrm{p}(s') = \lambda c_D(s')\sqrt{n_u m} \sum_{(i,k)\in B(s')} \rho \tag{60}$$

where

n_u: number of customers that have not been visited (or pairs of customers in the case of PDVRPTW),
m: current number of routes,

λ : positive value parameter to control the intensity of diversification,
ρ_{ik}: addition frequency parameter equal to the number of times the attribute (i, k) has been added to a solution.

The value of the addition frequency parameter, which controls the intensity of diversification, is updated regularly and at the end of each iteration of DTS.

The aspiration criteria defined for the DTS accepts a solution if its cost improves the best solution found so far. Also, in order to achieve quick online solutions, we added a stopping criterion which takes into account the rate of improvement in the search process. When the κ number of iterations has been reached without observing an improvement larger than ε, then the search process is stopped.

Similarly as in UTS (Cordeau et al. [14]), in DTS we employ a relaxation mechanism facilitating the exploration of the solution space. The mechanism is particularly useful in the cases when tight constraints are defined (e.g., hard time windows, pairing, and precedence constraints). The relaxation is achieved by dynamically adjusting the values of the parameters: α, β, and γ. When the solution s' is feasible, the value of the best feasible solution is updated, and the current values of the three parameters are reduced by dividing them by the factor $(1 + \delta)$. In the contrary case, the current values of the parameters are increased by multiplying them by the same factor. δ is a parameter of fixed value.

DTS was designed in a way, so that it becomes a flexible framework in which various local search operators can be embedded. As a result, depending on the addressed problem, a different operator can be enabled. Algorithm 7 provides a general description of the DTS. The reader interested in details is directed to Barceló et al. [4, 5].

Algorithm 7: Dynamic Tabu Search

1. **If** solution s is feasible **then**:
2. Set $s^* = s, \alpha = 1, \beta = 1, \gamma = 1$
3. Set $c(s^*) = c(s)$ **else** set $c(s^*) = \infty$
4. **For** $i = 1, \ldots, \eta$ **do**:
5. Select solution $s' \in N(s)$ that minimizes the objective function $\Delta = f(s') + p(s')$ such that s' is not tabu **or** satisfies aspiration criteria
6. **If** s' is feasible **and** $c(s') < c(s^*)$, **then** set $s^* = s$' **and** $c(s^*) = c(s$')
7. **If** $q(s') = 0$, **then** $\alpha = \alpha/(1 + \delta)$, **else** $\alpha = \alpha(1 + \delta)$
8. **If** $\mathrm{d}(s') = 0$, **then** $\beta = \beta/(1 + \delta)$, **else** $\beta = \beta(1 + \delta)$
9. **If** $\mathrm{w}(s') = 0$, **then** $\gamma = \gamma/(1 + \delta)$, **else** $\gamma = \gamma(1 + \delta)$
10. Set $s = s$'
11. Update α, β and γ
12. **If** number of iterations without improvement $= \kappa$, **and** last improvement $< \varepsilon$, **then** STOP

Extensions

The variants of pickup and delivery problems with time windows and time-dependent link travel times discussed in section "Operational Decisions: Routing Problems", as core components of the real-time fleet management applications analyzed in section "Real-Time Management" (as we have already mentioned), provide another area of application in urban scenarios which can be considered advanced implementations of demand-responsive transport systems. Examples of such could be the special shared taxi services provided by Uber [56] or Kutsuplus, uber-like minibus demand-responsive transit system experimented in Helsinki KUTSUPLUS [33].

A summary description of the Real-Time Multiple Passenger Ridesharing system and how it works could be the following. A customer asks for a service at a given time; the service could consist of either picking up a passenger (or various passengers) or a parcel, at a given location pickup location, at a given time (or within a time window) and delivering the passenger(s) or the parcel, at a delivery location at a given time (or within a time window). The service vehicles already in operation follow routes individually calculated depending on the customers' initial and final positions, the current traffic conditions, and the defined passengers' time windows.

Figure 12 illustrates conceptually how the demand-responsive mobility services work. Let's assume a fleet consisting of two vehicles V1 and V2, both with initially assigned plans which have been previously optimized. At a given time a customer C1 calls the system for a service, the customer's location is automatically recorded by the system. The customer tells the system which is his/her time expectancy of pickup, in other words the time window (e_1, l_1) of his/her waiting time expectancy (e.g., e_1 could be the time at which the call is made, and l_1 the latest time he/she expects to be picked up). The customer also informs the system of his/her destination that is delivery point, D1, and likely the time at which he/she would approximately like to arrive at the destination, let's say $(a_1 \pm \varepsilon_1)$, where ε_1 represents an acceptable slack time.

The system, which is aware of locations and status of each vehicle in the fleet (e.g., fleet vehicles are GPS tracked, and the ICT functions inform the system on the current level of occupancy of the vehicle, i.e., the number of passengers, their destinations, and time constraints), as well as the current network conditions (e.g., a real-time traffic information system keeps the decision support system updated about travel times, congestions, incidents, and so on), determines which of the vehicles is the most appropriate to provide the service to customer C1 both in terms of quality of the service and profitability. Let's assume that on the basis of the available information, the dispatching system assigns the service to vehicle V1 and the route R1 to pick up the customer and take him or her to his/her destination.

In a similar way, let's assume that customer C2, who is located at C2, has to be picked up within the time window (e_2, l_2) and wants to travel to destination D2. He

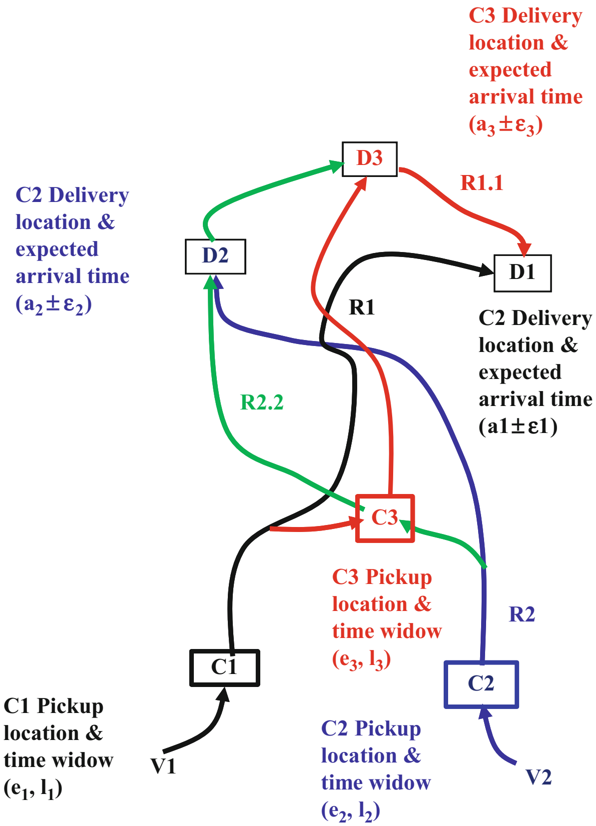

Fig. 12 Example of demand-responsive mobility services

or she expects to arrive around $(a_2 \pm \varepsilon_2)$ and is assigned to vehicle V2 that will follow route R2 to pick him/her up and travel to the destination D2.

The critical situation showing how the performance of the entire system depends on the quality of the decision support system that manages the fleet, and dispatches the services, arises when some time later, let's say at time t, a new customer C3, at location C3, asks for a pickup service within the time window (e_3, l_3) to travel to destination D3 where he/she expects to arrive around $(a_3 \pm \varepsilon_3)$.

In order to provide the new customer the requested service, the system faces many alternatives. First, it can open a new route assigning one of the empty vehicles of the fleet to the new client, but this action may imply a high cost. A better alternative would be to assign one of the en route vehicles that are closer to the client, if the time constraints of the customers that are already being served allow this. In this example, both proposed solutions accept a diversion policy, so, either of the vehicles could divert from their original routes to serve the new client and return to their originally assigned schedules.

One of the alternatives is to assign the new customer service to the vehicle V1, which exchanges its route R1 for the new route R1.1 (described in the figure with red arrows). This vehicle picks up customer C3 within the accepted time window, and then it drives to the D3 destination to deliver the customer. After this, vehicle V1 follows its new route and delivers customer C1 at the corresponding destination D1 taking into account the time constraints of all the served customers. The second possibility is that the new service of customer C3 is assigned to vehicle V2, which diverts its route to pick up the customer by following route R2.2 (described in the figure with green arrows). In this case, the vehicle delivers customer C2 at its destination D2 first, and then, it goes to the destination D3 of customer C3. Also in this case, we need to take into account the time constraints with respect to all involved customers. The decision will be made accounting for criteria that, while ensuring the quality of the service provided to the customers, achieve the maximum system profitability.

The management of the system is based on a decision support system similar to the one described in section "Real-Time Management". It allows making decisions on which vehicle to assign to each new coming customer. The dynamic rerouting is a particular case of the pickup and delivery problem with time windows, with time-dependent travel times, similar to the one described in section "Operational Decisions: Routing Problems".

Linares et al. [34, 35] provide details on a simulation study on the performance of these types of systems as a function of the expected demand for service relative to the total demand of conventional car trips in the selected urban scenario, the size of fleet providing the service (i.e., 500, 750, 1000... vehicles), and the capacity of the fleet vehicles, six or eight passengers.

Concluding Remarks

The main objective of this chapter is to introduce the main characteristics of city logistics problems that make them a special category – clearly differentiated from the general logistics problems. The analysis of these characteristics and their peculiarities regarding the type of decisions to make (i.e., strategic, tactic, and operational) allows to identify various classes of problems (i.e., location, location routing, routing with time windows, etc.) each one becoming a fertile domain for heuristics, given the complexity and size of the problem to solve in real life. A selected set of examples of such heuristics has been described in this chapter, with special attention paid to those particularly relevant to urban scenarios due to the imposed constraints such as the regulatory policies imposed by the authorities, time constraints imposed by the conditions of servicing customer in these scenarios, and the time dependencies implied by the variability of travel times in urban congestion. For the interested reader the chapter is complemented with a wide set of references.

Cross-References

▶ GRASP
▶ Matheuristics
▶ Supply Chain Management
▶ Tabu Search

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