Optimizing Real-Life Freight-Distribution Problems

Real-life freight-distribution problems present high degrees of complexity mostly derived from needing to respect a variety of constraints and addressing complex objective functions in which different factors are taken into account. The aim of this article is to point out relevant issues arising in real-life freight-distribution problems and to describe still-open issues and gaps between models and real-life applications. Furthermore, a real-life vehicle-routing problem is presented and a real instance related to regional freight distribution in Piedmont (northwest Italy) is solved by a fast heuristic method. The extreme portability of this method is then discussed.

Key words: freight distribution, vehicle routing, optimization, time windows, heterogeneous fleet

Introduction

Real-life freight-distribution problems are characterized by a high degree of complexity. Although this kind of problem has been addressed broadly by the operation research community, models proposed in the literature are not able to completely describe real distribution problems, and while attempting to simplify and generalize the problem, they neglect aspects that could be of crucial importance. In real-life applications a huge variety of constraints may be faced. Some concern vehicle features, such as multi-dimensional vehicle capacity (weight and volume) and vehicle characteristics (refrigerated vehicles for perishable food, armored vehicles for jewelry items, special vehicles for hazardous materials or for medicines, etc.). Some others deal with time restrictions. In fact, route duration and length restrictions may be found in drivers’ national contract agreements, customer time windows, and road accessibility time windows (traffic-limited zones). Others constraints address product-product, product-vehicle, and/or customer-vehicle compatibility. Moreover, real-life applications often present objective functions more complex that go beyond the classical distances minimization. Different factors may be taken into account, such as driving costs, environmental costs, risk level (for hazardous materials transport), customer satisfaction, and others. In several cases multi-objective function optimization is required. The aim of this article is to describe relevant issues arising in real-life freight-distribution problems and to discuss the varying degree of importance they assume in different contexts. The article provides a deep investigation of models and algorithms addressing real-life problems presented in the literature and a critical dissertation on still-open issues and gaps between models and real-life applications. Promising avenues to be followed to create powerful and

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Introduction

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versatile tools, which also may deal with different distribution problems, are proposed. The article is organized as follows. For the literature part, each section is devoted to a different issue: time constraints, time-dependent travel times, heterogeneous fleet and compatibility, environmental aspects, integration with other optimization problems, and multi-objective functions. After that a real-life vehicle-routing problem is presented and a real instance related to regional freight distribution in Piedmont (north-west Italy) is solved by a fast heuristic method. The extreme portability of this method is then discussed. Finally, conclusions and future developments are reported.

**Time Windows and Time Constraints**

Nowadays, logistics operators are expected to offer more reliable and reasonably priced delivery services. Customers have become more exigent, and their requirements in terms of delivery conditions have strongly increased; they require goods to be delivered as soon as possible or within specific time windows during the day. Therefore time has assumed a crucial role in logistics operation decision making. Vehicle-routing problems with time windows (VRPTW) have been broadly addressed in the literature (Toth & Vigo, 2002). Three kinds of time windows (TWs) are considered (see Table1):

- **Hard time windows**: deliveries must be performed within the TW
- **Soft time windows**: deliveries could be performed outside the TW paying a penalty
  - Fixed penalty: applied every time a TW is violated
  - Variable penalty: proportional to the length of the violation (this approach is more adapted to describe real situations in which missing a time window by 1 hour is much worse than missing it by 5 minutes)
  - Composed penalty: more complex functions, in which, generally, if the delay is within a certain threshold a small penalty is due, whereas penalties increase proportionally (linearly or not linearly) to the extension of the further violation; another common function used in the practice is a step function, in which different thresholds, characterized by different penalty values, are imposed
- **Mixed time windows**: in which both soft and hard time windows are considered. This is the most common situation in practice. For instance, in a supermarket that has a morning delivery time window from 9 am to 1 pm, it would be possible to perform the delivery arriving at 1:10 p.m., paying a penalty, but if the carrier arrives at 1:40 p.m., it probably wouldn’t be able to carry out the delivery because no employees are still available. This situation can be represented defining a soft time window included in a larger hard time window

The VRPHTW has been broadly addressed in the literature. A huge number of solution methods, using both heuristics and metaheuristics, have been proposed. For a complete survey, the reader may refer to Toth and Vigo (2002) and the references therein. This problem is common in practical applications in distribution and logistics because of the rising importance of just-in-time (JIT) production systems and the increasingly tight coordination of supply chain operations. Because the vehicle-routing problem with soft time windows (VRPSTW) better describes realistic

<table>
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<tr>
<th>Type of Time Window</th>
<th>Characteristics</th>
<th>Applications</th>
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<tbody>
<tr>
<td>Hard time windows</td>
<td>TW must be respected.</td>
<td>Broadly studied in the literature; rarely used in practical applications</td>
</tr>
<tr>
<td>Soft time windows</td>
<td>A penalty is paid if the TW is not respected:</td>
<td>Sometimes addressed in literature; sometimes used in practical applications</td>
</tr>
<tr>
<td></td>
<td>- fixed penalty</td>
<td></td>
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<tr>
<td></td>
<td>- variable penalty depending on the entity of the violation</td>
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<tr>
<td>Mixed time windows</td>
<td>A tolerance around the time window is added: within this tolerance the TW can be missed paying a penalty; outside the tolerance the delivery is not permitted</td>
<td>Rarely addressed in the literature; commonly used in practical applications</td>
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situations, in which flexibility is allowed and must be considered in the problem modeling phase, in this article more attention is given to the literature addressing this version of the problem. Different from the VRPHTW, the VRPSTW has received a limited attention. VRPHTW can be described as a VRPSTW with an infinite violation penalty. The VRPSTW also has many practical applications (Chiang & Russell, 2004). In fact, relaxing time windows can result in lowering total costs without hurting customer satisfaction significantly. Travel times cannot be accurately known in many practical applications; therefore, a small variation in the travel times may imply a hard time window should be preferred. In addition, the provided solution. In this case, a soft time window approach is preferred. In addition, VRPSTW solutions provide a workable alternative plan of action when the problem with hard time windows is infeasible or produces a high-cost solution in terms of distances of travel times. In fact, it could happen that allowing a slight time window violation would possibly obtain a solution, with a much lower cost or a lower number of vehicles required, which would be infeasible for the VRPHTW.

The VRPHTW has been the subject of intensive research efforts using both heuristic and exact optimization approaches. Early surveys of solution techniques for the VRPHTW can be found in Golden and Assad (1986, 1988). Because of the high complexity level of the VRPHTW and its wide applicability to real-life situations, solution techniques capable of producing high-quality solutions in limited time, that is, heuristics, are of prime importance. A detailed survey of route construction methods using classical local search–based algorithms may be found in Bräysy and Gendreau (2005a), whereas Bräysy and Gendreau (2005b) review metaheuristic approaches.

Literature on VRPSTW is much more spare. The earliest work is the one proposed by Balakrishnan (1993) in which the author addresses the VRPSTW with linear penalty functions. Further, more complex metaheuristics have been proposed for the same problem in Taillard et al. (1997) and Chiang and Russell (2004).

Calvete et al. (2007) propose a mixed-integer formulation for the VRP with soft time windows, a heterogeneous fleet of vehicles, and multiple objectives in which the goal is to minimize time window violations. Penalties linearly depending on the amount of time by which the time windows are violated, are used. We are not aware of any scientific work handling step penalty functions or mixed time windows although these situations are very common in practical applications.

**Time-Dependent Travel Times**

Another important issue that has been addressed rarely in the literature is the time dependency of travel times on the time of the day. Travel times fluctuations occur both in urban contexts and in long-distance distribution. The largest part of available models assumes constant travel times or exploits simple procedures to adjust them, such as multiplier factors associated with different periods of the day. These assumptions cannot give accurate approximations of the real-world conditions in which travel times are subject to more complex variations over time. Crainic et al. (2012) present different scenarios in which travel time for each arc is different but it is supposed to be constant along all the delivery phase. This approach could be adopted to analyze different periods of the day – such as early morning, lunch time, late afternoon – under the assumption that delivery operations are performed within the same time period. This holds only for some practical applications or when just qualitative responses are needed (i.e., How much do we gain by making deliveries during the afternoon instead of doing them in the early morning?), and it requires too strong approximations in problems in which more precision is requested or in which travel time fluctuations are very frequent. In Malandraki and Daskin (1992), the authors examine the time-dependent vehicle-routing problem (TDVRP). They provide mixed-integer linear programming formulations including time windows and vehicle capacities and allow for waiting at customer locations. Travel times are computed using simple-step functions. A nearest neighbor-based heuristic and a branch-and-cut algorithm for solving small problems (10–25 nodes) are proposed, whereas in Malandraki and Dial (1996), a dynamic programming algorithm is used to solve the time-dependent traveling salesman problem (TDTSP), a special case of the TDVRP in which a single vehicle is considered. Hill and Benton (1992) consider a TDVRP without time windows and propose a model based on time-dependent travel speeds.

The main weakness of these kinds of models is that they do not satisfy the first-in–first-out (FIFO) property, using a step function it would happens that a vehicle i leaving node A after a vehicle j (having the same characteristics as i) and so will then reach node B before j. This fact makes step functions totally unadaptable to realistically represent travel time (or speed) evolution in real applications. Continuous travel time functions seem to be more appropriate to model real-world conditions. Ichoua et al. (2003) present a time-dependent travel speed model in which time is discretized into time slots, which could be as small as necessary to correctly describe speed fluctuation, and travel speed is given by a different linear function for each slot, ensuring continuity across time slots. In this way, travel speed is defined as a continuous function and could be better represent real cases. Nevertheless, this approach could not correctly represent peak sharpness because travel speed is supposed to vary linearly. To avoid this inconvenience and to have a more precise description of reality, polynomial functions could be
considered (Mancini, 2014). The positive and negative points of each approach are described in Table 2.

Another important time-related issue concerns periodic visits to customers; in fact, in several applications, from fuel distribution to fuel stations to waste collection, from food delivery to supermarkets to pharmacy supply, customers require multiple visits with the time horizon analyzed. The periodic vehicle-routing problem (PVRP) has been introduced in Christofides and Beasley (1984). A very large number of heuristics for the PVRP has been proposed across the years, which for brevity are not explicitly reported here because the standard version of the PVRP is of limited interest from an application point of view.

The problem addressed may be described as follows: the PVRP consists of serving a set of customers, who need to be visited one or more times within a time horizon. The set of dates in which a vehicle serves the customer is fixed a priori, but instead, a list of a feasible set of dates is associated with each customer. The goal of the problem is to minimize the total distance traveled by the vehicles within the whole time horizon. An interesting extension of the PVRP (other than being a classical extension concerning time windows and multi-depot deliveries) addressing a more realistic problem has been presented in the literature, such as the PVRP with intermediate facilities in Angelelli and Speranza (2002), in which a set of intermediate facilities is introduced in order to serve as a loading-unloading platform where the good is located. The main lack of practical application relies on the definition of periodicity. In fact, there are several applications in which not only the periods in which the customers are served but also the exact moment within the period in which the visit is performed are of crucial importance. For instance, in pharmacy supplies, each pharmacy is generally visited up to four times a day to provide medicines requested by new incoming orders received during the day. The four different time periods are early morning, late morning, early afternoon, and late afternoon, but at most one delivery for each pharmacy may be carried out within each period. This problem cannot be correctly modeled as a standard PVRP because it could happen that a pharmacy is visited at the end of late morning period (just before the lunch break) and at the beginning of the early afternoon period (just after the lunch break). Even if this solution is feasible for the PVRP it would be not appropriate for this problem because no new medicine requests may arrive during the lunch break when the pharmacy is closed; therefore, the early afternoon delivery demand may be almost null. Another problem with similar characteristics is waste collection. In fact, collecting waste from the same location that must be visited every day, one day in the late evening and the day after in the early morning, does not make sense from a practical point of view because on the second day the waste container would be almost empty (making the visit completely useless), whereas on the third day it would be overfilled. For all this, practical applications of more complex models may be developed and could handle the minimum time space between two consecutive visits. This kind of problem has yet to be studied in the literature.

### Heterogeneous Fleet and Compatibility

In classical VRPs we deal with a homogeneous fleet, that is, all the vehicles in the fleet have the same characteristics in terms of capacity, frequency, etc. However, in real-world applications, it is common to use a heterogeneous fleet, where the vehicles have different characteristics. This can be due to various reasons, such as different routes, different types of good, or different costs. In this case, it is necessary to consider the compatibility of the fleet, which means determining which vehicles can work together. This is important because it can affect the feasibility of the solution.

### Table 2

<table>
<thead>
<tr>
<th>Type of Approach</th>
<th>Positive Points</th>
<th>Negative Points</th>
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<tbody>
<tr>
<td>Step functions</td>
<td>Easy to implement</td>
<td>Cannot represent realistic situations</td>
</tr>
<tr>
<td>Linear functions</td>
<td>If we discretized the solution space in very small time slots, it could be able to sufficiently describe real travel time fluctuations.</td>
<td>If time slots are very small and a different linear function is assigned to each time slot, data storage space requested will be too large for real road networks with a large number of arcs.</td>
</tr>
<tr>
<td>Polynomial functions</td>
<td>Can perfectly describe real travel times fluctuations; only one function must be kept in memory, with a huge savings of storage space</td>
<td>An interpolation on traffic data is requested for each arc of the network.</td>
</tr>
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travel cost, and travel speed. This assumption is quite strong and cannot hold for several real applications in which vehicles of different size and cost may be used. An extension of the VRP allowing different types of vehicles has been broadly addressed in the literature: the heterogeneous fleet vehicle-routing problem (HVRP), in which customers are served by a heterogeneous fleet of vehicles with various capacities, fixed usage costs, and variable cost per distance unit, Golden et al. (1984). An extensive literature review on HVRP is reported in Baldacci et al. (2008). Most of the papers consider both fixed and variables costs, except Salhi et al. (1992) and Taillard (1999), in which travel costs do not depend on vehicle type.

Heterogeneous fleet problems arising in reality are generally more complex than the HVRP because vehicles may have different characteristics that can be required by some customers (for example, refrigerated vehicles for perishable foods, armored vehicles for valuable items, etc.) or must be avoided for other ones (for example, large trucks cannot enter urban centers, etc.).

In city logistics contexts (see Taniguchi et al., 2001) vehicle classes not only differ from each other in terms of use, travel cost, and product compatibility but also may have different access restriction rules to the limited traffic zones (LTZ) within the city center. Regulations may be different from city to city, but common aspects may be found. Alternative fuel vehicles generally have free access during the whole day, standard vehicles may access LTZ only during fixed time windows, and large trucks cannot enter them at any time. This means that not all the routes may be performed by all the vehicles. This aspect becomes more relevant when dealing with tight customer open time windows. Moreover, more complex constraints, such as on the compatibility of product storage within the same vehicles, may hold: fresh food cannot be transported together with hazardous or organic material. These further extensions, very common in practice, have been rarely addressed in the literature.

Environmental Aspects

In the last four decades, more attention has been given to respecting the environment and reducing the impact of nuisance factors in order to preserve the quality of life, even in large urban areas, while avoiding a slowdown of economic, social, and cultural development. In response to this problem a new area of transport planning, called city logistics, has emerged. City logistic is the process of totally optimizing urban logistics activities by considering the social, economic, and environmental impacts of urban freight movement, and it provides an opportunity for the development of innovative solutions that allow improvement to the quality of life in urban areas. Great innovations in this field have been reached by the development of new technology in vehicle engine design, but more attention also has been given to the optimization in the use of already available resources.

Smart distribution systems have been broadly studied in the literature in the last decade. For a complete survey on the subject, readers may refer to Mancini (2012) and Mancini et al. (2014). One of the most commonly used approaches in practice is multi-echelon distribution systems (Mancini, 2013), in which the delivery from one or more depots to customers is managed by routing and consolidating the freight through intermediate depots called satellites (Crainic et al., 2009). These systems keep large trucks far from city centers, carrying out deliveries to customers with small environmentally friendly vehicles. The basic version of the multi-echelon vehicle-routing problem, the two-echelon vehicle-routing problem (2E-VRP), has been deeply studied in the literature. Best-known results on benchmark instances have been reached by Crainic et al. (2011) and Hemmelmayr et al. (2012). A comparison with a standard single-echelon distribution approach has been reported in Crainic et al. (2010), showing the convenience of adopting a two-echelon system. An analysis on the behavior of two-echelon distribution systems in the presence of generalized travel costs on arcs (depending not only on the distance but also on the time of the day in which they are used and the related congestion traffic level) has been provided in Crainic et al. (2012).

Similar problems related to the multi-echelon distribution problems are addressed in Gonzalez-Feliu (2012, 2013) and Cattaruzza et al. (2014). Smart distribution systems allow a more efficient exploitation of already available resources. Another important aspect to be addressed concerns the exploitation of new technologies as electric vehicles. This kind of vehicle strongly reduces pollution in the air and at the same time saves natural resources. Nevertheless, this technology is not yet commonly used because of the vehicles’ limited autonomy and recharging stations’ meagre presence in the territory. These issues yield to the necessity of explicitly planning recharging stops during the route-planning phase.

This problem, named green VRP, has been introduced and formalized in Erdogan and Miller-Hooks (2012), and an extension allowing partial battery recharging has been addressed in Schneider et al. (2014). In order to analyze the competitiveness of a green distribution approach with respect to the standard one, it could be interesting to analyze a VRP with time windows and with a heterogeneous fleet in which both electric and traditional vehicles are available, with different autonomy, recharging (or refilling) stations, times, and costs and different access limitations to the city center.
Integration with Other Optimization Problems

In real applications, routing problems are often interconnected with other optimization problems, such as item packing and driver scheduling. In standard vehicle-routing problems, vehicle capacity is expressed in volume or weight units. If this simplification holds in some cases, especially when dealing with homogenous product deliveries, it does not hold anymore, when objects of different shapes, sizes, and weight must be carried together in the same vehicle. To this purpose a novel family of problems, called vehicle-routing problems with loading constraints, has been introduced in the literature. An extensive review on this subject can be found in Iori and Martello (2010). Different loading constraints may arise in practical applications, which go beyond simple weight and volume limits, such as fragility and weight balance within the vehicle. Furthermore, items should be loaded respecting customers’ visiting orders avoiding unnecessary loading-unloading operations carried out at customer locations, which could yield, in addition to being a waste of time, a further risk of breaking fragile objects.

A feasible routing plan must match driver contract rules in addition to satisfying customer demand and match time and vehicle compatibility restrictions. Literature on combined vehicle and crew scheduling is not highly available but there are still several basic works of different natures and for various applications. Such problems still have not been synthesized in general literature reviews (as occurs with the most classical variants of VRP), but the main works are in general of applied nature and have been developed to deal with specific practical issues. A first attempt of classification is proposed by Raff (1983), where the state-of-the-art counted a few number of works in which the integration between vehicle routing and crew scheduling was not systematic. In Hollis et al. (2006) the authors deal with a multi-depot VRCS with route length constraints (in terms of driving time) for the Australian Post operational planning. In Zapfel and Bogl (2008) authors deal with a multi-period vehicle routing and crew scheduling problem with outsourcing options for a post distribution company. Authors take also into account time constraints in terms of availability of vehicles and crews.

Multi-Objective Vehicle-Routing Problems

Standard vehicle-routing problems present simple objective functions related to distance or travel time minimization or to a generalized cost obtained as a weighted sum of traveling and vehicle-usage cost; but in practical applications, many different aspects play a role in the objective functions definition, and often conflicting objectives must be addressed, such as cost minimization and customer satisfaction level. Other objectives may address the workload balancing in the solution. Such objectives are often introduced in order to bring an element of fairness into play. To define a balancing objective, it is necessary to define a tour’s workload, which can be expressed as the number of customers visited, the quantity of goods delivered, the time required or the tour length, or as specific requirements for the applications are addressed. For instance, in El-Sherbeyn (2001), the case of a Belgian transportation company is studied, and the tour workload corresponds to the sum of the time needed to travel between the different pick-up and delivery locations, the time required to load and unload the trucks, and the waiting time spent at the customers when a vehicle arrives earlier than the customer’s time windows begins. Workload balancing should be ensured among different contemporary tours and among different tours performed during different days of the week by the same driver. In problems in which not all the requests must be satisfied, a profit value is associated with each served node, and the objective function results from the maximization of profit while minimizing tour length (or duration) (Keller & Goodchild, 1998). In hazardous materials transportation, there is a risk associated with the path taken by a vehicle. Because of the drastic consequences on the people and the environment near an accident site, the risk of accidents must be minimized (Giannikos, 1998; Zografos & Androuststopoulos, 2004). For an extensive review on multi-objective vehicle-routing problems readers may refer to Jozefowiez et al. (2008).

A Real-Life Distribution Problem

This research comes from a transport carrier who needs to make weekly delivery operations plans for a company that visits several depots where goods are stored and/or produced, has a known fleet of vehicles that are located at the depots, and has a set of available drivers for which a fixed cost, in addition to a variable cost determined by the driving time multiplied by a hourly driving cost, must be paid if they are scheduled on the week’s plan. This is a multi-period problem because each customer must be served in one of the time slots (typically, but not necessarily, days) in which he or she is available. Furthermore, other constraints on the periods in which the delivery can be carried out may be given by the fact that customers need to receive the goods within a given deadline or the goods must be delivered after a given time slot because it is not available before.

The problem is multi-depot, but different from what happens in classical multi-depot vehicle-routing problems (MDVRP), because routes must end at the same depot from which they started and routes end at different depots than the starting one are both considered (Toth & Vigo 2002). This version of MDVRP, which did not receive greatest interest by the academic community, is very common in practical applications. In fact, it could be more convenient to end a
route in a different depot than the starting one, avoiding long trips back to the depot. A heterogeneous fleet is considered, composed of vehicles characterized by different capacities (expressed in terms of loading units), and a cost per km, as occurs in most of the VRPs with heterogeneous fleets in the literature. Furthermore, we consider that vehicles may have different characteristics (for instance, refrigerated vehicles), which can be required by some customers and must be avoided for others. If one knows the average speed, it is easy to transform the cost per km into a cost per hour in order to make it comparable with driving cost analyses. The location of each vehicle at the beginning of the time horizon analyzed is supposed to be known in advance. Not every customer may be served by all the vehicles and from all the depots. This restrictions may be because of specific requirements of the product (for instance, refrigerated vehicles for perishable food, freezer vehicles for ice cream and frozen foods) or to the customer location (for instance, customers located in the city center cannot be served by very large vehicles, which are not allowed to enter that zone). Restrictions on the depots from which customers may be served hold when the products requested by the customer are not available at each depot. Restrictions on the maximum route duration coming from drivers working hour limitations are considered too. The problem has been tested in a real instance with two depots and 100 customers located in 30 towns in Piedmont, a region in northwest Italy. In Figure 1 the destination towns are indicated by red circles and the depots by blue triangles. The planning horizon is five days (time slots) and the fleet is composed of 20 vehicles, each of which can perform only one route a day. The maximum route duration is fixed to 11 hours.

The problem has been solved by means of a greedy randomized adaptive search procedure (also known as GRASP), which is a metaheuristic algorithm commonly applied to combinatorial optimization problems (Feo & Resende, 1995; Festa & Resende, 2009). GRASP typically consists of iterations made up of successive constructions of a greedy randomized solution and subsequent iterative improvements of it through a local search. The greedy randomized solutions are generated by adding elements to the problem’s solution set from a list of elements ranked by a greedy function according to the quality of the solution they will achieve.

The GRASP proposed works as follows. At each iteration of the algorithm, a greedy solution is constructed. At each step of the construction phase, the next customer to be visited is randomly drawn according distance-based probability, that is, the probability of each customer to be chosen as next is based on the inverse of the distance of the customer and the last visited one (or, when the first customer of a route must be selected, based on the inverse of the distance of the customer and the depot). If a customer cannot be served by the same vehicle of previously scheduled customers or within the current time window or the day in which the current route is scheduled, its probability to be chosen at this point is forced to zero.

A route is closed when no more available customers may be inserted in or a maximum duration is reached. After a route is closed, it is assigned to an available vehicle, and if there are still unrouted customers, a new route is created. Once a feasible solution is constructed, a local search is applied consisting of destroying almost empty routes and trying to relocate the unrouted customers within the remaining routes at the minimum generalized cost. This overall procedure is repeated a large number of times, and the best solution, that is, the one associated with the minimum cost, is kept.
This algorithm obtained very good results in very few seconds. Moreover, this method is extremely portable and can be easily adapted to other routing problems. The idea is that how the properties of each customer are computed according to the choosing probability may vary depending on the characteristics of the addressed problem. For instance, in a standard VRP, probabilities may be based only on distance, whereas in more complex problems with time windows the time component also must be taken into account. For problems with incompatibility, in which two kind of products cannot be carried on the same vehicle or a product is not compatible with a given vehicle, different rules may be used to determine the case in which the customer-choosing probability must be considered equal to zero. In this way, it is possible to easily obtain feasible solutions even for highly constrained problems, for which it could be very difficult to obtain them with a classical constructive heuristic.

**Conclusions and Future Developments**

In this article, a detailed description of the main issues arising in a real-life freight distribution application and a critical and reasoned review on how these issues have been addressed in the literature across the years are presented. Although many important steps have been done in order to create more realistic models, there is still a lack between modeling and real-life applications. Promising avenues to follow to fill this lack and the still-open issues to study are proposed and deeply discussed.

The main lack of the modes presented in the literature is related to a too strong simplification in order to make the models as general as possible. This simplification neglects some relevant aspects of real-life problems and, therefore, the general model results are unable to correctly describe specific problems. A further effort is then requested to properly model different features that may occur in real-life applications.

A real-life vehicle-routing problem is described and a GRASP algorithm has been proposed. The extreme versatility of the method is discussed and an explanation of how the method could be adapted easily to different routing problems is provided.

The goal of the article is to provide a deep investigation of models and algorithms addressing real-life problems presented in the literature, pointing out gaps between models and real-life applications so as to propose a flexible and powerful tool to address different distribution problems arising in real-life contexts. This article aims also to make city managers and companies aware of the need to develop ad hoc models for real distribution problems because the standard models broadly studied in the literature cannot correctly describe real problems. The risk in using these models is to simplify reality too much, neglecting crucial constraints and issues, obtaining solutions that cannot be applied in real contexts. Further perspectives could address the massive use of this fast, portable metaheuristic method to address very complex problems arising in reality that are able to quickly provide good-quality solutions even in very large-size instances.

**References**


About the author

Simona Mancini received a PhD in computers and systems engineering at Politecnico di Torino, where she currently holds a post-doctoral position. She is the author of several papers published in international journals in the field of operations research and transportation.