Resource Constrained Routing and Scheduling: Review and Research Prospects

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Abstract

In the service industry, it is crucial to efficiently allocate scarce resources to perform tasks and meet particular service requirements. What considerably complicates matters is when these resources, for example skilled technicians, nurses, and home carers have to visit different customer locations. This paper provides a comprehensive survey on resource constrained routing and scheduling that unveils the problem characteristics with respect to resource qualifications, service requirements and problem objectives. It also identifies the most effective exact and heuristic algorithms for this class of problems. The paper closes with several research prospects.

Keywords: routing, scheduling, technician routing, resource allocation

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1. Introduction

Vehicle Routing Problems (VRP) are emblematic in the transportation logistics and operations research literature, with major practical relevance. Research on "rich" and "multi-attribute" VRPs is very active (Vidal *et al.*, 2013, 2014; Drexl, 2012b; Schmid *et al.*, 2013), especially for problems with realistic settings and combinations of practical constraints that raise theoretical challenges and also capture real-world needs (Lahyani *et al.*, 2015; Caceres-Cruz *et al.*, 2015). Problems in the field of combined routing and scheduling of resources has recently emerged and gained significant interest. The so-called technician routing and scheduling problem, the skill VRP, the field service planning problem, and the home care crew scheduling and routing problem are typical examples. The distinctive feature of these problems is that they incorporate various resources to meet specific customer requirements and other service specifications.

In resource constrained routing and scheduling problems, customers have specific requirements that can only be met by specialised resources (e.g., skilled technicians, nurses and operators, vehicles, machinery and equipment) who have to travel and deliver products or service to the customer locations.

The available resources may differ in terms of skills and qualifications. For example, if the product is very heavy to carry, one will need a vehicle equipped with an elevator, in addition to a technician capable of operating the elevator. In some multi-cultural urban environments, customers appreciate dealing with drivers who speak their mother tongue, while in some extreme cases this is the only way of communication. Perishable products need special care when being transported by specialised vehicles, and special skills are required to assemble furniture or install white goods. Having a limited number of these resources complicates matters further, and the goal is then to allocate the resources to vehicle routes in such a way that all the customer requirements are met considering various objectives.

This review paper focuses on resource constrained routing and scheduling problems, in which the resources are mainly renewable (vehicles, machinery, manpower). Renewable resources in a vehicle routing context with cross-docking were also considered in Grangier *et al.* (2017). The consideration of resource allocation is prevalent in other fields, such as shop and project scheduling (Slowinski, 1978; Demeulemeester and Herroelen, 2002). The resources can be renewable (e.g., machines, manpower, vehicles), non-renewable (e.g., money, raw materials), or doubly constrained (e.g., electric energy, steam power) (Tiwari *et al.*, 2009; Beşikci *et al.*, 2015). Project scheduling problems may also involve multiple activity execution modes, in which the activity duration and resource consumption vary accordingly (Naber and Kolisch, 2014;

Van Peteghem and Vanhoucke, 2014). These multi-mode project scheduling problems are usually associated with multiple objectives e.g., the minimisation of the resource idle time and the makespan (Slowinski, 1981; Gutjahr, 2015). Interested readers may refer to Hartmann and Briskorn (2010) for a comprehensive survey of variants and extensions of project scheduling problems.

There also exists a rich literature on personnel scheduling and rostering problems, as witnessed by the thorough review of Van den Bergh *et al.* (2013). In addition, Castillo-Salazar *et al.* (2014) presented a survey on routing and scheduling problems that summarises the key characteristics of the problems as well as the corresponding solution methodologies developed and applied to realistic problem settings. Compared to this review paper, our definition of resource constrained problems is broader since it covers all possible types of resources, including vehicles, machinery, specialised equipment and anything that can enable the delivery of service and products to the customers, i.e., not only skilled personnel as in the Castillo-Salazar *et al.* (2014) survey. Also, to the best of our knowledge no comprehensive and up-to-date survey on resource constrained routing and scheduling problems yet exists.

Taxonomies and classification schemes are essential tools to consolidate knowledge in a more user-friendly manner (Reisman, 1992). They are also dynamic and need to be reconsidered, renewed and updated with the publication of new papers and research trends, thus enabling knowledge building and expansion. Vehicle routing has been a well-established research field since the late 1950s, and there exist several survey papers on different classes of problems (Parragh *et al.*, 2008a,b; Laporte, 2009; Drexl, 2012a; Schmid *et al.*, 2013; Coelho *et al.*, 2014; Toth and Vigo, 2014; Bektaş *et al.*, 2014; Demir *et al.*, 2014; Koç *et al.*, 2016). Lately, the works of Lahyani *et al.* (2015), Vidal *et al.* (2013), Drexl (2012b), and Caceres-Cruz *et al.* (2015) presented various surveys and taxonomies for rich VRPs with multiple combinations of constraints, features, and objectives.

Our paper focuses on a class of realistic routing and scheduling problems and contributes to the existing body of knowledge by (a) introducing a new taxonomy and a base model, (b) presenting the latest advances in the field and, most importantly, (c) identifying, discussing and analysing research prospects from a modelling, methodological and problem-specification point of view. We exclusively examine resource constrained routing and scheduling problems, as opposed to pure scheduling problems that have been thoroughly discussed in Van den Bergh *et al.* (2013). A key feature for the unity and solidity of our proposed taxonomy is the consideration of different types of resources that can enable the service and delivery of products, which is why we believe that the introduction of the broad family of the resource constrained routing and scheduling problems is essential.

The remainder of this paper is organised as follows. Section 2 introduces important problem variants, with a focus on the two most prominent ones, the Skill VRP and Technician Routing and Scheduling problems. It also provides a base model and a motivating example to illustrate the impact of the resource feasible routes on solution quality and structure. Section 3 discusses popular applications of resource constrained routing and scheduling problems. Section 4 presents a brief overview of the literature and introduces a taxonomy. The taxonomy paves the ground for Section 5, which reviews several problem characteristics based on personnel qualifications, service requirements, and objectives. Exact and heuristic algorithms for various deterministic and stochastic problem settings are discussed in Section 6. The paper closes with conclusions and research prospects in Section 7. We present in the Appendix a list of abbreviations used in the paper.

2. Preliminaries and base model

In the broader field of resource constrained vehicle routing and scheduling problems, the Skill VRP and the Technician Routing and Scheduling Problem are the most popular variants and have been used as the basis for most theoretical, modelling and algorithmic developments. The first flow-based mathematical formulation for the asymmetric Skill VRP was introduced by Cappanera *et al.* (2011). In this archetypal problem setting it is assumed that each customer (or service call) requires one technician (or resource) to provide the service with an adequate skill level. Cappanera *et al.* (2013) later extended and improved their model. Specifically, technicians with given skills must perform routes to serve customers, each of whom requires a set of skills. The aim is to minimise the total routing costs while satisfying constraints defining the available and required skill levels.

The model of Cappanera *et al.* (2013) is defined as follows. Consider a complete directed graph $G = (V, A)$, where $V = \{1, ..., n\}$ is the vertex set, vertex 1 is the depot, and the remaining vertices are customers; $A = \{(i, j) : 1 \leq i, j \leq n,\ i \neq j\}$ is the arc set. Each customer i requires service from a technician possessing a set of skills S_i. Also consider a crew T of available technicians, and let S^t denote the set of the skills of technician $t \in T$. Technician t can service vertex i only if $S_i \subseteq S^t$. Lastly, a non-negative technician-dependent travel cost c_{ij}^t is associated with each arc (i, j) and each technician t.

In this so-called aggregated model, Cappanera *et al.* (2013) introduced two groups of variables. The first contains the route design binary variables x_{ij}^t for each $(i, j) \in A$ and $t \in T$, such that $(S_i \cup S_j) \subseteq S^t$, which determine the visiting sequence and the assignment of technicians to customers. The binary variable x_{ij}^t is equal to 1 if and only if customer i immediately precedes customer j visited in the tour of technician t. The second group of continuous non-negative variables, denoted by y_{ij} models the flow of each arc (i, j). The goal is to design minimum cost depot-returning tours for the technicians and to determine the visiting sequence of customers, such that all customers are served by exactly one technician and the skill level requirements are satisfied. The objective of the asymmetric Skill VRP can be written as follows:

$$\underset{x,y}{\text{minimize}} \sum_{(i,j)\in A} \sum_{t\in T:(S_i\cup S_j)\subseteq S^t} c_{ij}^t x_{ij}^t. \tag{1}$$

There exist two sets of constraints. The first set is composed by the degree constraints. These characterise the flow on the path to be followed by each technician; they ensure the continuity of each tour and force each customer to be served by exactly one technician:

$$\sum_{i\in V} \sum_{t\in T:(S_i\cup S_j)\subseteq S^t} x_{ij}^t = 1 \qquad j \in V \setminus \{1\} \tag{2}$$

$$\sum_{i\in V:S_i\subseteq S^t} x_{ij}^t = \sum_{i\in V:S_i\subseteq S^t} x_{ji}^t \qquad j \in V \setminus \{1\}, t \in T : S_j \subseteq S^t. \tag{3}$$

The second set of constraints is widely used in single-commodity flow vehicle routing formulations and prevents subtours. Note that the flow y_{ij} indicates the remaining number of customers to be visited after traversing arc (i, j):

$$\sum_{(1,j)\in A} y_{1j} = n - 1 \tag{4}$$

$$\sum_{(i,j)\in A} y_{ij} - \sum_{(j,i)\in A} y_{ji} = 1 \qquad j \in V \setminus \{1\} \tag{5}$$

$$y_{ij} \leq (n-1) \sum_{t\in T:(S_i\cup S_j)\subseteq S^t} x_{ij}^t \qquad (i, j) \in A. \tag{6}$$

In the work of Cappanera *et al.* (2013) two levels of hierarchical disaggregation are performed on the flow variables in an effort to strengthen the LP bounds of the above model. The first level splits the flow by destination. This corresponds to the multi-commodity reformulation of the aggregated model. The second level adopts a skill-based split of the flow variables and seeks to combine disaggregation by destination with disaggregation by technician. The resulting model produces very tight LP bounds, but the number of variables and constraints increases significantly with the number of skills and technicians, and thus, the computational effort for solving the model is high.

Various extensions of the Skill VRP have been studied. Schwarze and Voss (2015) presented the so-called Bi-Criteria Skill VRP with (hard) Time Windows for pushback tractors in airport terminals. Let $a_i, b_i \geq 0$ denote the earliest and the latest times during the planning period that service at vertex $i \in V \setminus \{1\}$ can take place, and let o_i denote the time needed to carry out the service at i. The pushback vehicles can carry out service only within the predefined time window $[a_i, b_i]$. Let w_i^t denote the time at which vehicle t starts servicing customer i. These service start times must respect the corresponding time windows, i.e., $a_i \leq w_i^t \leq b_i$ for every $t \in T$ and $i \in V \setminus \{1\}$. In addition to the routing cost, the minimisation of the total completion time (i.e., $\min_w \sum_{i \in V \setminus \{1\}} \sum_{t \in T} w_i^t$) is considered as another objective. Both single- and multi-objective settings are examined, assuming a hierarchical ordering of the objectives.

The archetypal asymmetric Skill VRP described above assumes that the tour of each technician corresponds to a vehicle route, or similarly to a path in G that starts and ends at the depot. Paraskevopoulos *et al.* (2015) described a more generalised setting, referred to as the Resource Constrained VRP. The service of each customer requires one or more resources (e.g., operators, vehicles and equipment) with particular specifications. The resources of each type are limited, and each of them is assigned to one route. Importantly, a route can be paired with one or more resources. The goal is to minimise the total travelled distance under resource availability and compatibility constraints.

Figure 1 shows in which ways the solution of the Resource Constrained VRP is different compared to the solution of the typical VRP. The left part depicts a typical VRP solution, without considering the limitations of the resources and the special requirements of the customers. For this example, there are sets of customers with different shapes representing different requirements A, B, AB and C. Note that the doughnut customers require both the A and B resources to be serviced, while the full circle ones do not have any particular requirements (they can be served by any resource). Also, the available resources are limited, i.e., two units for A, two units for B and one unit of the combined resource BC. The combined resource means that the particular resource is equivalent to having one resource B and one C together (e.g., a vehicle with an elevator and a fridge compartment).

When designing the resource constrained vehicle routes, one has to consider the customer requirements and the limited resources to satisfy these requirements. This means that sometimes less efficient routes are generated (compared to the VRP with no resources) at the expense of meeting all customer requirements. For example, because the resource BC is unique (only one unit of BC resource is available), BC has to serve all customers that have

C requirements, even if the resulting route (shown in the right part of the figure) is not very cost efficient and a subset of C customers could have been better served by another route. The resource allocation is shown in the legend at the bottom of the figure.

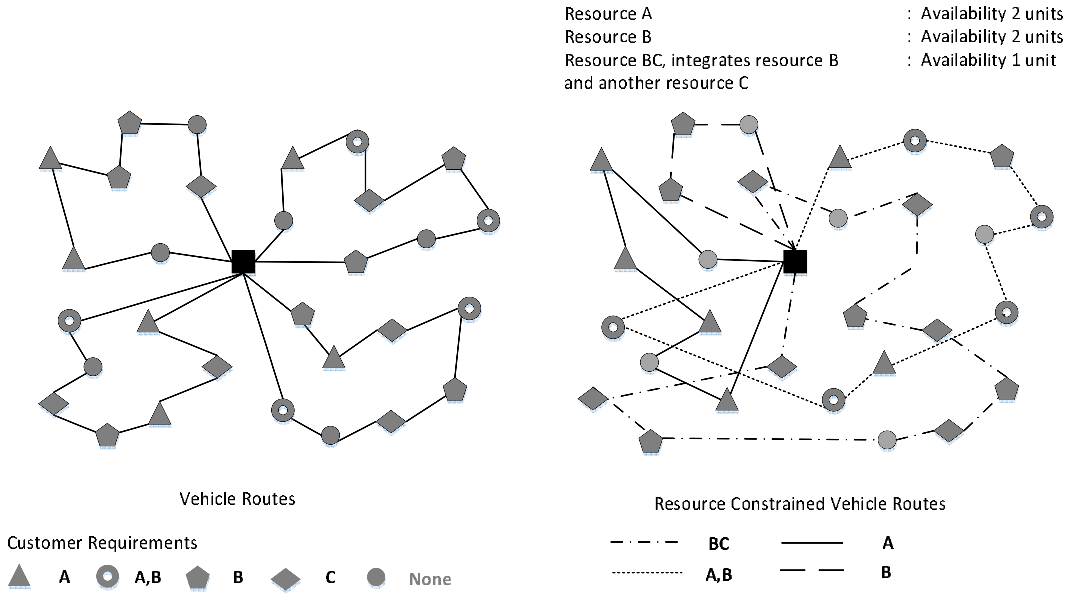

Figure 1: Solution of the Resource Constrained VRP (Paraskevopoulos *et al.*, 2015)

Another problem setting that can be seen as a generalisation of the Skill VRP with multiple resource constraints is captured by the Technician Routing and Scheduling Problem (TRSP) introduced by Pillac *et al.* (2013). Each technician possesses a set of skills and may carry a set of tools and spare parts, while each customer requires a subset of them. Each service request has a service time window; if the technician arrives earlier he must wait until the opening of the time window. The goal is to design minimum duration tours for the technicians so that all customer requests are served by one technician with the required skills, tools, and spare parts. The compatibility constraints between technicians and requests refer to all types of resources. Besides technicians and their known skill levels, tools can be seen as renewable resources, and spare parts as non-renewable resources that are consumed when the technician serves a request. As described by Pillac *et al.* (2013), technicians start their tour with a set of spare parts and tools, and they also have the option to replenish their tools and spare parts at any time at the depot.

In the broader area of field service and technician routing problems, there exist various more specialised variants involving mainly a single type of resource with no tools or spare parts. Applications are provided in Cordeau *et al.* (2010) and Xu and Chiu (2001). In the former work, discrete skill levels are assumed for the technicians (i.e., different sets of skills with different proficiency levels) and every customer may demand multiple different skills with given levels. In the latter work, no compatibility restrictions are assumed; however, the technician's proficiency levels are used to weigh the task assignment in the objective function. Kovacs *et al.* (2012) extended the technician task scheduling problem by considering the routing aspect. In the special case where technicians are grouped into teams, each of these completes all tasks assigned to it.

Tricoire *et al.* (2013) studied a multi-period field service problem in which the availability of technicians varies during the planning period. According to their definition, a resource is a pair that associates a technician with a day. During the day a technician is available only for a given time interval. There is also a validity period (i.e., one or more consecutive days) during which a given request must be served. To facilitate this, a matrix with compatibility restrictions among requests and resources can be used, similar to that of technician skills and proficiency levels. Finally, we mention the papers of Bredström and Rönnqvist (2008) and Rasmussen *et al.* (2012) which do not consider skills but instead introduce temporal dependencies and synchronisation constraints between technician visits. We refer readers to the survey paper of Drexl (2012a) for multiple synchronization constraints in VRPs.

As mentioned in the introduction section, our survey focuses only on resource constrained routing and scheduling problems as opposed to pure scheduling problems. For example, Firat and Hurkens (2011) introduced a technician task scheduling problem with hierarchical skill levels and produced competitive results for well-known benchmark instances. However, the routing component is missing from that paper and therefore we do not include it into our survey. Similar papers are those of Bellenguez-Morineau *et al.* (2005), Yoshimura *et al.* (2006), Gutjahr *et al.* (2008), Heimerl and Kolisch (2010).

3. Overview of important applications

There exists a wide variety of applications in resource constrained routing and scheduling problems. We have classified the applications into four main categories: home and health care, installations maintenance and repairs, forest management, and airport operations. In the following, we discuss the basic characteristics of these applications with an emphasis on common elements and differences.

3.1. Home and health care

Home health care routing and scheduling problems can be seen as special cases of the Skill VRP and of the Technician Routing Problem. Most of these problems are multi-period in nature. Furthermore, besides matching supply with demand, complying with skill levels and other service qualifications for the care givers, hard or soft synchronisation and priority constraints often appear in home health care delivery problems. Speaking in VRP terms, home care delivery problems often involve multiple depots, heterogeneous vehicles, customer and vehicle time windows, complex cost functions for outsourcing, reimbursement or overtime for the resources, visit requirements, breaks, multiple shifts or multiple sessions per day, and other constraints (Begur *et al.*, 1997).

Specifically, home and health care problems involve the assignment of operators to residences and the execution of tasks requiring specific skills within a time frame. These tasks may involve the nursing of patients at their home (health care) and helping elderly or disabled people with housekeeping and other daily activities (home care). These two families of problems share common characteristics, although the service time in home care is much larger than in home health care. For example, in health care an injection may take a few minutes, while in home care bathing elderly people may take an hour.

The main element of these problems is that nurses and carers travel independently using their own vehicles or public transport, or just walk to reach the patients' residences. Furthermore, because of this flexibility, the routes may be open, and the start and end locations may vary. For example, nurses usually start from medical centres and return home at the end of the day. A particular skill set is required to perform the tasks and sometimes more than one operator is needed to complete the service, and therefore they often work in teams. Multi-period scheduling also occurs and precedence constraints determine the sequence of visits. For example, when multi-dose medications are involved, specific time intervals must be imposed between two consecutive doses. Lastly, priorities are given to specific patients according to the requirements imposed. For example, a diabetic patient will be prioritised over elderly or disabled people.

3.2. Installation, maintenance and repairs

A wide variety of resource routing and scheduling problems arise in the installation and maintenance of equipment, such as elevators, heating devices, and photocopiers. Similarly, in telecommunications such tasks have to be performed by a set of engineers (Tsang and Voudouris, 1997; Weigel and Cao, 1999; Cordeau *et al.*, 2010; Hashimoto *et al.*, 2011; Barz and Kolisch, 2014). To that end, operators with particular skills must travel to customer locations and deliver the service, usually within time windows. Technicians vary in terms of experience and knowledge, thus there are different skill levels assigned to them as well as different costs and overtime rates. The execution of a task may require more than one technician, and various other resources, and therefore teams are formed to deliver the service. Furthermore, synchronisation constraints are imposed to enable the formation of teams at customer locations rather than at the depot (Drexl, 2012a).

3.3. Forest management

Resource routing and scheduling problems are often encountered in forest management. These involve two stages: harvesting and forwarding. Two types of operations take place in harvest areas. First, the harvesters fell the trees and sort them into piles. Forwarders then pick them up and transport them to mills and terminals. Different types of vehicles and resources are used to complete these operations. Trucks with or without cranes can be used as well as other vehicles, such as loaders that integrate cranes. Synchronisation constraints apply when trucks and loaders have to be at the harvest area at the same time. Precedence constraints also apply since the forwarding must take place within a specific time after the harvesting has been completed. There are also teaming constraints since forwarders and harvesters form separate teams. Time windows can also be relevant, since the harvest areas are available and open only during a certain time of year. The goal is to determine the resource allocation and truck routing so as to minimise total costs. Interested readers may refer to Palmgren *et al.* (2003) and Karlsson *et al.* (2004) for details on models and solution methods.

3.4. Airports

Schwarze and Voss (2013) applied a Skill VRP with Time Windows to sort push-back operations at airports. Because airplanes are not allowed for safety reasons to move backwards by using their turbines, one must use tugs for these operations. Each tug requires a certain skill, and time window constraints apply according to flight plan restrictions. Also, each airplane requires a minimum tug skill. The goal is to assign tugs to push-back operations so as to minimise the total routing cost and the completion time needed of the operation.

4. Taxonomy and prominent properties

In total, we selected 51 papers published since 1997. In order to classify the key elements and characteristics of the relevant problems, we follow a three-field system: the resources' qualifications, the service requirements, and the objectives. Our taxonomy is presented in Table 1 and the three main fields are summarised below:

- **Resource qualifications**: These are the special qualifications that the resources (e.g., personnel) may have, in a hierarchical fashion or not.

Table 1: Classification of the papers according to the basic characteristics of the resources routing and scheduling problems

Reference	Resource qualifications			Service requirements				Objectives					
	Skill levels	Skills	Site dependencies	Temporal	Precedence	Multi-period	Importance	Outsourcing overtime	Time-delays	Distance	Workload balance	Priorities	Other or several
Tsang and Voudouris (1997)	✓	✓		✓				✓	✓				
Chao *et al.* (1999)			✓							✓			
Weintraub *et al.* (1999)							✓		✓			✓	
Cordeau and Laporte (2001)			✓	✓		✓				✓			
Xu and Chiu (2001)	✓	✓		✓			✓	✓	✓			✓	
Lim *et al.* (2004)				✓					✓	✓			✓
Cordeau *et al.* (2004)			✓	✓		✓				✓			
Chao and Liou (2005)			✓							✓			
Li *et al.* (2005)		✓			✓				✓				✓
Bertels and Fahle (2006)		✓		✓					✓				
Tang *et al.* (2007)							✓					✓	
Akjiratikarl *et al.* (2007)				✓					✓	✓			
Pellegrini *et al.* (2007)			✓	✓		✓			✓				✓
Pisinger and Ropke (2007)			✓							✓			
Goel and Gruhn (2008)			✓	✓	✓								✓
Alonso *et al.* (2008)			✓	✓		✓				✓			
Ceselli *et al.* (2009)			✓	✓					✓	✓			✓
Baldacci and Mingozzi (2009)			✓							✓			
Zäpfel and Bögl (2008)					✓	✓		✓					
Goel (2010)			✓	✓	✓								✓
Kim *et al.* (2010)	✓				✓	✓			✓	✓			✓
Trautsamwieser *et al.* (2011)	✓	✓		✓				✓	✓				✓
Cappanera *et al.* (2011, 2013)	✓	✓								✓			
Amorim *et al.* (2012)			✓	✓				✓	✓				✓
Cordeau and Maischberger (2012)			✓	✓						✓			
Kovacs *et al.* (2012)	✓	✓		✓				✓		✓			
Nickel *et al.* (2012)	✓	✓		✓		✓		✓	✓				✓
Rasmussen *et al.* (2012)	✓			✓	✓		✓		✓			✓	✓
Shao *et al.* (2012)	✓	✓		✓		✓		✓	✓	✓			
Tricoire *et al.* (2013)				✓		✓				✓			
Souyris *et al.* (2012)	✓			✓					✓				
Pillac *et al.* (2013)	✓			✓					✓				
Schwarze and Voss (2013)	✓	✓								✓	✓		
Allaoua *et al.* (2013)	✓			✓									✓
Vidal *et al.* (2014)			✓	✓					✓	✓			
Cortéz *et al.* (2014)				✓			✓		✓			✓	✓
Mankowska *et al.* (2014)	✓				✓				✓	✓			
Yalçindağ *et al.* (2014)	✓	✓		✓		✓				✓	✓		
Cappanera and Scutellà (2015)	✓	✓		✓	✓	✓		✓	✓		✓		
Misir *et al.* (2015)	✓			✓	✓	✓	✓	✓	✓	✓			
Schwarze and Voss (2015)	✓	✓		✓					✓				
Yuan *et al.* (2015)	✓	✓		✓					✓				
Hiermann *et al.* (2015)	✓	✓		✓					✓				✓
Reisabadi and Mirmohammadi (2015)			✓	✓						✓			
Binart *et al.* (2016)				✓		✓	✓		✓			✓	
Braekers *et al.* (2016)	✓	✓		✓				✓	✓				✓
Song and Ko (2016)			✓	✓	✓								✓
Yalçindağ *et al.* (2016)	✓	✓		✓		✓				✓	✓		
Chen *et al.* (2016)	✓	✓				✓			✓				

For example, when the resources qualifications differ in terms of the level of proficiency, this is represented by different hierarchical levels, and thus column "Skill levels" is ticked. Also, when there are not levels of proficiency, only the "Skills" column is ticked.

- **Service requirements**: The service requirements include all the requirements that customers may have, not directly related to resource qualifications. Note that Table 1 includes the most common constraints, but more details are given in Section 5.2.
- **Objectives**: Various objectives are considered. The prevalent one is the minimisation of the total service time. For the sake of completeness, we also included a column "Other and several" for some special cases e.g., the minimisation of the number of resources used or the maximisation of the satisfied requests within a day, which we discuss in detail throughout the paper.

To construct Table 1, we have considered only those papers in which mathematical models and algorithmic details are included, as opposed to less technical managerial papers but we refer to them if appropriate. We generally focus on journal papers and we review some selected conference proceedings. It is worth mentioning that in Table 1 we included some papers that do not consider skills, for the sake of completeness. In the following sections, the taxonomy fields are analysed.

5. Prominent properties

We now describe the key elements and characteristics of relevant problems by means of a three-field system: the resources' qualifications, the service requirements, and the objectives. The first two fields are usually expressed as constraints, and in some cases are part of the objective function.

5.1. Resources' qualifications

Delivering high quality service requires qualified personnel. The daily pay rates for qualified personnel are typically higher than the average employee rates, and thus efficient allocation of employees to tasks is critical in terms of costs to the company. Sometimes, more than one resource (e.g., nurses) may be needed to perform a task, each having different set of skills, but most importantly at a different level of proficiency. Braekers *et al.* (2016) solved a home care routing and scheduling problem in which nurses and carers are allowed to take lunch breaks under specific working regulations.

Personnel may also use different transportation means, work full or part time, require breaks, have variable pay rates, etc. (Van den Bergh *et al.*, 2013). Nevertheless, in this survey we are more interested in the personnel qualifications and skills needed to serve customers with special requirements.

Chen *et al.* (2016) introduced an interesting extension of the personnel skills in which the technicians are scheduled throughout a time horizon (e.g., a week) and their skills proficiency improves over time as they learn how to perform the tasks, and thus the service times become smaller. The authors conducted extensive experiments and showed that explicitly considering experience-based learning significantly improves the routing solutions in terms of the total cost, compared with solutions obtained when learning is ignored.

It is common to use a team of technicians to perform a task, especially when the service is delivered in a multi-stage fashion. Team building is appropriate in these cases, where individual skills matching or complementing takes place (Li *et al.*, 2005; Kim *et al.*, 2010; Kovacs *et al.*, 2012). On the other hand, the paper by Goel and Meisel (2013) considers homogeneous workers, which means that all workers can perform all tasks. This problem does not comply with our definition for the resource constrained vehicle routing and scheduling problem; i.e., specialised resources that can satisfy specific customer requirements. Hiermann *et al.* (2015) solved a multi-modal home health care problem where incompatibility constraints between nurses and patients apply. In particular, nurses may refuse to visit specific patients who, for example, own dogs or cats, or are smokers, male or female etc.

It is worth mentioning that because site-dependency constraints are very similar to compatibility constraints between resources and customers, in our survey we also include site-dependent VRPS (SDVRPs). In SDVRPs, there exist compatibility constraints between resources (e.g., vehicles) and customers (e.g., sites), a fixed-fleet of heterogeneous vehicle types is used and there exist a vehicle-dependent variable cost. The general class of heterogeneous VRPs is not considered, because there is not any link between vehicles types and specific requirements of the customers. Nevertheless, interested readers may refer to Koç *et al.* (2016) for the Heterogeneous VRP. Nag *et al.* (1988) were the first to consider site dependencies as compatibility constraints between customers' sites and specific vehicle types.

5.2. Service requirements

Another distinctive feature of the class of problems we examine is that customers have special requirements that can only be met by specialised resources. The service requirements include, among others, a specific set of skills that the resources (e.g., personnel) must have. The skill requirements have already been discussed in Section 5.1. The focus of this section is thus on the other service requirements the customers may have.

5.2.1. Planning horizon and temporal constraints

Time windows are prevalent, as shown in Table 1, and can be either as hard or soft. In the case time windows are softly imposed the goal is typically to minimise the deviations from the desired time window. This is typically reflected through penalty terms in the objective function.

Table 2 summarises the papers that involve time constraints. Most of the authors have modelled the problem as a Vehicle Routing Problem with Time Windows (VRPTW), i.e., hard time windows are considered. The VRPTW usually involves route duration constraints as well, by assigning a time window to the depot. Nevertheless, some papers consider separately route duration restrictions and we therefore report them in Table 2. Tricoire *et al.* (2013) considered a validity period of several days for the execution of a task within a time horizon, during which the tasks must be executed by one of the available resources. Therefore, the validity period can be considered as a hard time window. Different resources are available at different validity periods, therefore compatibility constraints apply between customers and resources, even though the technicians can perform all tasks. Shao *et al.* (2012) considered flexible and fixed customers, imposing soft and hard time windows, respectively.

Pellegrini *et al.* (2007) addressed a rich vehicle routing problem, where customers require to be serviced by a specific type of vehicle and have multiple time windows within a day and throughout the days of a week. Regarding the problem addressed by Trautsamwieser *et al.* (2011), nurses can work several shifts per day, as long as the work force-related constraints are not violated.

The jobs performed at the customer locations may involve a degree of uncertainty which is modelled as stochastic service times (Souyris *et al.*, 2012; Yuan *et al.*, 2015). Nevertheless some papers also consider stochastic travel times (Binart *et al.*, 2016). Thus, Weintraub *et al.* (1999) studied the routing and scheduling of technicians to repair breakdowns, where customer locations and demands are dynamic. Similarly, Pillac *et al.* (2012) looked at the dynamic technician routing and scheduling problem, where new requests appear while service is taking place.

5.2.2. Precedence

Contrary to the classical vehicle routing problems that the customers are visited only once by exactly one vehicle (resource), in the class of problems we examine the customers may be visited multiple times by different resources. Also there exist often precedence constraints that dictate the sequence that these resource must visit specific customers. Note that precedence constraints often come with a maximum or minimum allowed time interval between two consecutive tasks. For example, to install a boiler, the electrician usually

Table 2: Classification of the papers according to the time window constraints

Reference	Time windows		Route duration
	Hard	Soft	
Xu and Chiu (2001)	✓		✓
Cordeau and Laporte (2001)	✓		✓
Cordeau *et al.* (2004)	✓		✓
Lim *et al.* (2004)	✓		
Bertels and Fahle (2006)		✓	
Tang *et al.* (2007)			✓
Akjiratikarl *et al.* (2007)	✓		
Pellegrini *et al.* (2007)	✓		✓
Goel and Gruhn (2008)	✓		✓
Alonso *et al.* (2008)			✓
Baldacci and Mingozzi (2009)			✓
Ceselli *et al.* (2009)			✓
Goel (2010)	✓		
Trautsamwieser *et al.* (2011)	✓	✓	
Amorim *et al.* (2012)	✓		✓
Cordeau and Maischberger (2012)	✓		✓
Kovacs *et al.* (2012)	✓		
Rasmussen *et al.* (2012)	✓		
Nickel *et al.* (2012)	✓		
Shao *et al.* (2012)	✓	✓	✓
Pillac *et al.* (2013)	✓		
Allaoua *et al.* (2013)	✓		
Tricoire *et al.* (2013)	✓		
Cortéz *et al.* (2014)		✓	
Vidal *et al.* (2014)	✓	✓	✓
Yuan *et al.* (2015)	✓		
Cappanera and Scutellà (2015)	✓		✓
Reisabadi and Mirmohammadi (2015)		✓	
Misir *et al.* (2015)		✓	
Schwarze and Voss (2015)	✓		
Hiermann *et al.* (2015)		✓	
Braekers *et al.* (2016)	✓	✓	
Chen *et al.* (2016)			✓

comes first and then the plumber has to arrive within approximately one hour to finish the job. The constraint is also applicable in home care services, where the time between consecutive visits from carers or nurses has to be at least a week or so. In a nutshell, upper and lower time bounds between visits may be imposed, in addition to the precedence relations.

Table 3 summarises the papers dealing with precedence constraints. Although the majority of these papers consider hard precedence constraints, Misir *et al.* (2015) introduced a class of home care scheduling problems where precedence relations come as soft constraints. Specifically, the authors used the penalty incurred upon a violation of a precedence constraint, for example, when one of the two connected visits does not start within the desired time interval. Also, Bredström and Rönnqvist (2008) considered temporal precedence and synchronisation constraints, but we do not include this paper since it does not consider different resources that meet specific customer requirements. Rasmussen *et al.* (2012) considered different precedence relations with temporal dependencies. In particular, different time constraints were imposed between two jobs, which include synchronisation, overlap, minimum difference of the starting times, maximum difference of the starting times and a combination of the two.

Table 3: Classification of the papers according to precedence constraints

Reference	Precedence constraints		
	Hard	Soft	Time restrictions
Li *et al.* (2005)	✓		
Kim *et al.* (2010)	✓		
Rasmussen *et al.* (2012)	✓		✓
Goel (2010)	✓		
Mankowska *et al.* (2014)	✓	✓	✓
Cappanera and Scutellà (2015)	✓		
Misir *et al.* (2015)		✓	

5.2.3. Importance

Servicing all customers is not always feasible given the available resources, e.g., technicians or nurses, or the time horizon, e.g., a day shift. This a typical characteristic of orienteering problems and vehicle routing problems with profits (Archetti *et al.*, 2014). Therefore, a subset of customers must be selected. For this purpose, in some cases some priorities are associated with customers according to their importance.

In Rasmussen *et al.* (2012), customers have priorities and the goal is to schedule as many high priority customers as possible. In Binart *et al.* (2016) there are two types of customers: mandatory and optional. The former must be served within a specific time window, whereas the latter do not have to be served within the time horizon. The goal is to serve as many optional customers as possible under the constraints imposed. However, note that Binart *et al.* (2016) did not consider customers with specific resource requirements.

5.3. Objectives

The routing and scheduling problems we examine in this survey mainly stem from real-life applications, and therefore, there exist a plethora of objective functions. In the following, we list the most popular components of the objectives used in the problems classified in Table 1, and we discuss some special cases.

5.3.1. Priorities

The focus typically tends to be more on customer satisfaction than on cost minimisation. Moreover, when timing restrictions are involved, the goal is to deliver the service on time. Because most of the times the resources are limited, not all customers can be served within a given day. The selection of customers to service first is modelled through the use of priorities, and different weights are assigned to customers according to their priority. These weights are multiplied by the time at which service starts for each particular customer, e.g., the earlier a high priority customer is served, the better it is in terms of the value of the objective function.

In home care routing and scheduling problems, patients usually have preferences for specific the nurses and carers. Braekers *et al.* (2016) modelled these preferences according to three levels: a preferred, moderately preferred and a non-preferred nurse for the execution of a job, and they assigned penalties accordingly.

5.3.2. Outsourcing and overtime

In order to service the unscheduled customers some papers consider overtime or the possibility of hiring extra resources rather than rolling these visits to the next days of the time horizon. Cordeau and Laporte (2001) dealt with the technicians scheduling problem and explicitly considered outsourcing costs if the available resources are not sufficient to service the selected customers. Table 4 summarises the papers dealing with overtime and outsourcing costs. The purpose of having an outsourcing budget in this problem setting is to get rid of so-called bottleneck jobs, although there exists a skill-feasible team for every job in the problem instances.

Table 4: Classification of the papers according to overtime and outsourcing

Reference	**Outsourcing**	**Overtime**
Tsang and Voudouris (1997)		✓
Zäpfel and Bögl (2008)	✓	✓
Trautsamwieser *et al.* (2011)		✓
Amorim *et al.* (2012)	✓	✓
Nickel *et al.* (2012)		✓
Kovacs *et al.* (2012)	✓	
Shao *et al.* (2012)		✓
Misir *et al.* (2015)		✓
Hiermann *et al.* (2015)		✓
Cappanera and Scutellà (2015)		✓
Braekers *et al.* (2016)		✓

5.3.3. Workload balancing

Workload balancing is important both in terms of vehicle fuel consumption (Zachariadis *et al.*, 2015), and in terms of fair distribution of tasks and routes to technicians and drivers (Schwarze and Voss, 2013). Because the focus is more on the service delivered to the customers than on products delivered or collected, the goal is to balance the workload instead of balancing the weight or volume among vehicles. Although one should expect that this aspect of the problem deserves attention very few papers consider it.

5.3.4. Service completion time and delays

The time dimension plays a significant role in cases when the goal is customer satisfaction and on-time service delivery. Problems that include time in the objective function minimise delays from a desired (soft) time window or aim to minimise the total time needed to serve the customers.

5.3.5. Other or several objectives

Beyond the popular objectives discussed above, alternative objectives have been used as well. For example, some papers (Lim *et al.*, 2004, Li *et al.*, 2005, Allaoua *et al.*, 2013) minimise the number of resources required to serve a given set of customers (e.g., technicians, home carers). Alternatively, other authors such as Nickel *et al.* (2012) minimised the number of unscheduled tasks given a limited number of resources available. Braekers *et al.* (2016) considered a home care routing and scheduling problem with a bi-objective function. The first objective is the minimisation of cost, while the second is the maximisation of the convenience of the patients. The authors conducted extensive computational experiments and concluded that with even small increments of costs, a significant improvement in the convenience of the patients can be achieved.

Ceselli *et al.* (2009) solved a rich vehicle routing problem with site - dependencies and a multi-criteria objective function. The cost of each vehicle was calculated according to fees that depend on the particular visits, the vehicle load, the distance travelled and the number of stops of the route. Another vehicle routing problem was presented by Goel and Gruhn (2008) and Goel (2010), where the objective is to maximise profits. In particular, revenue is generated by servicing customer requirements and the goal is to maximise revenue and minimise travelling costs. Similarly, Amorim *et al.* (2012) solved a rich food distribution problem where the goal is to minimise costs, composed by vehicle renting costs, driver costs and variable travelling costs. The authors considered the option of hiring extra vehicles if the eight-hour shift is not sufficient for the current fleet of vehicles. In the domain of food distribution, Song and Ko (2016) solved a rich vehicle problem that uses both refrigerated and regular vehicles for servicing specific requirements of the customers for both dry and fresh or frozen food. The objective is to maximise customer satisfaction, expressed by the freshness condition of the products they receive. The food is assumed to be fresh at the depot and then along the route the freshness decreases in a non-linear fashion. When refrigerated vehicles are used, the freshness deterioration rate becomes smaller.

Kim *et al.* (2010) solved a combined manpower-vehicle routing problem where technicians form teams that can perform different tasks. The objective is to minimise the makespan and the total travelled distance as well as the total team waiting time. Towards maximising customer satisfaction, Rasmussen *et al.* (2012) and Cortéz *et al.* (2014), among other objectives, minimise the unsatisfied demand.

6. Solution methods

The combinatorial nature and intrinsic complexity of VRPs have given rise to major contributions during the last three decades. A comprehensive review of early and recent developments in theory building and application of exact and heuristic solution methods for VRPs can be found in the first chapters of the book edited by Toth and Vigo (2014). For the majority of well-known VRP variants it is evident that instances with more than 150 customers are typically intractable. This is also the case for the Skill VRP, the TRSP, and other resource-constrained routing and scheduling problems.

Below, we provide an overview of exact and heuristic algorithms for deterministic problems. This is followed by stochastic programming and robust optimisation methods for stochastic problems, as well as periodic re-optimisation algorithms and Markov decision processes for dynamic problems. At the beginning of each section we provide a table summarising for each reference the algorithm (in chronological order), the main algorithmic features, the application domain and the data set used.

6.1. Exact algorithms

This section describes exact solution methods developed for solving a variety of deterministic resource constrained routing and scheduling problems. Table 5 provides an overview.

Rasmussen *et al.* (2012) developed a branch-and-price algorithm for the Home Care Crew Scheduling Problem. The problem involved soft preference constraints between carers and patients, time window constraints, as well as temporal dependencies between the starting times of the visits. The authors applied Dantzig-Wolfe decomposition and modelled the problem as a set partitioning problem with side constraints. A dynamic column generation was used within the branch-and-price framework. The authors took advantage of the preference constraints to group visits and applied a clustering scheme before solving the problem. Computational experiments on real-life data and on randomly generated instances showed that the clustering approach substantially reduces the running times without a significant loss of solution quality.

Cappanera *et al.* (2013) developed a cutting plane algorithm for the Skill VRP, based on a multi-commodity flow mathematical formulation with disaggregation of the flow variables by destination or by technician. These projections lead to tighter formulations. However, as the level of disaggregation

Table 5: Overview of exact algorithms

Reference	Algorithm	Algorithmic Features	Application	Data Set
Baldacci and Mingozzi (2009)	B&C&P	Set partitioning, reduction rules	N/A (SD-VRP)	Nag *et al.* (1988) benchmark data set
Rasmussen *et al.* (2012)	B&P	Dantzig-Wolfe decomposition, set-partitioning	Home health care	Real-life data, randomly generated data, Bredström and Rönnqvist (2008) data set
Cappanera *et al.* (2013)	Cutting planes	Disaggregation of the flow variables, separation of two-cycle inequalities	Field service	Randomly generated up to 71 service requests
Tricoire *et al.* (2013)	B&P	Local search, dynamic programming	Field service	Randomly generated data, 5 days horizon, 3 technicians, 100 customers
Schwarze and Voss (2015, 2013)	B&B	Bicriteria	Field service	Randomly generated data using Solomon (1987) instances, randomly generated data for airport application, 3 skills, 17 gates, 6 tugs

B&C&P : Branch and cut and price, B&P: Branch and price, B&B: Branch and bound

increases, the number of cuts increases exponentially. Also, the valid inequalities that are implied by the models having a stronger LP relaxation can be added to weaker and less detailed models, which leads to substantially lower bounding improvements. In the case where the flow variables are split by destination, the LP relaxation exhibits two cycles in the subgraphs associated with the technicians. Valid inequalities, whose number is polynomial, are added to eliminate part of the two-cycle structures, i.e., a cycle of type (i, j, i), while a heuristic separation procedure is used to find other subsets of violated two-cycle inequalities. Computational experiments with up to 71 service requests and nine skills showed the trade-off in terms of LP bound quality and computational burden.

Based on the mathematical models described in Section 2, enhanced bicriteria variants of the single-period Skill VRP with load balancing and time windows were studied in the works of Schwarze and Voss (2013), Schwarze and Voss (2015). In Schwarze and Voss (2013), a minmax approach was proposed by minimising the maximal tour without consideration of total routing costs, and minimising the routing cost while taking the length of a maximal tour as an upper bound on the tour lengths within a distance constrained model. This minmax model improves resource utilisation and load balancing compared with the ordinary Skill VRP. In Schwarze and Voss (2015), the routing cost and the total completion time were enforced as hierarchical objectives. As reported by the authors, the total completion time objective leads to reduced integrality gaps, while it appears that if a routing cost is adopted as the primary objective, the increase in total completion time (with respect to the optimal value) is smaller than that in the routing cost in the reverse case.

Tricoire *et al.* (2013) considered a field service problem and proposed both exact and metaheuristic algorithms. The problem can be seen as a multi-period multi-depot uncapacitated VRP with specific requirements. Regarding the exact algorithm, a set covering formulation was adopted and the problem was solved by a column generation scheme. The pricing subproblem corresponds to the well-known elementary shortest path problem with resource constraints and lunch break constraints (see also Feillet *et al.* (2004)). Both the exact algorithms and the local search algorithms were applied to solve the pricing subproblem optimally or to generate good upper bounds. Overall, three single-point trajectory local search frameworks were presented, namely steepest descent iterative improvement, tabu search (TS), and iterated local search (ILS), using insertion, removal, moving and swapping neighbourhoods. Computational experiments for small and large sale problem instances were conducted based on realistic data adapted from an industrial application.

Lastly, research on exact approaches for the SDVRP has been rather limited. Currently, the most effective approach is the branch-and-cut-and-price algorithm of Baldacci and Mingozzi (2009) in which the columns are associated with elementary routes. Capacity cuts and clique inequalities are separated. The core of the algorithm consists of two bounding procedures based on three relaxations. Also two reduction methods are applied to resize and define both lower and upper bounds on the number of vehicles of each type to be used in the solution. The reduced set partitioning problem was fed into a mixed integer programming solver. Computational experiments on 13 test instances involving up to 108 customers are conducted.

6.2. Heuristic algorithms

This section discusses heuristic algorithms for a variety of resource constrained routing and scheduling problems. It covers three groups of contributions, namely local search algorithms, evolutionary algorithms, and matheuristic and decomposition algorithms. Among them local search algorithms are the most prevalent. Tables 6, 7 and 8 provide overviews for each group of algorithms. Note also that many problem instances stem from real-life applications and often use real data.

6.2.1. Local search algorithms

Early works in the field of heuristics for the TRSP are those of Xu and Chiu (2001) and Tsang and Voudouris (1997). Both papers are motivated by service providers in the telecommunications industry. Specifically, Xu and

Table 6: Overview of local search based metaheuristic algorithms

Reference	Algorithm	Algorithmic features	Application	Data Set
Tsang and Voudouris (1997)	GLS	Fast hill climbing, swap	Telecoms (TRSP)	Real-life data, 118 engineers, 250 jobs
Chao *et al.* (1999)	LP-relaxation based heuristic	Local search	N/A (SDVRP)	Randomly generated data, benchmark instances ≤325 customers, up to three types of vehicles
Xu and Chiu (2001)	GRASP	Semi-exact construction, exchange, swap	Telecoms (TRSP)	Randomly generated data, ≤ 999 jobs, ≤ 166 technicians
Cordeau and Laporte (2001)	TS	Relocate, exchange, GENI	N/A (SDVRP)	Benchmark instances, ≤1008 customers
Lim *et al.* (2004)	TS, SA, SWO	3-edge-swapping, shift, exchange and rearrange operators, multi-objective	Service work at ports	Solomon (1987) based instances, ≤ 42 servicemen, 100 customers
Cordeau *et al.* (2004)	TS	Infeasible region, exchange, relocate	N/A (SDVRP)	http://people. brunel. ac. uk/∼ mastjjb/ jeb/ info.html, benchmark instances, ≤288 customers
Chao and Liou (2005)	TS	Exchange, relocate, intensification and diversification strategies	N/A (SDVRP)	Randomly generated data, benchmark instances ≤325 customers, up to three types of vehicles
Li *et al.* (2005)	SA	Block-transposition and block-reverse neighbourhoods, greedy heuristics	Maintenance	Data from ports of Singapore and Hong Kong, 300 jobs
Bertels and Fahle (2006)	TS, SA, CP	LP, pool of solutions	Home health care	Randomly generated data, ≤ 600 jobs, 50 nurses, 200 patients
Pisinger and Ropke (2007)	ALNS	Fix and optimise operators	N/A (SDVRP)	http://neumann.hec.ca/ chairedistributique/ data/ sdvrp, benchmark instances, ≤ 1008 customers
Goel and Gruhn (2008)	LNS, VNS	Swap, relocate, exchange	EU airports	Real-case data, ≤ 1500 customers, ≤ 500 vehicles
Alonso *et al.* (2008)	TS	GENIUS	N/A (SDVRP)	Randomly generated data, http://people. brunel. ac. uk/∼ mastjjb/jeb/ orlib/sdmtpvrpinfo.html, ≤ 1000 customers
Trautsamwieser *et al.* (2011)	VNS	SA, Segment relocation, cross-exchange and 3-opt neighbourhoods	Home health care	Randomly generated data ≤ 100 jobs and 20 nurses, real data ≤ 411 clients, 512 jobs, 75 nurses
Amorim *et al.* (2012)	ALNS	Destroy and repair neighbourhoods	Food distribution	Real-case data ≤ 366 customers
Kovacs *et al.* (2012)	ALNS	Destroy and repair neighbourhoods	Field service	Real data, data based on Solomon (1987) instances, http://prolog.univie.ac.at /research/STRSP/ ≤ 627 tasks
Shao *et al.* (2012)	Parallel GRASP	Insertion and swap neighbourhoods	Home health care	Randomly generated and real data, ≤ 140 patients and 16 therapists
Cordeau and Maischberger (2012)	ILS, TS	Perturbation, GENI operator	N/A (SDVRP)	VRP Benchmark instances, http://www.bernabe. dorronsoro.es/ vrp/index.html? VRP-Intro.html, ≤ 1008 customers
Nickel *et al.* (2012)	Two-stage decomposition	TS , ALNS, CP heuristic	Home health care	Real data, ≤ 361 tasks, 7 days, 12 nurses
Mankowska *et al.* (2014)	Adaptive VNS	Matrix representation	Home health care	Randomly generated data with 300 patients, 40 employees, and six types of skills.
Misir *et al.* (2015)	Hyper-heuristics	Adaptive list based TA	Home care, security, maintenance	Randomly generated data, ≤ 74 patients,154 tasks and 15 carers
Braekers *et al.* (2016)	Multi-directional local search	Biobjective, LNS	Home health care	Real and randomly generated data, http://alpha.uhasselt.be/ kris.braekers ≤ 300 jobs, 6 skill levels, 8-hour shift

GLS: Guided local search, GRASP: Greedy randomised adaptive search procedure, TS: Tabu search, SA: Simulated annealing, swo: Squeaky wheel optimisation, LP: Linear programming, CP: Constraint programming, ALNS: Adaptive large neighbourhood search, LS: Local search, LNS: Large neighbourhood search, VNS: Variable neighbourhood search, ILS: Iterated local search, TA: Threshold accepting

Chiu (2001) maximised the number of requests served considering skill constraints and request urgency. They developed a greedy randomised adaptive search procedure (GRASP) consisting of a semi-exact greedy-plus construction heuristic algorithm and of an iterative improvement local search method. An extended model formulation and various upper bounds were also presented. Fast hill climbing and guided local search (GLS) approaches were developed by Tsang and Voudouris (1997). In the proposed GLS implementation, the number of unallocated jobs is penalised.

Lim *et al.* (2004) and Li *et al.* (2005) proposed local search algorithms for routing and scheduling technicians. More specifically, Lim *et al.* (2004) developed a hybrid TS and simulated annealing (SA) algorithm as well as a squeaky wheel optimisation (SWO) algorithm (Joslin and Clements, 1999) combined with local search for a manpower allocation problem with time windows and a composite objective. Similarly, Li *et al.* (2005) presented an SA algorithm for a manpower allocation problem with time windows and teaming constraints. The proposed method is coupled with greedy insertion heuristics as well as the so-called block-reverse and block-transposition neighbourhood structures. Block-reverse reverses the order in the permutation of a randomly selected sequence (block) of jobs, while block-transposition swap two blocks of jobs in the permutation.

More recent works regarding the field service domain are those of Kovacs *et al.* (2012) and Shao *et al.* (2012). More specifically, Kovacs *et al.* (2012) developed an adaptive large neighbourhood search (ALNS) metaheuristic algorithm for the field service routing problem with and without team building. For both problem variants various solution destroy and repair neighbourhood structures were proposed, as well as a new adaptive mechanism. The authors ran computational experiments on real-life and benchmark data sets with up 200 customers. Shao *et al.* (2012) developed a parallel GRASP to construct weekly schedules and routing plans for a set of heterogeneously skilled therapists and a set of jobs with known preferences. The aim is to match patients' demands with therapist skills, while minimising treatment, travel, administrative and mileage reimbursement costs. In the first phase of the GRASP, the treatment patterns for every patient are selected and the corresponding daily therapist assignment and routing subproblems are solved in parallel. This subproblem can be seen as multi-Travelling Salesman Problem (TSP) with time windows, lunch breaks, and piecewise-linear mileage reimbursement rates. The second phase applies a local search improvement procedure based on insertion and swap neighbourhood structures. Computational experiments were conducted on both randomly generated and real life data provided by a United States rehabilitation agency.

Another very popular class of problems is the home health care routing and scheduling problem. Bertels and Fahle (2006) proposed a solution framework consisting of linear programming (LP) and constraint programming (CP), as well as SA and TS metaheuristic algorithms. The problem is solved via a two-stage framework: in the first stage, sets of jobs are assigned to nurses and in the second stage the execution order of jobs for each nurse is determined. The authors use a pool of solutions where they store good quality local optima met during local search. The information extracted from this pool guides the CP to improve the solutions produced. The authors tested their framework on randomly generated instances of up to 50 nurses and 600 jobs.

Trautsamwieser *et al.* (2011) considered the daily planning of home health care services that occur during or following a natural disaster such as an earthquake, a flood or an epidemic. The authors proposed a mixed integer programming formulation that takes into account various operational realities, including assignment constraints, working time restrictions, time windows, and mandatory break times. The model uses a weighted objective function that minimises the driving and waiting times as well as the dissatisfaction level of both clients and nurses (it considers a total of seven components in the objective function). The authors reported computational experiments on artificial data sets and on real-life instances provided by the Austrian Red Cross. Small instances are solved optimally using the Xpress solver, while a variable neighbourhood search (VNS) is also developed for real-life-sized instances with up to 512 jobs and 75 nurses. The VNS algorithm is equipped with segment relocation, cross-exchange and 3-opt neighbourhood structures. During the local search process non-improving solutions are accepted to diversify the search. For this purpose, an acceptance criterion similar to that of SA algorithms is used.

Nickel *et al.* (2012) solved short- and mid-term planning problems arising in home health care services. Initially, the authors focused on formulating and solving the detailed weekly routing, scheduling and nurse rostering problem. The goal is to provide a service plan with nurses and patients, such that the patients are served by the provided nurses. Four objectives are combined through a weighted sum: the patient-nurse loyalty, the number of unscheduled tasks, the overtime costs, and the travelling distance. This model is solved via a two-stage solution framework. Patients-nurses loyalty is measured through preference index for a particular nurse with whom a patient is familiar. First, a CP heuristic is used to generate a feasible solution. An ALNS is then applied for further improvement. The authors also examined a mid-term planning problem, referred to as the master scheduling problem. In this model, the requirement to provide rosters for the nurses is relaxed. On this basis, a so-called operational planning problem is also formulated to assign nurses to the master schedule and to incorporate last minute changes into the existing plan.

The objective of this model is to limit the perturbations of the plans. As in the previous hybrid algorithm, the authors used a CP heuristic layer to insert the new jobs in the current best positions, and then applied a TS algorithm to improve the solution until a time limit or a move limit was reached. They performed computational experiments on real-life data sets.

In the domain of home health care, Mankowska *et al.* (2014) developed a mixed integer LP formulation for the resource routing and scheduling problem with precedence constraints on activities and services. They applied an adaptive VNS to realistic-scale problem instances. The method is based on a new solution representation, which is a matrix with as many rows as the number of the operators and as many columns as the number of patients. The proposed representation stores all the information needed and enables local search operators to perform local moves effectively. Extensive experiments were conducted on randomly generated instances with up to 300 patients, 40 employees, and six types of skills.

Braekers *et al.* (2016) solved a bi-objective home care routing and scheduling problem with various side constraints, such as qualifications, work regulations, overtime costs, multi-mode travel costs and time windows. The first objective is to minimize the operating costs, while the second is to maximize the offered service level based on the client preferences. The authors employed the so-called multi-directional local search framework (Tricoire, 2012) to generate a set of efficient solutions. A solution is selected iteratively from the efficient set and two single objective local searches are performed via a subordinate LNS algorithm. Non-dominance checks are applied to decide whether to update the set, while the overall process is repeated until a termination condition is met. Computational experiments on real and randomly generated data sets are performed. Optimal solutions on small instances are also reported. The analysis revealed a considerable trade-off between costs and client convenience; however, as the authors report, even small additional costs can improve the inconvenience levels drastically.

Misir *et al.* (2015) considered a general class of problems that involve the routing and scheduling of resources via a hyper-heuristic solution framework. This framework uses a set of low-level heuristics guided by problem-independent strategies which are appropriately utilised for different problem settings and specifications. The goal is to provide an analysis of the performance for the different components of the hyper-heuristic. In particular, the authors presented a selection hyper-heuristic, which rather than progressively building the low level heuristics (generation-hyper-heuristics), chooses one or more low-level heuristics to produce or amend a solution at each decision step. For this purpose, a score is used that indicates how well a heuristic performs with regards to the solution cost and the computing time. Pairs or single heuristics are selected at each decision step and an adaptive list-based threshold accepting strategy is used as a high-level strategy. The computational experiments show that the planning horizon, the number of activities and the number of resources seem to affect the performance of different heuristics.

Nag *et al.* (1988) were the first to consider site dependencies as compatibility constraints between customers sites and vehicle types. There now exists a rich literature on the SDVRP. Cordeau and Laporte (2001) developed a TS algorithm for the SDVRP with time windows. This algorithm was later adapted to solve the multi-depot and the multi-period VRP in Cordeau *et al.* (2004), and was enhanced to consider both the infeasible and feasible regions of the solution space. Another TS algorithm was proposed by Chao and Liou (2005), which uses exchange and relocate operators along with intensification and diversification strategies to guide the search. Chao *et al.* (1999) introduced an LP-relaxation-based heuristic for producing initial solutions for the SDVRP and integrated a local search algorithm to improve solution quality. The above papers used the benchmarks of Nag *et al.* (1988) as the test-bed for their experiments and presented results on other randomly generated data. Alonso *et al.* (2008) solved a multi-period multi-trip SDVRP by means of a TS algorithm, which uses the GENIUS heuristic for inserting and removing customers from routes (Gendreau *et al.*, 1994). Computational experiments were conducted on randomly generated data with up to 1000 customers.

Pisinger and Ropke (2007) proposed an ALNS algorithm for a variety of routing problems, including the SDVRP. The authors adopted the LNS framework of Shaw (1998) and enhanced it with an adaptive mechanism that controls the number of insertion and removal operators used to intensify and diversify the search. A transformation to a rich pick up and delivery vehicle routing problem enables solving the VRPTW, the CVRP and the multi-depot VRP, the SDVRP and the open VRP within a unified ALNS solution framework. Instead of the standard ruin and recreate functions of a typical ALNS framework, the authors present a fix and optimise procedure. The fix operation fixes some variables and the optimise operation tries to apply improvements to the remaining unfixed variables. The operators for each function (fix and optimise) are chosen independently according to a separate adaptive probability. Computational experiments were conducted on benchmark instances.

Goel and Gruhn (2008) considered a general vehicle routing problem with real-life constraints, i.e., compatibility constraints between specific customers orders, heterogeneous vehicle types, and the presence of vehicles having two drivers in the case of long-haul shipments. This problem is an excellent example of our resource constrained vehicle routing and scheduling family of problems, a combination of resources (e.g., drivers and vehicles) is used to enable the fulfilment of a particular customer order. The authors developed an LNS and a VNS algorithm and used a tour dependent customer closeness function to assist the ruin and recreate function in the selection of customers to remove and reinsert. Computational experiments are reported on real-case data with up to 1500 customers and 500 vehicles.

Cordeau and Maischberger (2012) proposed an iterated local search framework that combines a TS algorithm and a perturbation strategy to solve a variety of routing problems including the SDVRP with and without time windows, which is relevant to our survey. The proposed TS uses well-known neighbourhood operators, including the GENI heuristic of Gendreau *et al.* (1994) to apply local search. A diversification mechanism considers the frequency of each solution attribute (e.g., an arc) during the search. For intensification purposes, a route refinement procedure is applied which tries to post-optimise the intra-route sequence. The authors implemented their algorithm in a parallel fashion and conducted runs on a cluster computer with 128 processors. Extensive experiments were conducted and results on small- to large-scale benchmark instances.

Amorim *et al.* (2012) developed an ALNS algorithm for a real-life vehicle routing problem for food distribution in Portugal. The problem involves a heterogeneous fleet of vehicles, and customers may require dry products and perishable products that need to be transported in refrigerated vehicles. This feature is modelled as a site-dependency constraint; if there is a customer requirement for both types of products, dry and fresh or frozen, a new dummy customer is created to accommodate the second commodity. The ALNS applied on this problem was adapted from Kovacs *et al.* (2012) for the technician routing and scheduling problem. The authors presented ruin and recreate operators that take into account distance, time and load to respect route duration and vehicle capacity constraints. Computational experiments were conducted on the real-case data and demonstrated the efficiency of the proposed method. In the same domain, Song and Ko (2016) modelled a vehicle routing problem that involves both refrigerated and regular vehicles for perishable food products delivery. The goal of the problem is to maximise customer satisfaction, expressed by the freshness of the products that they receive. At the depot, the products are considered fresh; as they travel their freshness decreases in a non-linear fashion. When the refrigerated vehicles were used, the freshness decrease rate was smaller. A greedy construction heuristic was proposed and computational experiments were conducted on randomly generated data with up to 500 customers.

Table 7: Overview of evolutionary algorithms

Reference	Algorithm	Algorithmic Features	Application	Data Set
Tang *et al.* (2007)	AMP-TS	Upper bounds	Maintenance	Real-data, two technicians, 4659 tasks, 90 buildings
Akjiratikarl *et al.* (2007)	PSO	Edge-exchange, swap, and insertion neighbourhoods	Home health care	Real data, 100 tasks, 50 customers, 12 care workers
Pellegrini *et al.* (2007)	ACO	TS, Edge-exchange	Food distribution	Randomly generated and real-data, $\leq$ 80 customers
Zäpfel and Bögl (2008)	GA	TS, edge-exchange	Maintenance	Randomly generated data, $\leq$ 279 customers
Kim *et al.* (2010)	PSO	CPLEX, triple representation	Maintenance	Randomly generated data, http://logistics.postech.ac.kr/CMVRP_benchmark.html, $\leq$ 480 customers
Vidal *et al.* (2014)	Unified hybrid GA	i-CROSS, generic split	N/A (SD-VRP)	A wide variety of benchmark problems
Hiermann *et al.* (2015)	Hyper-heuristic	SS, MA, VNS, SA	Home health care	Real-data, $\leq$ 509 nurses and 717 jobs
Reisabadi and Mirmohammadi (2015)	ACO, TS	Pheromone strategies, 2-opt, cross-over	N/A (SD-VRP)	Randomly generated data based on Solomon (1987) instances, $\leq$ 150 customers

AMP-TS: Adaptive memory programming - Tabu search, PSO: Particle swarm optimisation, ACO: Ant colony optimisation, GA: Genetic algorithm, TS: Tabu search, SS: Scatter search, VNS: Variable neighbourhood search, SA: Simulated annealing

6.2.2. Evolutionary algorithms

Early works on evolutionary algorithms for maintenance and personnel planning problems are provided by Tang *et al.* (2007) and Zäpfel and Bögl (2008). Requests with different urgency levels are considered in the work of Tang *et al.* (2007) for a planned maintenance scheduling problem. These authors developed an adaptive memory programming (AMP) method coupled with TS. The adaptive memory structure maintains a set of diversified high-quality solutions. Greedy randomised procedures were also employed to explore small and large neighbourhoods during the local search process. The authors performed experiments on large scale real-life data sets. Zäpfel and Bögl (2008) developed a generalised guided metaheuristic framework for a combined tour and personnel planning problem that can be seen as a multi-period vehicle routing and crew scheduling problem with outsourcing.

Akjiratikarl *et al.* (2007) developed a particle swarm optimisation (PSO) algorithm for a home care delivery and care-worker scheduling problem. The goal is to design minimum-cost routes for the care workers, while satisfying the duration and service time window constraints. The algorithm applies a heuristic assignment scheme to descretise the time in the schedule, while the so-called earliest start time priority with minimum distance assignment technique is employed to guide the search direction of the particles. The proposed evolutionary framework is also coupled with a local search improvement method that explores edge-exchanges and insertion neighbourhoods. Computational experiments and a parameter study were performed on real demand data sets. Similarly, Kim *et al.* (2010) presented a PSO algorithm for the combined routing and scheduling of manpower teams performing multi-stage tasks at customer locations. The proposed PSO operates on a solution representation based on three lists: the vehicle list, the available team list, and the customer-demanded team list. The authors performed computational experiments on randomly generated benchmark instances.

Hiermann *et al.* (2015) solved a real-life multi-modal home care scheduling problem faced by an Austrian home health care provider. Their model takes into account various side constraints, such as (preferred) time windows, employer, nurse and patient satisfaction levels, and travel times dependent on the transportation mode employed. Overall, 13 penalty terms are considered in the objective function, reflecting hard and soft constraint violations. The authors proposed a two-stage solution approach. CP and a random procedure are used to generate initial solutions in the first stage, while four metaheuristic algorithms compete to improve these solutions: a VNS algorithm, a memetic algorithm (MA), a scatter search (SS) algorithm, and a SA hyper-heuristic algorithm. The authors report computational results on real-life data sets. Overall, the MA consistently outperformed all other metaheuristic algorithms.

Site-dependencies are usually encountered in rich vehicle routing problems within a wider range of constraints. Pellegrini *et al.* (2007) developed two ant colony optimisation (ACO) algorithms for a rich vehicle routing problem involving multi-period, multiple time windows for customers for the day and across the week, maximum route duration, heterogeneous fleet, and multiple visits for each customer. Most importantly, the features that are relevant to our survey are that the vehicle fleet is heterogeneous and customers may require to be serviced by different types of vehicles. The ACOs use edge exchange to perform local search while two hierarchical objectives are used, i.e., the minimisation of the number of vehicles and the minimisation of the total route time. The authors compared the efficiency of their algorithm with that of a TS, and used randomly generated data based on real-case data as the testbed for their experiments. Similarly, Reisabadi and Mirmohammadi (2015) proposed an ACO algorithm that applies local search and a TS algorithm for the SDVRP with soft time windows. Computational experiments were performed on randomly generated data based on those of Solomon (1987).

Vidal *et al.* (2014) presented a unified genetic metaheuristic for a wide variety of problems with rich vehicle routing features. The proposed framework uses non-problem-specific strategies and mechanisms and applies diversity management methods to move efficiently in the search space. The solution is represented by a giant tour that includes all customers, but no depots. The depots are then reinserted in the solution by solving a shortest path problem on an auxiliary graph. Widely used neighbourhood operators are used to define the local moves, including i-CROSS and 2-opt*. During the evolution of generations, sub-populations are managed independently to ensure diversity and to avoid premature convergence. Extensive experiments on a very wide variety of benchmark instances were conducted, proving the efficiency of the proposed unified solution methodology.

6.2.3. Overview of matheuristics and decomposition algorithms

Table 8: Overview of decomposition algorithms

Reference	**Algorithm**	**Algorithmic Features**	**Application**	**Data Set**
Ceselli *et al.* (2009)	Column generation	Bidirectional dynamic programming algorithm	N/A (rich VRP)	Real-data sets
Goel (2010)	Column generation	Removal and insertion procedure	N/A (SD-VRP)	Randomly generated data
Allaoua *et al.* (2013)	ILP, two-stage decomposition	Set partitioning, rostering-first, route-second scheme	Home health care	Randomly generated data, 30 services, 9 staff, 3 skills
Cortéz *et al.* (2014)	CP based B&P	CP for the pricing problem	Technician routing	Real data, up to 70 service requests
Yalçindăg *et al.* (2014)	Two-stage decomposition	Kernel regression technique	Home health care	Real-data, $\leq$ 56 patients
Cappanera and Scutellà (2015)	ILP	multi-period, pattern generation policies	Home health care	Real-data, Nickel *et al.* (2012) data set
Yalçindăg *et al.* (2016)	Pattern-based two-phase decomposition	Different levels of flexibility	Home health care	Real data, 34 problem instances, up to 300 patients, 16 operators and 2 skills

ILP: Integer linear programming, CP: Constraint programming, B&P: Branch and price,

Ceselli *et al.* (2009) and Goel (2010) developed column generation algorithms. In particular, Ceselli *et al.* (2009) described a very rich variant with multiple capacities, time windows, incompatibility constraints, duration restrictions, driving upper bounds and rest periods, the possibility of skipping some customers and using express courier services, split delivery, and open routes. The objective function considers a cost based on fees, the distance traveled, the vehicle load, and the number of stops along the route. The proposed multi-phase column generation scheme employs a bounded bidirectional dynamic programming algorithm to compute optimal solutions for the pricing subproblem, while a heuristic pricing algorithm with modified dominance criteria is also applied. Computational results are reported on a real-data set obtained from a software company. Goel (2010) used a simpler scheme for the so-called General VRP with compatibility constraints. The author applied a heuristic removal and insertion procedure to identify negative reduced-cost routes.

Allaoua *et al.* (2013) developed exact and matheuristic algorithms. An integer linear programming formulation was first used to capture the routing and rostering of the staff. The resulting mathematical model is similar to that of the VRPTW with multiple depots, where the objective is to minimise the number of operators in the solution. Based on this model, a rostering-first route-second heuristic decomposition scheme was adopted. The first part can be viewed as a set partitioning problem, i.e., the assignment of staff to shifts and the clustering of the set of services. The second part corresponds to a multi-depot TSP with time windows for each cluster. Two methods were used to solve the assignment and partitioning problem, while the routing counterpart was solved optimally.

Cortéz *et al.* (2014) put forward a CP-based branch-and-price method for a technician routing problem with soft time windows faced by a company that provides repair services of office machines in Chile. To solve the subproblems, the authors devised a set partitioning based branch-and-price algorithm that uses the constraint branching strategy of Ryan and Foster (1981), along with the CP method of Yunes *et al.* (2005) to solve the subproblem. Compared to graph-inspired dynamic programming methods, the CP requires fewer variables and takes advantage of the fact that each technician visits only a small fraction of the overall daily clients. Computational experiments on real data sets were conducted.

Yalçindăg *et al.* (2014) developed a two-stage decomposition algorithm for an assignment and routing problem arising in home health care. Instead of solving simultaneously the assignment and routing problem, the authors first determined the assignment of operators to patients, followed by the corresponding routes. In order to appropriately decompose the problem, it is essential to have an estimation of the travel time. Instead of using the average value approach, they used a kernel regression technique and then applied a genetic algorithm to the associated assignment problem. Subsequently, the corresponding TSPs, which are as many as the number of operators used, are solved. The authors report that more extensive experimentation should be conducted to draw solid conclusions about the proposed method.

Cappanera and Scutellà (2015) studied a challenging multi-period home care routing and scheduling problem and extended the bicriteria minmax and maxmin approach of Schwarze and Voss (2013). A multiple-day planning horizon is assumed, and balancing is achieved with respect to both routing and service times accumulated by an operator in the planning horizon. This is in contrast with the work of Schwarze and Voss (2013) who considered a daily planning horizon and performed balancing only with respect to routing costs. Furthermore, the focus was the operator utilisation factor: in maxmin the objective is the maximisation of the minimum operator utilisation factor, whereas in minmax the goal is the minimisation of the maximum utilisation factor. The authors introduced the concept of “pattern” to handle the incumbent optimisation problems. A pattern is a possible schedule for the operators that satisfies all skill compatibility constraints and coordinates all the routing and scheduling decisions. Both heuristics and exact procedures are used to generate the patterns. The exact procedures are based on a multi-commodity flow problem using an auxiliary layered network. The layers of this network represent days in the time horizon, and directed source-destination paths within the network correspond to potential patterns. By determining which arcs should be selected for these paths, the model minimises the number of used arcs, and therefore it implicitly minimises the number of generated patterns. Extensive computational experiments were conducted on real-life data. The maxmin approach returns more balanced solutions, but minmax is more suitable for minimising the operating costs.

Lastly, a new family of two-phase methods, based on patterns and different levels of flexibility, are introduced for human resource planning in home health care services in the paper of Yalçindăg *et al.* (2016). The problem addressed is characterized by skill qualifications, continuity of care, and multi-period planning horizon. The main concept is to decompose the linked decisions and constraints of each planning level, i.e., assignment (A), scheduling (S) and routing (R), in two steps coordinated by means of a pattern mechanism, as defined by Cappanera and Scutellà (2015). Overall, the authors evaluated four schemes, considering cost minimization and the balancing of the operator workload under different conditions of skill management. The most flexible scheme incorporates all decisions and linking constraints into a single phase scheme $(A + S + R)$, and it is shown to be affordable only for small-size instances and only when a balancing criterion is considered. The most rigid two-phase scheme is guided only by assignment decisions $(A|S + R)$, and it failed to generate feasible solutions. On the other hand, the intermediate two-phase schemes $(A + R|S)$ and $(A + S|S + R)$ provided a good trade-off between computational efficiency and solution quality in terms of balance between workload and total travel time. Especially, the $(A + S|S + R)$ was capable to produce near-optimal solutions even when short time limits were imposed.

6.3. Stochastic programming and robust optimisation algorithms

Souyris *et al.* (2012) formulated a robust optimisation model for the VRP with soft time windows and uncertain service times. They did not consider compatibility restrictions in terms of technician skills, but only correlations

Table 9: Overview of stochastic programming and robust optimization methods

Reference	Algorithm	Algorithmic Features	Application	Data Set
Souyris *et al.* (2012)	B&C	CP, robust service times	Home health care	Real data set, 41 customers and 15 technicians
Yuan *et al.* (2015)	B&P	Label algorithm, acceleration strategies, stochastic service times	Home health care	Solomon (1987) instances, 50 customers, 3 skills
Binart *et al.* (2016)	Two-stage B&C	Lagrangian, dynamic programming, stochastic service and travel times, simulation	Field service	TOP data set, real data set, up to 50 customers and 3 vehicles

B&C: Branch and cut, CP: Constraint programming, B&P: Branch and price

between the service times that the technicians face. In particular, closed, convex, and bounded uncertainty sets were considered for each technician. The main assumption is that the worst case will not concentrate on a single technician, and thus, the uncertainty can be distributed uniformly across technicians. The resulting robust counterparts lead to slightly more complicated models compared to the deterministic equivalent. The authors proposed a branch-and-price method to solve the robust problem coupled with a CP method for the pricing subproblem, and performed computational experiments on real data sets with 41 customers and 15 technicians.

Yuan *et al.* (2015) developed column generation algorithms for a home health care routing and scheduling problem with stochastic service times and skill requirements. They first presented a stochastic programming with recourse model to minimise the total travel cost, the fixed cost of care-givers, the expected service cost and the expected penalty cost for late arrivals. The stochastic customer service times are treated as independently normally distributed random variables. On this basis, they provided approximate expressions for the expected service cost and arrival time delays. The authors proposed an equivalent set partitioning formulation and solved it by alternating between a master problem and a pricing subproblem. A labeling algorithm was used to solve optimally the pricing problem with new dominance rules. Overall, a multi-phase scheme was applied to perform the column generation process. Various acceleration strategies are also applied. The authors performed computational experiments with up to 50 customers and care-givers divided into two and three skill levels.

Binart *et al.* (2016) solved a field service routing problem with stochastic travel and service times, as well as mandatory and optional customers. The goal is to maximise the number of optional customers served given the limited available resources. Overall, the problem can be viewed as an uncapacitated Multi-Depot VRPTW with stochastic service and travel times and with priority, and is solved in two stages. During the planning stage, routes are initially generated with mandatory customers using branch-and-cut, and optional customers are then inserted by applying a Lagrangian heuristic. At the execution stage (real-time modification of the planned route), two dynamic programming algorithms are used to define the optimal policy to face stochasticity. The concept is to use the optional customers as buffer to absorb the variations. The stochastic travel and service times are modelled assuming discrete triangular distributions. Computational experiments are reported using benchmark data sets for team orienteering problems (TOP) as well as on realistic data sets with up to 50 customers and three vehicles.

6.4. Algorithms for dynamic problems

Weintraub *et al.* (1999) proposed a periodic re-optimization method for the real-time routing and scheduling of service technicians for energy providers in Chile. The problem is dynamic in the sense that customer service requests (with different priority levels) are not known in advance, and service technicians have to be dynamically assigned to these requests. The objective is to minimise the weighted total response time of all routes. Note that the weights assigned to the blackouts reflect their priority level. An initial solution is constructed following a cluster-first route-second framework. To this end, a generalised insertion method is employed to generate the routing for each technician, while an initial forecast of the daily demands for each geographical zone is derived using an exponential smoothing method. A post-optimisation heuristic is also applied to balance the load (i.e., number of service requests and total travel times) of the technicians. This two-phase heuristic is executed periodically in fixed time intervals or whenever new high priority requests are received.

Table 10: Overview of re-optimization methods and Markov Decision Processes

Reference	**Algorithm**	**Algorithmic Features**	**Application**	**Data Set**
Weintraub *et al.* (1999)	Periodic re-optimization	Cluster-first route-second, GENI	Technician routing and scheduling	Real data
Pillac *et al.* (2013)	ALNS	Parallel algorithm, set covering, post-optimization	Technician routing and scheduling	Data based on Solomon (1987) instances, up to 100 service requests
Chen *et al.* (2016)	Markov decision process	Record-to-record travel	Technician routing and scheduling	Randomly generated data

ALNS: Adaptive large neighbourhood search

Pillac *et al.* (2013) developed a parallel ALNS algorithm for the routing and scheduling of heterogeneously skilled and equipped technicians who must serve requests with compatibility constraints, tools and spare parts. Besides the parallel implementation itself, one prominent feature of the proposed

ALNS framework is the maintenance of a shared pool of promising solutions. The solutions are selected not only according to their quality, but also with respect to a diversification metric that counts which arcs were removed from the solution. A post-optimization procedure based on a set covering model was used to optimally design the best possible solution considering all tours generated during the ALNS iterations. Computational experiments on problem instances with up to 100 service requests are reported. Pillac *et al.* (2012) adapted the above ALNS for periodic re-optimization of the problem with dynamic service requests.

Chen *et al.* (2016) developed a rolling horizon procedure for the multi-period technician routing and scheduling problem with experience-based service times. In this problem setting, the technicians learn through experience and the productivity increases (or equivalently the service time decreases) over the multi-day planning horizon. The daily demand is not known a priori and is revealed on the day of service. The objective is to minimise the total daily makespan (completion time of the last task) over a finite horizon. The problem was modelled using a Markov decision process, and a myopic solution framework (i.e., minimising the current state costs while ignoring information about the future) was adopted. Given the observed daily demand realisation, a sequence of deterministic daily routing problems are solved and the technician productivity is updated according to the experience gained on the previous day in a roll-out fashion. Specifically, the routing problem is solved using a record-to-record travel algorithm (Li et al, 2010), which is a two-phase local search algorithm. In the first phase non-improving neighbouring solutions are accepted according to a particular threshold of the record, towards diversification. In the second phase, only improving moves are accepted.

7. Conclusions and research prospects

We have presented a survey of resource constrained routing and scheduling problems where the use of various resources is essential to complete the service according to special customer requirements. Our review has revealed that there exist several interesting variants of such problems, the Skill VRP and the Technician Routing and Scheduling problems being the most prominent. We also showed that maintenance activities and home health care are the main areas where routing and scheduling of resources is crucial not only in terms of customer satisfaction, but also in terms of operational efficiency.

The research topic considered in this survey, is still open, raises various challenges and has interesting applications with high socio-economic impact. Although significant work has been conducted on this field, we believe that the field has not yet reached a high level of maturity, and therefore many challenges still stand while new ones emerge. Below we provide a list of potential directions for further research:

- **Combined product and service delivery:** The only work that looked at product as well as service delivery was by Paraskevopoulos *et al.* (2015). If the product delivered needs installation, configuration or assembly, determining how many resources and what types are needed to accommodate this service and what the capacity of the vehicle should be are two relevant questions.

- **Multi-mode on the tasks:** A prevalent feature in project scheduling problems (Naber and Kolisch, 2014; Van Peteghem and Vanhoucke, 2014) is the multi-mode nature of the tasks according to the different availability of the resources (Hartmann and Briskorn, 2010). For example, painting a wall takes less time when more workers are used, but this generates additional costs and the gain in efficiency is not necessarily linear. Tsang and Voudouris (1997) considered that the more experienced is the technician the less it takes to finish a particular job. To the best of our knowledge, no study has yet considered the different combinations of resources needed to minimise the service times, and there is therefore room for research in this area.

- **Soft time windows:** Because the type of the service delivered at the customer locations is most of the times highly variable and unknown with precision, it does not make much sense to consider hard time window constraints, since these would rarely be satisfied in practice. It is also evident that very few papers consider soft time windows. Therefore, we believe there is scope for more research on modelling and solving problems with soft time windows.

- **Stochastic elements:** Even though stochastic environments are prevalent in real-life routing and scheduling problem settings, there exists only a very limited literature on this topic, which suggests fruitful research opportunities.

- **Workload balancing:** We believe that since the main focus of routing and scheduling of resources is the efficient use of resources, workload balancing should be of high priority in relevant problem settings. Nevertheless, very few papers have considered resource balancing (Schwarze and Voss, 2013; Cappanera and Scutellà, 2015).

- **Working regulations:** Operators may have their own preferences, breaks, different shifts, days of leave, and other restrictions. However, very few studies have looked at resource routing and scheduling problems with working regulations (Trautsamwieser *et al.*, 2011; Braekers *et al.*, 2016).

- **Multiple products and vehicle qualifications:** Some vehicles can carry several different types of products (e.g. fresh and freezed, perishable), or they can be dedicated to a particular product category. They can also involve multiple compartments for the storage of non-mixable products. To our knowledge, very little research has been conducted on settings with heterogeneous vehicle qualifications and multiple products.
- **Synchronization:** Even though some temporal constraints are considered by researchers in the field, synchronisation has not thoroughly explored in the resource constrained vehicle routing and scheduling problems, as discussed in the review paper of Drexl (2012a).

From a practical perspective, it is also important to consider combinations of additional constraints that are likely to appear in joint scheduling and routing problems. These constraints can be related to the locations of customers, to the vehicle fleets, to number of depots, or to the order and frequency of customer visits over a given time horizon. They can also result from the assignment of customers and routes to resources, to the sequence choices and to the evaluation of objective functions. We refer to the multilevel taxonomy of Caceres-Cruz *et al.* (2015) for a comprehensive discussion on VRP constraints and future methodological trends.

Most of the suggestions listed above create room for further research regarding mathematical models as well as computationally efficient solution methodologies. However, routing and scheduling of resources define a class of problems with realistic specifications and a wide variety of real-life applications. We therefore believe that it is essential to develop efficient solution methods that will produce high quality solutions very fast. This is in line with the existing literature since there exists a wide body of research on exact methods for deterministic and stochastic problem settings. However, the focus of most researchers has been on the design and implementation of heuristics capable of yielding high quality solutions for medium and large-scale problem instances within short computational times.

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Appendix A. List of abbreviations

Abbreviation	**Full name**
VRP	Vehicle routing problem
TRSP	Technician routing and scheduling problem
SDVRP	Site dependent vehicle routing problem
VRPTW	Vehicle routing problem with time windows
TOP	Team orienteering problem
B&C&P	Branch and cut and price
B&P	Branch and price
B&B	Branch and bound
GLS	Guided local search
GRASP	Greedy randomised adaptive search procedure
TS	Tabu search
SA	Simulated annealing
SWO	Squeaky wheel optimisation
LP	Linear programming
CP	Constraint programming
ALNS	Adaptive large neighbourhood search
LS	Local search
LNS	Large neighbourhood search
VNS	Variable neighbourhood search
ILS	Iterated local search
TA	Threshold accepting
AMP	Adaptive memory programming
PSO	Particle swarm optimisation
ACO	Ant colony optimisation
GA	Genetic algorithm
SS	Scatter search
ILP	Integer linear programming