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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, have to visit different customer locations. This paper provides a comprehensive survey on resource constrained routing and scheduling. The latter 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: Vehicle routing and scheduling, technician routing, resource allocation.

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1. Introduction

The latest advances on the Vehicle Routing Problem (VRP) favour realistic settings with practical constraints that pose theoretical challenges and also address real-world needs (Lahyani *et al.*, 2015). A generic class of routing problems of increasing interest is the field of synchronised routing and scheduling of resources. This class of problems is also known as the technician routing and scheduling problem, the skill vehicle routing problem, the field service planning problem, or the home care crew scheduling and routing problem. In all cases, it is necessary to synchronise different resources to meet specific customer requirements. These resources correspond to special skills required in order to complete a specific service without compromising the associated safety and quality standards. For the purpose of the survey the following definition applies:

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

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. Having a limited number of these resources complicate 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 under various objectives.

The explicit consideration of resource allocation is prevalent in shop and project scheduling problems (Slowinski, 1978; Demeulemeester and Herroelen, 2002). The resources can be renewable (e.g., machines, manpower), nonrenewable (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; 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 on 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) provide 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. However, no comprehensive and up-to-date survey on the synchronised routing and scheduling of resources 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 classes of problems (Parragh *et al.*, 2008a,b; Laporte, 2009; Drexl, 2012; Schmid *et al.*, 2013; Coelho *et al.*, 2014; Toth and Vigo, 2014; Demir *et al.*, 2014; Koç *et al.*, 2016). Lately, Lahyani et al. (2015) presented a taxonomy of VRPs characterised by realistic constraints and objectives. Similarly, the present survey paper focuses on a class of realistic routing and scheduling problems and contributes to the existing body of knowledge by (a) introducing a new classification scheme, (b) presenting the latest advances in the field and, most importantly, (c) identifying, discussing and analysing research prospects from a modelling, methodological or problem-specification point of view. We focus on combined routing and scheduling problems, as opposed to pure scheduling problems which as the latter have been thoroughly discussed in Van den Bergh *et al.* (2013).

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

2. 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, maintenance of buildings, maintenance of telecommunications systems, and airport operations. In the following, we discuss the basic characteristics of these applications with an emphasis on common elements and differences.

2.1. Home and health care

Home health care scheduling and routing problem can be seen as special cases of the Skill VRP and of the Technician Routing Problem (see Section 3 for descriptions). 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, break, multiple shifts or multiple sessions per day, and other constraints (Begur *et al.*, 1997).

Specifically, home and healthcare problems involve the assignment of operators to residences and the performance of tasks requiring specific skills within a desired time frame. These tasks may involve the nursing of patients at their home, which we call health care, and helping elderly or disabled people with housekeeping and other daily activities, which we call 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 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, public transport or by foot to reach 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.

2.2. 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 this 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, as well as various other resources, and therefore teams are normally needed to deliver the service. The latter usually comes with synchronisation constraints that enable teams to be formed on customer locations rather than at the depot (Drexl, 2012).

2.3. Forest management

Beyond these applications, resource routing and scheduling problems are 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.

2.4. Airports

Schwarze and Voss (2013) apply a Skill VRP with Time Windows to sort push-back operations at airports. Because aeroplanes 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 aeroplane requires a minimum tug skill. The goal is to assign tugs to push-back operations so as to minimise the total routing cost.

3. Preliminaries

The Skill VRP and the Technician Routing and Scheduling Problem 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) requests 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, i.e. $S_i \subseteq S_t$. Lastly, a non-negative technician-dependent travel cost c^t_{ij} is associated with each arc (i, j) and each technician t.

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 be 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^t_i denote the time vehicle t starts the service at node i. These service start times must respect the corresponding time windows, i.e., $a_i \leq w^t_i \leq b_i$ 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., $\min_{x,y,w} \sum_{i \in V \setminus \{1\}} \sum_{t \in T} w^t_i$) 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) describe 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 depicts how the solution of the Resource Constrained VRP is different from that of the classical VRP. Specifically, there are sets of customers with different colours representing different requirements A, B, AB and C. Note that the green customers require both the A and B resources to be serviced, while the grey ones do not have any particular requirements (they can be served by any resource). The availability of the resources is limited to two units for A, two units for B and one unit of the combined resource BC. The latter means that the particular resource is equivalent to having one resource B and one C together. Apparently, less efficient "resource constrained" routes are generated (compared to the VRP with no resources) at the expense of meeting all customer requirements. The resource allocation is shown in the legend below the solution.

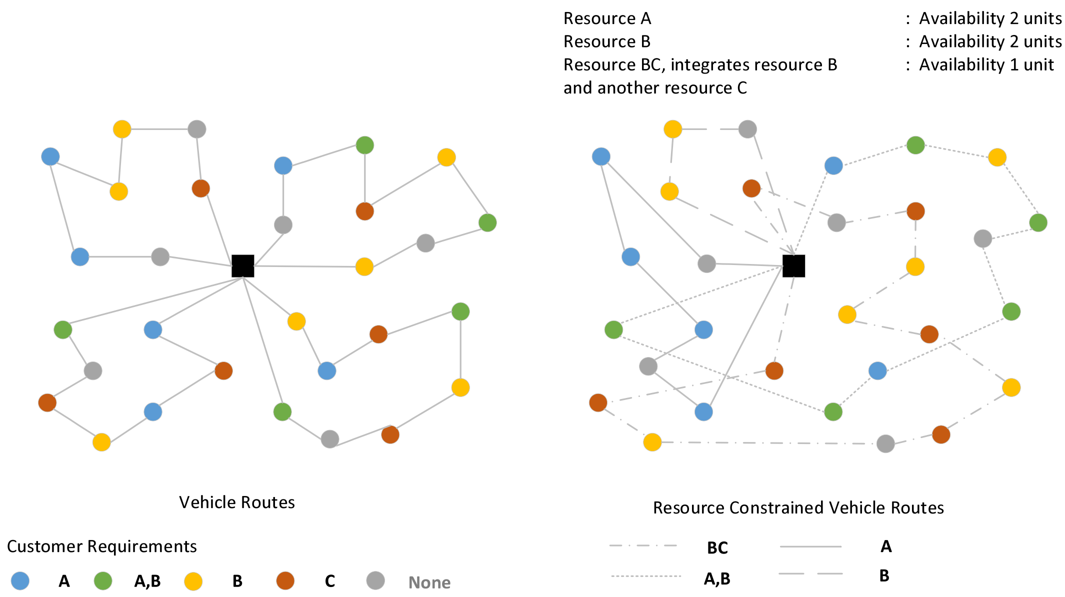

Figure 1: Solution of the Resource Constraint VRP (Paraskevopoulos *et al.*, 2015)

A problem setting that can be also 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 needs to 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 and with no tools or spare parts. Applications are provided in Cordeau *et al.* (2010) and Xu and Chiu (2001). In the former study, 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, 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 these studies by considering both routing and outsourcing costs as well as team building. In the special case where technicians are grouped into teams, each of these completes all tasks assigned to it. Note that single technician tours can be viewed as a team with only one technician.

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 the latter settings, a matrix with compatibility restrictions among requests and resources is 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 skill levels but instead introduce temporal dependencies and synchronisation constraints between technician visits.

4. Related work and taxonomy

In this survey we consider papers on resource routing and scheduling problems, as explicitly defined in Section 1. The pure scheduling papers are very relevant and have interesting applications, mainly in home and health care. Comprehensive and thorough surveys already exist for these problems (Van den Bergh *et al.*, 2013). In total, we selected 39 papers published since 1997.

The classification scheme proposed in this survey is summarised in Table 1. The five main fields are the following:

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

Reference	**Applications**			**Resource qualifications**		**Service constraints**		**Objectives**					**Solution methods**	
	Home health care	Maintenance	Telecoms	Skill levels	Skills	Time windows	Precedence	Outsourcing overtime	Time-delays	Distance	Load balance	Priorities	Exact methods	Heuristics
Tsang and Voudouris (1997)			✓	✓	✓			✓	✓					✓
Weintraub *et al.* (1999)		✓							✓		✓	✓		✓
Xu and Chiu (2001)			✓	✓	✓	✓			✓			✓		✓
Lim *et al.* (2004)	✓				✓			✓	✓				✓	
Li *et al.* (2005)		✓			✓		✓		✓					✓
Bertels and Fahle (2006)	✓				✓	✓			✓				✓	✓
Tang *et al.* (2007)		✓										✓		✓
Akjiratikarl *et al.* (2007)	✓					✓			✓	✓				✓
Bredström and Rönnqvist (2008)	✓				✓	✓	✓		✓		✓		✓	✓
Zäpfel and Bögl (2008)					✓		✓	✓					✓	
Kim *et al.* (2010)		✓					✓		✓	✓				✓
Trautsamwieser *et al.* (2011)	✓			✓	✓	✓		✓	✓					✓
Cappanera *et al.* (2011, 2013)				✓	✓					✓			✓	
Kovacs *et al.* (2012)		✓		✓	✓	✓		✓						✓
Nickel *et al.* (2012)	✓			✓	✓	✓	✓		✓					✓
Rasmussen *et al.* (2012)	✓				✓	✓	✓		✓			✓	✓	
Shao *et al.* (2012)		✓			✓	✓		✓	✓	✓				✓
Pillac *et al.* (2012)		✓			✓	✓			✓					✓
Pillac *et al.* (2013)		✓			✓	✓			✓					✓
Souyris *et al.* (2013)		✓				✓			✓				✓	
Schwarze and Voss (2013)				✓	✓					✓	✓			
Allaoua *et al.* (2013)	✓				✓	✓							✓	✓
Tricoire *et al.* (2013)		✓			✓	✓				✓			✓	✓
Barz and Kolisch (2014)			✓	✓	✓				✓				✓	✓
Cappanera and Scutella (2014)	✓			✓	✓	✓	✓	✓	✓		✓			✓
Lanzarone and Matta (2014)	✓				✓			✓	✓				✓	
Cortez *et al.* (2014)		✓				✓			✓			✓	✓	
Yalçindağ *et al.* (2014)	✓									✓	✓			✓
Mankowska *et al.* (2014)	✓				✓	✓	✓		✓	✓			✓	
Chen *et al.* (2015)		✓		✓	✓				✓				✓	✓
Misir *et al.* (2015)	✓	✓		✓	✓	✓	✓	✓	✓	✓				✓
Schwarze and Voss (2015)				✓	✓	✓			✓				✓	
Paraskevopoulos *et al.* (2015)					✓					✓				✓
Yuan *et al.* (2015)	✓			✓	✓	✓			✓				✓	
Hiermann *et al.* (2015)	✓			✓	✓	✓			✓				✓	✓
Binart *et al.* (2016)		✓			✓	✓			✓			✓	✓	✓
Braekers *et al.* (2016)	✓			✓	✓	✓		✓	✓			✓		✓

- **Applications** (see Section 2): We have selected the three main themes of home health care, building and equipment maintenance, as well as installations and repairs in telecommunications. We have also come across applications in the airline industry (Schwarze and Voss, 2015) and forest management, which we discuss in a separate section.

- **Resource qualifications** (see Section 5.1): These are the special qualifications that the resources (e.g., personnel) may have, in a hierarchical fashion or not. When the latter is the case, only column "skills" is ticked.

- **Service constraints** (see Section 5.2): The service constraints include all the requirements that customers may have. Note that Table 1 includes the most common constraints, but more details are given in Section 5.2.

- **Objectives** (see Section 5.3): Various objectives exist, a prevalent one being the minimisation of the total service time. The fourth field of Table 1 indicates that there are some prioritised visits, which is expressed by the objective function.

- **Solution methods** (see Section 6): The solution methods are generally classified as exact and heuristic algorithms. Nevertheless more details are discussed in Section 6. When both columns are ticked, the paper includes both types of algorithms or a hybrid matheuristic.

To construct Table 1, we have considered only papers in which mathematical models and algorithmic details are included, as opposed to less technical managerial papers. Nevertheless, wherever appropriate we refer to the managerial papers for the sake of completeness. Lastly, we focus on journal papers and on some selected conference proceedings. In the following sections, the classification fields mentioned above and shown in Table 1, will be 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 constraints, 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

In general, personnel may 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.

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.

Chen *et al.* (2015) 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).

5.2. Service constraints

The main characteristic of the class of problems we examine in this survey 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. Time Windows

Time windows constraints are prevalent, as shown in Table 1, and appear either as hard or soft constraints. In the latter case the goal is typically to minimise any deviation from the desired time window of the customer, which is reflected through the introduction of a penalty term in the objective function.

Table 2 summarises the papers that involve time window 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. Normally, the VRPTW considers route duration as well, by assigning a time window to the depot. For the sake of simplicity, in Table 2 we do not tick route duration when hard time windows are considered. Nevertheless, some papers explicitly consider route duration and we thus report them in Table 2. Tricoire *et al.* (2013 consider a validity period for the execution of a task within a time horizon of several days during which the tasks must be executed by one of the available resources. This is why we have included this paper within the hard time windows family of papers. One can observe that only few papers consider soft time windows, which creates opportunities for further research.

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

Reference	**Time windows**		**Route duration**
	Hard	Soft	
Xu and Chiu (2001)	✓		
Lim *et al.* (2004)	✓		
Bertels and Fahle (2006)		✓	
Tang *et al.* (2007)			✓
Akjiratikarl *et al.* (2007)	✓		
Bredström and Rönnqvist (2008)	✓		
Trautsamwieser *et al.* (2011)	✓	✓	
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)	✓		
Cortez et al. (2014)		✓	
Cappanera and Scutella (2014)			✓
Chen *et al.* (2015)			✓
Misir *et al.* (2015)		✓	
Schwarze and Voss (2015)	✓		
Hiermann *et al.* (2015)		✓	
Braekers *et al.* (2016)	✓	✓	

5.2.2. Precedence

In job shop environments and project scheduling problems (Demeulemeester and Herroelen, 2002), precedence constraints between operations and among activities, respectively, are prominent. However, the latter are less popular in the VRP area. The class of problems we examine in this survey combine job scheduling with vehicle routing properties and specifications, and therefore precedence constraints are relevant, as Table 1 shows. 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 comes first and then the plumber has to arrive within approximately one hour to finish the job. The latter 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) introduces a class of home care scheduling problems where precedence relations come as soft constraints. Specifically, the authors use a 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.

Table 3: Classification of the papers according to precedence constraints

Reference	Precedence constraints		
	Hard	Soft	Time restrictions
Li *et al.* (2005)	✓		
Bredström and Rönnqvist (2008)	✓		✓
Kim *et al.* (2010)	✓		
Rasmussen *et al.* (2012)	✓		✓
Cappanera and Scutellà (2014)	✓		
Mankowska *et al.* (2014)	✓		✓
Misir *et al.* (2015)		✓	

5.2.3. Other features

In the vehicle routing literature, there exist problems in which a subset of the customers are served in order to maximise a profit function that depends on priorities associated to particular customers. These problems include the Orienteering Problem (Golden, 1987) and the Vehicle Routing Problem with Profits (Archetti *et al.*, 2014). These features also appear in the problems we examine. Specifically, there exist priorities given to customers according to their importance. Sometimes, the service of the whole set of customers is not feasible given the available resources, e.g., technicians or nurses, or the time horizon, e.g., a day shift. To this end, relevant papers look at multi-period variants, where the time horizon is a week and the routing plan is given for a week rather than a day (Chen *et al.*, 2015).

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. Note that Binart *et al.* (2016) do not consider customers with specific resource requirements.

Typically, more than one resource is needed to perform a task. A combination of skills that come from different employees (e.g., nurses, technicians) is often more cost efficient (and sometimes the only feasible way), instead of using an all-in-one operator. Therefore, it is often required to form teams at the depot or at the customer locations (Li *et al.* 2005, Kim *et al.*, 2010, Kovacs *et al.* 2012).

Hiermann *et al.* (2015) solved a multi-modal home healthcare 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 due to pet allergies, or they are smokers, males or females etc.

Finally but yet importantly, the jobs performed at the customer locations involve a degree of uncertainty which is modelled as stochastic service times at the customer locations (Souyris *et al.*, 2012; Yuan *et al.*, 2015). Nevertheless some papers also consider stochastic travel times (Binart *et al.*, 2016). Weintraub *et al.* (1999) study the routing and scheduling of technicians to repair breakdowns, where customer locations and demands are dynamic. Lanzarone and Matta (2014) explicitly consider both stochastic service times at patients' locations, as well as stochastic demands for new patients. Similarly, Pillac *et al.* (2012) look at the dynamic technician routing and scheduling problem, where new requests appear while service is taking place.

5.3. Objectives

The routing and scheduling problems we examine in this survey mainly stem from real-life applications, and therefore, the associated objective functions are mostly multi-criteria. 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

Since it is the customers who typically impose specific service requirements, the focus 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 on 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 of the service 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. Priorities usually correspond to a component of a multi-criteria objective function and they do not constitute an autonomous single objective.

In home care routing and scheduling problems, patients usually specify some preferences regarding the nurses and carers. Braekers *et al.* (2016) model these preferences according to three levels: a preferred, moderately preferred and a non-preferred nurse for the execution of a job, and they assign 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 *et al.* (2010) deal with the technicians scheduling problem and explicitly consider outsourcing costs if the available resources are not sufficient to service the selected customers. In contrast, Cappanera and Scutellà (2014) and Blakeley *et al.* (2003) are among those who consider additional overtime costs for the given set of resources, instead of outsourcing. Table 4 summarises the papers dealing with overtime and outsourcing costs.

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

Reference	**Outsourcing**	**Overtime**
Tsang and Voudouris (1997)		✓
Zäpfel and Bögl (2008)	✓	✓
Cordeau *et al.* (2010)	✓	
Trautsamwieser *et al.* (2011)		✓
Nickel *et al.* (2012)		✓
Kovacs *et al.*(2012)	✓	
Cappanera and Scutellà (2014)		✓
Lanzarone and Matta (2014)		✓
Blakeley *et al.* (2015)		✓
Shao *et al.* (2015)		✓
Misir *et al.* (2015)		✓
Hiermann *et al.* (2015)		✓
Braekers *et al.* (2016)		✓

5.3.3. Load balancing

Load 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. 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, this is not what we have observed, as Table 1 shows, and we therefore believe there is scope for further research in this area.

5.3.4. Service completion time and delays

The time dimension plays a significant role since the main 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 over all customers.

5.3.5. Other 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) minimise the number of unscheduled tasks given a limited number of resources available. Braekers *et al.* (2016) addressed 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 of the convenience of the patients can be achieved.

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 intractable. This is also the case for the Skill VRP, the TRSP, and other resource routing and scheduling problems. There exists a significant body of work on exact methodologies for resource routing and scheduling problems. However, the focus of most researchers has been on the design and implementation of metaheuristics capable of yielding high quality solutions for medium and large-scale problem instances within short computational times. Below, we provide an overview of both exact and metaheuristic algorithms.

6.1. Exact algorithms

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 increases, the LP relaxation implies an exponential sized set of cut constraints. Also, the valid inequalities that are implied by these models with a stronger LP relaxation, can be added to weaker and less detailed models, which leads to substantial the lower bounding improvements. In particular, in the case the flow variables are split by destination, the LP relaxation of this model 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.

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 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 above described objective of the asymmetric Skill VRP can be written as

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

It is subject to the following sets of constraints. The first are 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:

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

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

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

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

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

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

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.

Based on the above mathematical models, enhanced bicriteria variants of the Skill VRP with load balancing and time windows were studied in the works of Schwarze and Voss (2013) and Schwarze and Voss (2015). At first, 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 the second paper, 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 the increase of the routing cost in the reverse case.

Cappanera and Scutellà (2015) followed a similar minmax and maxmin approach to the one proposed by Schwarze and Voss (2013). However, the focus here was the operator utilisation factor: in maxmin a maximisation of the minimum operator utilisation factor is in place, whereas in minmax the goal is the minimisation of the maximum utilisation factor. The authors introduced the concept of "pattern" to address both optimisation problems. A pattern is a possible schedule for the operators that satisfies all skill compatibility constraints and includes all the routing and scheduling decisions. To generate the patterns the authors propose both heuristics and exact procedures. The latter 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 the minmax is more suitable for minimising the operating costs.

Tricoire *et al.* (2013) presented both a branch-and-price method and local search metaheuristics to solve multi-period field service routing problems. The column generation approach is based on a set covering formulation of the problem. The pricing subproblem corresponds to the well-known elementary shortest path problem with resource constraints. It is solved optimally via a label correcting algorithm.

Rasmussen *et al.* (2012) developed a branch-and-price algorithm for the Home Care Crew Scheduling Problem. The problem involved soft preferences 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 apply a clustering scheme before solving the problem. Computational experiments on real-life data and on randomly generated instances showed that the clustering approach reduces the running times significantly without a significant loss of solution quality.

Lastly, Allaoua *et al.* (2013) developed exact and matheuristic solution methods. 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 Travelling Salesman Problem (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.

6.2. Heuristic algorithms

Early works in the field of metaheuristic algorithms for technician routing and scheduling problems are those of Xu and Chiu (2001) and Tsang and Voudouris (1997). Both are motivated from service providers in the telecommunications industry. Specifically, Xu and Chiu (2001) seek to maximise 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.

Metaheuristic algorithms were also proposed by Li *et al.* (2005), Lim *et al.* (2004) and Zäpfel and Bögl (2008). More specifically, Li *et al.* (2005) presented a simulated annealing 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-transposition and block-reverse neighbourhood structures. Zäpfel and Bögl (2008) developed a generalised guided metaheuristic framework for a combined tour and personnel planning problem which can be seen as a multi-period vehicle routing and crew scheduling problem with outsourcing. Similarly, Lim *et al.* (2004) developed a hybrid tabu search and simulated annealing algorithm as well as a squeaky wheel optimisation algorithm combined with local search for a manpower allocation problem with time windows and a composite objective.

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.

Requests with different urgency levels were considered in the work of Tang *et al.* (2007) who solved a planned maintenance scheduling problem. They developed an adaptive memory programming (AMP) method coupled with tabu search. 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.

Synchronisation and temporal precedence constraints between visits were modelled by Bredström and Rönnqvist (2008). The authors proposed exact and MIP-based heuristic algorithms for the vehicle routing problem with time windows and precedence and synchronisation constraints. They used three-index vehicle flow formulation. The heuristic iteratively solves restricted MIP problems in an effort to improve the best known feasible solution. Specifically, it restricts the associations of customers with one or more vehicles, and considers at each iteration only the positive flows from the LP relaxation. Although the restricted set of arcs is extended and reduced randomly, the arcs of the best found feasible solution are always kept. It also uses dummy variables to indicate whether a customer is visited by any vehicle. Note that the MIP has at least one trivial solution if the dummy variables are penalised in the objective function. Numerical experiments on randomly generated instances (similar to those of Everborn *et al.* (2006)) are reported, considering different proportions of synchronised pairs of visits.

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 transform the continuous schedule to a discrete 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-exchange swap 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 results on randomly generated benchmark instances.

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 patient 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. The latter can be seen as an m-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 on both randomly generated and real life data provided by a U.S. rehabilitation agency are reported.

In addition to their branch-and-price method, Tricoire *et al.* (2013) developed a metaheuristic that uses insertion, removal, moving and swapping to create large neighbourhood structures. Overall, three single-point trajectory local search frameworks were used, namely steepest descent iterative improvement, tabu search, and iterated local search. The reported experimental results on realistic data adapted from an industrial application.

In order to solve a similar home health care problem, Mankowska *et al.* (2014) developed a MILP formulation for the resource routing and scheduling problem with precedence constraints on activities and services. They applied an adaptive variable neighbourhood search (AVNS) to realistic-scale problem instances. The latter operates 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, which enables local search operators to perform local moves effectively. The authors conducted extensive experimentation on randomly generated instances of up to 300 patients and 30 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) for deriving 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 large neighbourhood search (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. The authors conducted computation experiments on real and randomly generated data sets and reported optimal solutions on small problem instances. 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.

Trautsamwieser *et al.* (2011) addressed the daily planning of home health care services that occur during a natural disaster such as an earthquake, flooding or an epidemic. The authors proposed a rigorous mixed integer programming formulation that takes into account various operations 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 both artificial data sets as well as on real life data sets provided by the Austrian Red Cross. Small problem instances are solved optimally using the Xpress solver, while a variable neighbourhood search (VNS) is also developed for real life-sized problems 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.

Hiermann *et al.* (2015) solved a real-life multi-modal home care scheduling problem faced by an Austrian home-healthcare 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. Constraint programming (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 variable neighbourhood search algorithm, a memetic algorithm (MA), a scatter search (SS) algorithm and a simulated annealing hyper-heuristic algorithm. The authors report computational results on real-life data sets. Overall, the memetic algorithm consistently outperformed all other metaheuristic algorithms.

Bertels and Fahle (2006) proposed an optimisation framework for solving a home health care routing and scheduling problem. The optimisation framework consists of linear programming, CP, simulated annealing, and tabu search. 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 constraint programming on order to improve the solutions produced. The authors tested their optimisation framework on randomly generated instances of up to 50 nurses and 600 jobs.

Nickel *et al.* (2011) addressed 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 with 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. First, a CP heuristic is used to generate a feasible solution. Then, an ALNS is 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 tabu search algorithm to improve the solution until a time limit or a move limit is reached. The authors report computational experiments on real-life data sets.

Yalçindăg *et al.* (2014) developed a two-stage approach to solve an assignment and routing problem arising in home health care. Instead of solving simultaneously the assignment and routing problem, the authors first solved the assignment of operators to patients problem, followed by the corresponding routing problem. 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 use a kernel regression technique and then apply a genetic algorithm to the associated assignment problem. Subsequently, the corresponding TSPs, which are as many as the operators used, are solved. The authors report that more extensive experimentation should be conducted to draw solid conclusions about the proposed method.

Misir *et al.* (2015) addressed the general class of problems that involve routing and scheduling of resources via a hyper-heuristic solution framework. The latter 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 present a selection hyper-heuristic, that rather than progressively building the low level heuristics (generation-hyper-heuristics), chooses one ore more low-level heuristics to produce or amend a solution at each decision step, according to a score that indicate 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.

Table 5 summarises the key characteristics of the heuristics that were developed for solving a variety of resource routing and scheduling problems. Local search techniques are prevalent and there exists some work on evolutionary algorithms. Most of the problems stem from real-life applications or make use of data inspired from real-life cases. There seems to be a need for the development of a comprehensive benchmark data set.

6.3. Stochastic programming and robust optimisation

Souyris *et al.* (2012) proposed 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 between the service times that the technicians face. In particular, closed, convex, and bounded set 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 tech-

Table 5: Summary of metaheuristic algorithms

Reference	**Evolutionary**	**Local search**	**Other features**	**Data set**
Tsang and Voudouris (1997)	N/A	GLS	fast hill climbing	real data, 118 engineers, 250 jobs
Xu and Chiu (2001)	N/A	exchange and swap neighbourhoods	GRASP; semi-exact construction heuristic	randomly generated data, 16 to 999 jobs
Lim *et al.* (2004)	N/A	TS; SA	squeaky wheel optimization	Solomon's VRPTW-based data, $\leq$ 4 technicians
Li *et al.* (2005)	N/A	SA; block-transposition and block-reverse neighbourhoods	greedy heuristics	Singapore and Hong Kong based data, up to 300 jobs
Bertels and Fahle (2006)	N/A	TS; SA	CP; pool of solutions	randomly generated data, $\leq$ 600 jobs, 50 nurses, 200 patients
Tang *et al.* (2007)	AMP	TS	upper bounds	real data, two technicians, 4659 tasks, 90 buildings
Akjiratikarl *et al.* (2007)	PSO	edge-exchange swap and insertion neighbourhoods	N/A	real data, 100 tasks, 50 customers, 12 care workers
Zäpfel and Bögl (2008)	GA	TS;2-opt, 1-1, 0-1 neighbourhoods	N/A	randomly generated data, $\leq$ 279 customers
Kim *et al.* (2010)	PSO	N/A	CPLEX; triple representation	randomly generated data, $\leq$ 480 customers
Trautsamwieser *et al.* (2011)	N/A	VNS	N/A	randomly generated data $\leq$ 100 jobs and 20 nurses, real data $\leq$ 411 clients, 512 jobs, 75 nurses
Kovacs *et al.* (2012)	N/A	ALNS	N/A	real data; randomly generated data based on Solomon's VRPTW, $\leq$ 627 tasks
Nickel *et al.* (2012)	N/A	ALNS	two-stage approach	real data, $\leq$ 361 tasks, 7 days, 12 nurses
Shao *et al.* (2012)	N/A	insertion and swap neighbourhood structures	parallel two-phase GRASP	randomly generated and real data, $\leq$ 140 patients and 16 therapists
Tricoire *et al.*(2013)	N/A	TS; iterated local search	large neighbourhoods	randomly generated data, 5 days horizon, 3 technicians, 100 customers
Yalçindăg *et al.* (2014)	N/A	N/A	two stage heuristic; Kernel regression technique	real data $\leq$ 56 patients
Mankowska *et al.* (2014)	N/A	AVNS	new efficient representation	randomly generated data with 25 patients and 5 employees
Misir *et al.* (2015)	N/A	adaptive listed threshold accepting strategy	hyper-heuristic framework	randomly generated data, $\leq$ 74 patients, 154 tasks and 14 carers, 142 tasks and 12 technicians
Paraskevopoulos *et al.* (2015)	N/A	exchange and swap neighbourhoods	double representation	randomly generated data, $\leq$ 3 resources and 199 customers
Hiermann *et al.* (2015)	SS; MA	VNS; SA	hyper-heuristic	real data, $\leq$ 509 nurses and 717 jobs
Braekers *et al.* (2016)	N/A	LNS	multi-directional local search	real and randomly generated data, $\leq$ 300 jobs, 6 skill levels, 8 hrs shift

nicians. The resulting robust counterparts leads to slightly more complicated models compared to the deterministic equivalent. The authors proposed a branch-and-price method to solve the robust problem, and performed computational experiments on real data sets.

Cortéz *et al.* (2014) proposed a constraint programming-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. Interested readers may also refer to the work of Binart *et al.* (2016) for field service routing problem with stochastic travel and service times, and to Lanzarone and Matta (2008) for analytical structural policies for the robust nurse-to-patient assignment problem.

Yuan *et al.* (2015) proposed a column generation approach for a home health care routing and scheduling problem with stochastic service times and skill requirements. They first presented a stochastic programming 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 provide approximate expressions for the expected service cost and arrival time delays. An equivalent set partitioning formulation was proposed, and solved by alternating between a master problem and a pricing subproblem. A multi-phase scheme was applied to perform the column generation process. The authors performed numerical experiments with up to 50 customer and care-givers divided into two and three skill levels.

6.4. Periodic re-optimisation algorithms and Markov Decision Processes

Weintraub *et al.* (1999) proposed a periodic re-optimization solution 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 assigned to these requests dynamically. 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 method is applied periodically in fixed time intervals or whenever new high priority requests are received.

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 parallel 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 takes into account the broken pairs distance. A post-optimization procedure based on a set covering model was used to optimally assemble 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) have adapted the above parallel ALNS for periodic re-optimization of the problem with dynamic service requests.

Chen *et al.* (2015) 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 gain experience (learning) 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, which is a two-phase local search algorithm. In the first diversification phase non-improving neighbouring solutions are accepted according to a particular threshold of the record. In the second phase, only improving moves are accepted.

7. Conclusions and research prospects

We have presented a review of combined routing and scheduling problems where the use of various resources is essential to complete the service according to special customer requirements. Our review showed 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.

Although significant work has been conducted on this topic, we believe that the field has not yet reached a high level of maturity, and therefore many challenges still stand and 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 which the capacity of the vehicle should be are two relevant questions.

- **Multi-mode on the tasks:** A feature that is prevalent in project scheduling problems (Naber and Kolisch, 2014; Peteghem and Vanhoucke, 2014) and neglected in the relevant literature, is the multi-mode nature of the tasks according of 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. 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 windows constraints, since these would rarely be satisfied in practice. Therefore, we believe these is scope for more research on modelling and solving problems with soft time windows.

- **Stochastic elements:** Even though stochastic environments are quite realistic in routing and scheduling problems, there exists only a very limited literature on this topic, which suggests fruitful research opportunities.

- **Load balancing:** We believe that since the main focus of routing and scheduling of resources is the efficient use of resources, load balancing should be of high priority in relevant problem settings. Nevertheless, very few papers have considered resource utilisation.

- **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).

Because routing and scheduling of resources define a class of problems with realistic specifications and a wide variety of real-life applications, we believe that it is essential to develop efficient solution methods that will produce high quality solutions very fast. Most of the suggestions listed above create room for further research regarding mathematical models as well as computationally efficient solution methodologies. This research topic is still open, raises various challenges and has interesting applications with high socio-economic impact.

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