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Vehicle routing problem and related algorithms for logistics distribution: a literature review and classification

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Abstract

The scheduling of deliveries and the routing of vehicles are of great importance for supply chain operations, as both determine to a great extent the distribution costs, as well as customer satisfaction. The fact that the distribution of goods is being affected by multiple factors, stemming from the demands of transportation companies, customers, and the external environment, has made the vehicle routing problem (VRP) among the most studied topics in operational research. These factors are transformed either to constraints or variables of the problem and finally lead to the creation of different variants of the VRP, formulated and studied by researchers. Moreover, the management of logistics and supply chain operations is being enhanced by the use of algorithms, integrated into information systems, enabling the optimization of real-life distribution cases. This paper presents a methodology for classifying the multiple VRP variants related to freight transportation, that most logistics and distribution companies face in their daily operations, as well as the algorithms solving the various problems. The application of the research methodology concluded to 334 papers, which were further sorted to 263 papers on the subject of freight transportation, aiming to identify the trends of the VRP variants and the applied algorithms, during the last decade. The correlation between the VRP variants and the applied algorithms is also identified. Finally, the paper presents the quantitative and qualitative results of the literature review and discusses the scientific publications with a significant impact on the research community.

Keywords Vehicle routing problem · VRP · Freight transportation · Logistics distribution · Literature review · Algorithms

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1 Introduction

The Vehicle Routing Problem (VRP) is one of the most critical challenges that logistics companies are facing nowadays. Researchers have been studying the routing of vehicles and scheduling of deliveries since 1959 when Dantzig and Ramser (1959) introduced the Truck Dispatching Problem. It is considered the paradigmatic case of the vehicle routing problem (VRP) and refers to the distribution of goods, from a central depot to geographically scattered customers.

Since then, several factors influencing the problem have been introduced, such as the variance of vehicles' capacities, time-related restrictions i.e. time windows set by customers, and the existence of multiple depots involved in the distribution. These, as well as other characteristics and requirements, are transformed either to constraints framing the problem, or variables defining the problem. This challenge creates a complex problem in which multiple criteria and limitations must be taken into account at the same time, including the requirements of each client. In any case, the variables and the constraints that originate from real-life cases that logistics companies face, are transformed from researchers to VRP variants. Therefore, the VRP variants that are analyzed below are connected to real-life cases. The objective, in most cases, both in practice and in theory, remains the same and is the minimization of the total distribution costs, while the distribution services remain at a high level.

The distribution cost constitutes a big part of the final selling price of a product and consists of both fixed and variable costs. Therefore, companies need to reduce either or both of these costs in order to achieve higher product demand from the customers. The fixed costs mainly originate from the wage of the driver or the vehicle usage costs and burden the distribution company just by using the vehicle, irrespectively of the route, and the number of customers that are served. On the other hand, the variable costs, mostly originate from the fuel costs or from the travelling time of each route. As a result, variable costs are affected by the length and the duration of the route. The restrictions and parameters that are included in routing real-life problems and are related to the different VRP variants, determine the routes, their length, and their duration. Therefore, it is primarily needed to define the VRP variants of a real-life case, the formulation of the problem, and the objective function that all together compose the total cost. All these factors will enable searching for the appropriate optimization method that can address the problem in the most cost-effective way.

In the past, the entire process of vehicle routing and scheduling was difficult for business executives to execute because it was almost exclusively based on the use of maps and on the empirical knowledge of the person in charge. Today, with the use of computers, the process has become easier, using vehicle routing and scheduling software, although challenges continue to arise mainly due to the large volume of data needed to be managed and to the increasing demands and requirements of the external environment. Of course, this does not mean that the experience of those responsible for planning deliveries is questioned. The experience of market leaders is the basis on which every computer developer will rely to be able to develop efficient algorithms, integrated into routing software. Today, the demand and the challenges faced by logistics companies are clearly more intense than ever, and it is becoming increasingly necessary to use advanced systems for the routing and execution of deliveries.

In this direction, it is vital for companies to adequately recognize not only the many variants and parameters that influence their daily operations but the algorithms as well. On this premise, the paper's main objective is firstly to define the most common VRP variants in logistics distribution and then to present the algorithms that are used for solving the specific variants. The algorithms are necessary for logistics companies in today's challenging and constantly changing environment. The number of customers, as well as their needs and requirements, are increasing, and the use of optimization algorithms is a key component for effective customer service and efficient operations.

The presented research recognizes the trends characterizing the VRP variants, and the algorithms proposed, as well as the correlation between them. More specifically, the different VRP variants are discussed and classified into sixteen (16) categories that represent the most real-life cases in logistics distribution. Some of the variants with similar characteristics are classified and discussed together in one of the 16 categories. Next, the algorithms solving the VRP variants are presented using a systematic literature review, and the relations between VRP variants and the various algorithms are discussed. To the best of our knowledge, no other paper has attempted to find the correlation between the VRP variants and algorithms at this level of analysis. Other literature reviews of VRP algorithms categorize them just in the high-level presented in Fig. 1: exact, heuristic, and metaheuristics. Our contribution is that we extend our analysis in lower levels of the categorization of the algorithms. So, the contribution of the paper is significant for researchers and practitioners in the logistics industry. Marinakis and Migdalas (2007) were the first to conduct a qualitative research of the VRP variants and the algorithms solving them, being a good starting point for the current research. These VRP variants were further enhanced by the other variants that have either presented in the publications of Eksioglu et al. (2009), Lahyani et al. (2015) and Braekers et al. (2016) either have been proposed the last few years and are considered significant in the VRP.

The remaining part of this paper is organized as follows: Sect. 2 presents the main VRP variants for logistics distribution and their classification applied in the literature review. Section 3 presents the research methodology that is followed for selecting the papers. Section 4 classifies the identified algorithms, while in Sect. 5, the literature review quantitative results and the correlation between applied algorithms and VRP variants are presented. In Sect. 6, some of the most significant publications found in the review process are further discussed, concerning the correlation between VRP and applied algorithms to solve logistics distribution cases. Finally, the conclusions and further research are drawn in Sect. 7.

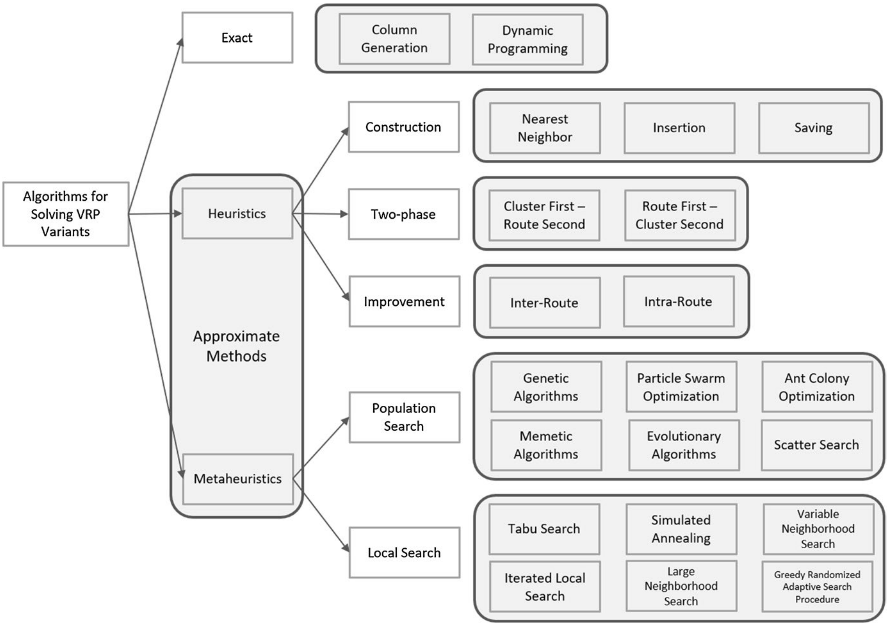

Fig. 1 Classification of algorithms for the VRP. Adopted from Labadie et al. (2016) and Lin et al. (2014)

2 VRP variants for distribution logistics

In this section, the variants that most logistics and distribution companies face in their daily operations, regarding the routing of vehicles and scheduling of deliveries, as well the way the variants are related to real-life cases are analyzed. Firstly, the capacity of the vehicles constitutes a key factor of the vehicle routing problem, as it is the most studied factor for real-life distribution cases (Kim et al. 2015; Mańdziuk and Nejman 2015) and the one that was first considered by researchers and practitioners. Capacity forms two variants of the VRP: (1) the Capacitated VRP (CVRP) in which all vehicles are identical and have the same capacity and (2) the heterogeneous fleet VRP (HFVRP), in which multiple types of vehicles exist, each of which is defined by a different capacity, fixed and variable costs (Prins 2009). In actual practice, few companies have a fleet of identical vehicles. Instead, in their effort to serve customers cost-effectively, companies use different types of vehicles. Small size vehicles mainly serve customers in city centers (last-mile distribution), while bigger size vehicles serve primarily customers and retailers who are separated by more considerable distances and that require larger volumes of orders. In both cases, when formulating the problem, it is assumed that vehicles, after the completion of their route, return to the central depot. However, it is common, especially for Third-Party Logistics (3PL) companies that seek to reduce their fixed costs, to cooperate with transportation companies that operate a fleet of vehicles at their disposal. In such cases, partners' vehicles do not necessarily return to the warehouse after the completion of the route.

This case is recognized as the Open VRP (OVRP) (Zachariadis and Kiranoudis 2010) in the research community.

Regardless of whether the fleet of vehicles is heterogeneous or homogeneous, some researchers, the last decade, consider either two dimensional (2D-VRP) either three dimensional (3D-VRP) loading constraints for ensuring that the distributed items can be feasibly loaded into the vehicles (Zachariadis et al. 2016). When considering these constraints, researchers most commonly split the problem into different problems, the one of packing and the one of routing. In the present paper, we consider the 2D and 3D loading constraints as a single variant of the problem, the 3D-VRP, and we focus only on the algorithms proposed for the routing of vehicles. Furthermore, another variant that is related to the loading capacity is the Truck and Trailer VRP (TTVRP). In the specific case, some customers may be serviced by a truck pulling a trailer, while others only by a single truck (Lin et al. 2010). It is related mainly to deliveries and collections in city centers and rural areas with accessibility restrictions (Usberti et al. 2013).

In other cases, traffic congestion, access restrictions, and environmental regulations in cities force companies to use vehicles with lower capacities (Quak and de Koster 2009; Sitek 2014; Perboli and Rosano 2019). In this case, the vehicles can visit only a few customers during the trip. However, they can execute more than one trip during the working day, leading to the Multi-Trip VRP (MTVRP) (Brandão and Mercer 1998). In order to optimize the procedure and execute the maximum number of trips during the drivers' shifts, satellite facilities (VRPSF) are commonly used for the replenishment of the vehicles. In this context, the Two-Echelon VRP is applied, and the delivery of goods from the depot to customers is managed by routing vehicles through satellite facilities (Grangier et al. 2016). Therefore, there are two routing procedures, one for the vehicles starting from the depot, delivering to satellites and returning to the depot, and a second one from satellites to customers and back to the satellites (Crainic et al. 2010). When more than two layers of distribution are considered, the variant is called Multi-Echelon VRP (MEVRP). Later in this paper, VRPSF, 2EVRP, and MEVRP are classified into one category, the MEVRP, as these variations have many common characteristics.

The requirements of the customers determine to a great extent, the setting of the VRP parameters. One of the most common variants of the problem is the VRP with time windows (VRPTW), where each customer determines a time interval in which the order must be delivered. If the vehicle arrives before the start of the time window, it must wait until it opens, while it cannot arrive after the end of the time window (César and De Oliveira 2010). In cases such as this, the time windows are characterized as hard. Another case is the time windows to be soft, meaning that the vehicle may arrive after the end of the time window, but at an additional cost. This variant is significant in logistics since most end-customers determine a time window in order for the goods to be delivered, and it has been inextricably linked to the accuracy of deliveries and to customer satisfaction. However, good interpersonal relationships can also improve the quality of services provided. In the last decade, a new variant of the VRP has emerged, the consistent (ConVRP), in which trust between distribution companies and customers becomes a priority. Therefore, companies construct consistent routes over a period of time, which reduces the number of drivers each customer has to deal with (Feillet et al. 2014), and consequently, the friction between them.

It is also essential to highlight that logistics operations do not end at the phase of the delivery of goods, as the phenomenon of customers returning products is common in practice. Both the VRP with backhauls (VRPB) and the VRP with simultaneous pickups and deliveries (VRPSPD) study the case of deliveries and pickups during the execution of the routes. In the case of VRPSPD, the goods start from the central depot and are delivered to customers, while pickups are simultaneously loaded to vehicles, before returning to the depot (Montané and Galvão 2006). In every phase, both the delivery and the pickup loads must be taken into account, as the total capacity of the vehicle cannot be exceeded. On the other hand, VRPB, which also involves pickups and deliveries, has an additional limitation, which, however, simplifies the problem, and is that all pickup items are collected after the deliveries in every route (Goetschalckx and Jacobs-Blecha 1989). These two variants are considered as a single one, under the name VRPPD (VRP with pickups and deliveries) in the classification of the literature, as both of them involve pickups and deliveries.

Environmental pollution has forced governments to set environmental regulations, in their effort to reduce noise, traffic, CO_2 emissions, and consequently to improve the quality of life for citizens. The fact that a big part of CO_2 emissions originates from road freight transportation could not leave transportation companies unaffected. Therefore, along with minimizing transportation costs, companies need to minimize CO_2 emissions, a problem that is identified in the literature as the Green VRP (GVRP) (Lin et al. 2014) or as the Pollution Routing Problem (PRP). The PRP is somehow more difficult to solve as the emissions depend not only on the speed of the vehicle but in the load of the vehicle in every step of the distribution process as well. Bektas and Laporte (2011) were the first that studied the specific variant of the VRP. Additionally, electric vehicles and hybrid vehicles, that can operate both electrically and with traditional fuel, contribute to the minimization of pollution and CO2 emissions. These versions of the problem are known as Electric VRP (EVRP), and Hybrid VRP (HVRP), respectively and have lately attracted companies' and researchers' attention (Mancini 2017). These four VRP variants (GVRP, PRP, EVRP, and HVRP) are considered as one category, under the name GVRP, in the classification of the literature.

The accuracy of deliveries depends on a great extent on the travel time between delivery points, pick up points, and depots. This problem has been tackled via the use of a function, in which the departure time is the independent variable, and is known as the Time-Dependent VRP (TDVRP) (Andres Figliozzi 2012). This attribute is crucial for the better prediction of traffic congestion and of travel time between nodes, as well as for checking the feasibility of routes. The initial routing and scheduling, where delivery and pickup orders are known before the start of the routes, can become much more reliable through this variant. However, orders and unforeseen events may appear dynamically during the execution of the route (Flatberg et al. 2007). In this case, changes in the scheduling of deliveries are made to satisfy new customer orders and to avoid delays caused by unforeseen events. The dynamic and stochastic version of the problem (known as Dynamic VRP—DVRP and Stochastic

VRP—SVRP), must be reinforced by real-time communication between the vehicles and the planners of the transportation companies, to face each case effectively (Pillac et al. 2013). Nowadays, the need for dynamic routing also arises from traffic congestion, which usually affects in a stochastic way the implementation of the schedule of deliveries (Yu and Yang 2019).

Another variable that is highly dependent on the number of distribution centers that collaborate for the distribution of goods is the Multi-Depot VRP (MDVRP). In cases that a single company manages multiple distribution centers, customers are most commonly assigned to the nearest warehouse, which contains the goods each customer ordered (Renaud et al. 1996). Therefore, the MDVRP can be treated as a series of multiple single depot problems, simplifying the initial one. With this assumption, the problem can be addressed adequately, especially in cases where new customers appear every day, leading to non-fixed routes. However, there are cases that this simplification cannot be made, such as in a collaborative distribution network (Collaborative VRP), where a group of companies cooperate in order to minimize the operating and distribution costs. The Collaborative VRP is usually considered as an extension of the MDVRP, which can improve the load factor of vehicles, reduce crisscross transportation and enhance the efficiency of logistics network operation (Wang et al. 2017). Therefore, the Collaborative and the Multi-Depot VRP are united in a single category in our classification under the name MDVRP.

Finally, two variants of the VRP that are less common among transportation companies are (i) the Split Delivery VRP (SDVRP) and (ii) the Periodic VRP. In the first case, the constrain that each customer must be visited exactly once and by one vehicle is relaxed, and the customers' demand is allowed to be split (Silva et al. 2015) among the available vehicles. The specific relaxation may prove to be advantageous in some distribution environments, such as when the mean customer demand is a little over than the vehicle's capacity (Archetti et al. 2008), offering, increased load factors of vehicles and reduced number of delivery routes, but at the expense of increased traveled distance. As for the PVRP, the routes are constructed over a planning horizon (Coene et al. 2010), which may be days or even weeks. This model is important for logistics companies that manage fixed orders every day, needing an optimal plan for that period.

Certainly, in most cases, both in practice and in theory, multiple constraints and challenging features are considered simultaneously, so that the problem addressed, reflects most in real-life routing cases. Some representative real-life constraints that are considered in such cases, according to Rabbouch et al. (2019) and (Caceres Cruz et al. 2014), are the capacity and the number of vehicles, ready and due times for serving each customer, the heterogeneous fleet of vehicles, and the different warehouses. These constraints are associated with some of the VRP variants that have already been analyzed, such as the Heterogeneous Fleet, the Multi Depot, the Pickup and Deliveries, the Open, and the Time Windows. More specifically, Penna et al. (2019) manage to tackle all the above VRP variants at the same time, while Belmecheri et al. (2013) and Belloso et al. (2019) address the heterogeneous fleet VRP with backhauls and time windows. In the last few years, the consideration of multiple constraints (and multiple VRP variants) at the same time is defined by researchers as the Rich VRP (Lahyani et al. 2015). The researchers, who study the Rich

VRP, use algorithms commonly dealing with the containing variants in order to simplify the problem. Since the current research studies the correlation between the VRP variants and algorithms, Rich VRP has been incorporated in the search term in order to include all the related variants discussed in these papers, but it is not classified as an individual variant of the problem as it refers to other VRP variants.

Over the years, more and more variations of the VRP are studied from researchers in order to address cases that logistics companies face in their daily operations. We consider that the VRP variants analyzed in this section are those that reflect most to the challenges logistics companies face in freight distribution. The existence of multiple variables and constraints forces logistics companies to find ways to optimize their operations and minimize their costs. Information Systems can strengthen this approach incorporating in their functionality the use of algorithms. Multiple algorithms have been developed and proposed to address the VRP. Initially, exact algorithms were proposed due to the high quality of the solutions produced, but in the case of large-scale problems (more than 100 customers), the computational time needed for an exact algorithm to find the optimum solution increases so much that it ends up being impractical. Consequently, heuristic and metaheuristic algorithms were developed, as both offer a better balance between solution quality and computational time.

3 Literature review research methodology

The VRP is a well-studied field as its variants deal with real-life cases and problems that most distribution and logistics companies face. Researchers have formed multiple variants in their effort to cover all cases and improve the routing of vehicles and scheduling of deliveries. The external environment in which logistics companies work, their size, their customers, and their partners determine to a great extent the problems and the variants which must be considered. In Sect. 2, the VRP variants which are related to freight transportation and distribution are thoroughly described in order to justify how these variants are related to real-life cases. More specifically, the selection of the VRP variants presented in this paper has resulted mainly by the annotated bibliography of Marinakis and Migdalas (2007), who considered and analyzed the Capacitated VRP, the VRP with Time Windows, the VRP with pickup and deliveries, the Multi-Depot VRP, the Stochastic and Dynamic VRP, the Heterogeneous Fleet VRP, the Periodic VRP, and the Open VRP. Also, the Split Delivery, the Time-dependent, the Green, the Truck and Trailer, and the Multi-trip VRP, are among the variants that emerged from the articles of Eksioglu et al. (2009), Lahyani et al. (2015) and Braekers et al. (2016) which are review papers similar to ours, while the VRP with 3D loading constraints, the Multi-echelon VRP and the Consistent VRP have emerged independently as they seem to have attracted the interest of researchers the last few years. Through this approach, we manage to include the VRP variants that fit most in our research about freight transportation. However, apart from the VRP variants, emphasis must be given in the algorithms that have been developed and proposed for solving those problems. Distribution companies that consider multiple VRP variants simultaneously cannot effectively face all variants without the contribution of algorithms. The integration of an algorithm into the system follows it's testing and evaluation process carried out through either benchmark instances presented in the literature or real-life cases.

As there is no previous research correlating VRP variants and algorithms solving them, the need for such research has emerged. Therefore, a literature review process adopted from the research of Braekers et al. (2016), Eksioglu et al. (2009) and Gayialis et al. (2019) is followed. The research protocol is well defined as it aims at an efficient and well-recorded review, which includes multiple VRP variants. The main goal of the present research is to identify the trends of VRP variants and the applied algorithms offered to tackle them, as well as their correlation. Additionally, papers that are considered significant, and pioneer in the research community are presented. The papers having the most citations were considered as significant, and they were further discussed in this review.

Scopus database (https://www.scopus.com) was used for an advanced search, as it covers a wide range of peer-reviewed academic publications. Only articles published in journals, in English language and the last decade, are considered. Initially, only publications containing at least one of the previously defined VRP variants, the term "algorithms", as well as, at least one of the terms "benchmark instances", "tested", "test", simulate", "simulation", "validate" and "validation" in their title, abstract, or keywords are selected. Through this procedure, we ensure that the resulted publications not only propose an algorithm but also test and validate the algorithm either to benchmark datasets, either to real-life cases, making them more reliable. Also, the fact that the VRP has been intensively studied, while this research concentrates on freight transportation, lead to the decision not to include terms such as "waste", "cash", "hazardous", "concrete", "healthcare", "care", "blood", "bus" and "transportation of people", as they cannot be considered commodities and they have special transportation condition which forms another field of study. Furthermore, the terms "bike", "bicycle", "flying robots" and "UAV" were excluded as they refer to different means of transportation than vans and tracks. The terms "location routing" and "inventory routing" were also excluded from our research as we made the decision to exclude any combined problems. Also, this research is limited to the Subject Areas of "Computer Science", "Engineering", "Mathematics", "Decision Sciences" and "Business, Management, and Accounting". The research term includes only specific journals, selected according to the Scimago Journal Rank (https://www.scimagojr.com) in order to reduce the number of papers analyzed, focusing on the most prestigious journals. More specifically, only journals that belong in the first quartile (Q1) are considered and contained in our research protocol. The exact search term applied to the Scopus database is presented in Table 1.

This specific research strategy resulted in 334 publications, each one of which was studied thoroughly in order to determine its relevance. The fact that the VRP is well studied in the literature has led to its connection with other research topics. Typical examples are the dial-a-ride and the team orienteering problems that do not refer to freight transportation. Also, the single-vehicle case, which is known as the Travelling Salesman Problem (TSP), was also decided to be excluded from the research. In this paper, it is not our intention to review the complete TSP literature, neither research topics related to the VRP, rather, to focus on the VRP and the

Table 1 Search term applied to scopus database

Literature review search term
TITLE-ABS-KEY (((“Time windows” OR “VRPTW”) OR (“Multitrip” OR “Multi-trip” OR “MTVRP”) OR (“Satellite Facilities” OR “Echelon”) OR ((“Hybrid” AND “VRP”) OR (“Green” AND “VRP”)) OR (“Time-dependent VRP” OR “Time dependent VRP” OR “TDVRP”) OR (“Pollution routing” OR “PRP”) OR (“Electric VRP”) OR (“Capacitated VRP” OR “CVRP”) OR (“VRP” AND (“two-dimensional” OR “three-dimensional” OR “3D loading constraints” OR “2D loading constraints”)) OR “Truck and Trailer” OR (“Dynamic VRP” OR “DVRP”) OR (“Simultaneous Pickups and Deliveries” OR “VRPSPD” OR “Backhauls” OR “VRPB”) OR (“Rich VRP”) OR (“Heterogeneous Fleet” OR “Heterogeneous” OR “HFVRP”) OR (“Multi depot” OR “Multi-depot” OR “MDVRP”) OR (“Open VRP” OR “OVRP”) OR (“Split Delivery VRP” OR “SDVRP”) OR (“Periodic VRP” OR “PVRP”) OR (“Stochastic VRP” OR “SVRP”) OR (“Collaborative VRP”) OR (“Consistent VRP” OR “ConVRP”) OR (“VRP with workload balance”) OR (“site-dependent”)) AND (“Vehicle routing” AND (“Benchmark Instances” OR “Benchmark” OR “validate” OR “validation” OR “test” OR “tested” OR “simulate” OR “simulation” OR “case study”) AND (“Algorithm”)) AND NOT (“Waste” OR “cash” OR “hazardous” OR “Concrete” OR “Healthcare” OR “Cold” OR “Care” OR “Location-routing” OR “Location routing” OR “UAV” OR “Transportation of people” OR “Flying robots” OR “Bus” OR “Asset localization” OR “Inventory routing” OR “Blood” OR “Bike” OR “Bicycle”)) AND (LIMIT-TO (SRCTYPE, “j”)) AND (LIMIT-TO (DOCTYPE, “ar”)) AND (LIMIT-TO (SUBJAREA, “COMP”) OR LIMIT-TO (SUBJAREA, “MATH”) OR LIMIT-TO (SUBJAREA, “ENGI”) OR LIMIT-TO (SUBJAREA, “DECI”) OR LIMIT-TO (SUBJAREA, “BUSI”)) AND ((PUBYEAR > 2009)) AND (LIMIT-TO (EXACTSRCTITLE, “Computers And Operations Research”) OR LIMIT-TO (EXACTSRCTITLE, “European Journal Of Operational Research”) OR LIMIT-TO (EXACTSRCTITLE, “Expert Systems With Applications”) OR LIMIT-TO (EXACTSRCTITLE, “Applied Soft Computing Journal”) OR LIMIT-TO (EXACTSRCTITLE, “Computers And Industrial Engineering”) OR LIMIT-TO(EXACTSRCTITLE, “Information Sciences”) OR LIMIT-TO (EXACTSRCTITLE, “International Transactions In Operational Research”) OR LIMIT-TO (EXACTSRCTITLE, “Soft Computing”) OR LIMIT-TO (EXACTSRCTITLE, “Annals Of Operations Research”) OR LIMIT-TO (EXACTSRCTITLE, “Journal Of The Operational Research Society”) OR LIMIT-TO (EXACTSRCTITLE, “Transportation Research Part C Emerging Technologies”) OR LIMIT-TO (EXACTSRCTITLE, “Transportation Science”) OR LIMIT-TO (EXACTSRCTITLE, “Applied Mathematical Modelling”) OR LIMIT-TO (EXACTSRCTITLE, “Engineering Optimization”) OR LIMIT-TO (EXACTSRCTITLE, “Operations Research”) OR LIMIT-TO (EXACTSRCTITLE, “Transportation Research Part B Methodological”) OR LIMIT-TO (EXACTSRCTITLE, “Transportation Research Part E Logistics And Transportation Review”) OR LIMIT-TO (EXACTSRCTITLE, “Journal Of Advanced Transportation”) OR LIMIT-TO (EXACTSRCTITLE, “Swarm And Evolutionary Computation”) OR LIMIT-TO (EXACTSRCTITLE, “IEEE Transactions On Automation Science And Engineering”) OR LIMIT-TO (EXACTSRCTITLE, “International Journal Of Advanced Manufacturing Technology”) OR LIMIT-TO (EXACTSRCTITLE, “International Journal Of Production Economics”) OR LIMIT-TO (EXACTSRCTITLE, “Journal Of Intelligent Manufacturing”) OR LIMIT-TO (EXACTSRCTITLE, “Optimization Letters”) OR LIMIT-TO (EXACTSRCTITLE, “International Journal Of Industrial Engineering Computations”) OR LIMIT-TO (EXACTSRCTITLE, “Neurocomputing”) OR LIMIT-TO (EXACTSRCTITLE, “Advances In Production Engineering And Management”) OR LIMIT-TO (EXACTSRCTITLE, “Flexible Services And Manufacturing Journal”) OR LIMIT-TO (EXACTSRCTITLE, “IEEE Access”) OR LIMIT-TO (EXACTSRCTITLE, “IEEE Computational Intelligence Magazine”) OR LIMIT-TO (EXACTSRCTITLE, “IEEE Systems Journal”) OR LIMIT-TO (EXACTSRCTITLE, “IEEE Transactions On Systems Man And Cybernetics Part C Applications And Reviews”) OR LIMIT-TO (EXACTSRCTITLE, “Informs Journal On Computing”) OR LIMIT-TO (EXACTSRCTITLE, “International Journal Of Bio Inspired Computation”) OR LIMIT-TO (EXACTSRCTITLE, “International Journal Of Geographical Information Science”) OR LIMIT-TO (EXACTSRCTITLE, “International Journal Of Shipping And Transport Logistics”) OR LIMIT-TO (EXACTSRCTITLE, “International Journal Of Sustainable Transportation”))

variants described in Sect. 2. Following the described process and as seen in the next section, 263 articles resulted and then categorized according to the classification of the proposed algorithms. In this way, an established statistical analysis is presented.

4 Classification of algorithms

The proposed research concerns the study of the algorithms which effectively deal with a set of VRP variants. The selected variants are the most common ones faced by logistics companies in distribution, and their characteristics and constraints meet the requirements of freight transportation, as presented in Sect. 2. Therefore, the taxonomy focuses on two key characteristics, namely the VRP variants, and the algorithms. The review of the literature deals with the algorithms addressing the selected variants of the VRP and is carried out to determine the research community's trends for both cases.

More specifically, the work of Labadie et al. (2016) and Lin et al. (2014) was adopted in order to form a complete classification of algorithms applied in the VRP. Their research was used as the basis for our new classification of algorithms shown in Fig. 1. This classification is a key component of the proposed work, as the correlation between VRP variants and algorithms is based on this analysis. Exact algorithms mainly include Lagrange Relaxation methods and Column Generation but are not further analyzed due to the limited research interest. On the other hand, heuristic algorithms are separated into three main categories, namely Construction, Two-Phase, and Local Improvement heuristics, each containing specific algorithms, as shown in Fig. 1. Our interest is mainly focused on this level of analysis, even if each category of heuristics contains specific algorithms. Other literature reviews, such as those of Eksioglu et al. (2009), Lahyani et al. (2015) and Braekers et al. (2016), either do not focus on algorithms, either do not present this level of analysis. More specifically, they only emphasize on the three main categories of algorithms, exact, heuristics, and metaheuristics, while we manage to extend the analysis to a more detailed level.

Emphasis is mainly given to Metaheuristic algorithms, which are more advanced procedures, and contain Population Search and Local Search methods. Population-based meta-heuristics aim at generating a new solution from a set of solutions, either by combining and pairing existing ones or by making them cooperate through a learning process. Genetic algorithms (GA's) are the most common metaheuristic algorithms and are inspired by the process of biological evolution. Initially, a population (parents) of solutions, known as chromosomes, is selected. Then in each iteration, two parents are selected form the population, according to their fitness function, and are combined through the crossover procedure to provide the offsprings (children). Consequently, the mutation procedure is applied to ensure the diversity of the population. Finally, the best solutions are selected to be used as parents in the next iteration. Memetic algorithms (MA's) are an "advanced" version of GA's as for each child, a local improvement method is applied. Both algorithms belong in the greater category of Evolutionary Algorithms (EA's) (Labadie et al. 2016). Scatter Search (SS) needs a smaller set of solutions, containing both good and diversified solutions in which local improvement methods are applied. The general category of swarm-based algorithms includes both Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO). In ACO, ants move in the graph, building paths, according to probabilistic rules. Commonly, ACO is combined with local improvement procedures. In PSO, a population of "particles" exists, and each one moves from its position to another one in the search space. The move of each particle is influenced both by the best position the specific particle has achieved, as well as, by the best solution of all particles.

On the other hand, Local Search metaheuristics aim at exploring the solution space by moving the current solution to another promising one in the neighborhood (Mekamcha et al. 2019). Tabu Search (TS) is one of the most frequently applied algorithms and depends on the principle of continuing the search even if a local optimum has been reached. Therefore, a move is applied in the current solution even if the objective deteriorates. It should be noted, however, that a previously visited solution cannot be revisited as the tabu list records the recent searches. Another algorithm, the Large Neighborhood Search (LNS), explores a wide search space, as the initial solution is partially destroyed according to the removal operators and finally repaired, according to the reinsertion operators. The Adaptive LNS method is similar, except that the most efficient operators that are subject to change during the search are applied in each iteration. Guided Local Search (GLS) method operates by assigning penalties in the objective function so that the search space becomes wider and avoid trapping in a local optimum. Simulated Annealing (SA), Variable Neighborhood Search (VNS), Greedy Randomized Adaptive Search Procedure (GRASP), and Iterated Local Search (ILS) are also local search metaheuristics that apply procedures for avoiding trapping in a local optimum.

Researchers, in their effort to optimally solve the VRP, combine algorithms to exploit the advantages of each procedure. Especially in the last few years, hybrid algorithms that combine meta-heuristics are developed in order to achieve better results (Kaboudani et al. 2018; Rajabi-Bahaabadi et al. 2019). This is an attribute that is studied in the literature review to determine which algorithms are used in solving multiple VRP variants.

5 Research results analysis

In this section, the numerical results that have emerged from the categorization of the relevant papers are presented. The detailed classification results of the 263 articles are shown in the electronic Appendix of this manuscript. These papers concluded from the methodological approach presented in Sect. 3. The classification of the articles has been separated into two strands, the VRP variants and the applied algorithms for solving these variants. The present research focuses on published articles from 2010 until the first quarter of 2020, in order to identify the trends of the last decade. The results of our research indicate that there is a constant interest in solving the selected VRP variants, as at about 26 papers are published every year. Most publications come from the journals "Computers & Operations Research", "European Journal of Operational Research", "Expert

Systems with Applications", "Applied Soft Computing Journal" and "Computers & Industrial Engineering". These journals, over the last decade, have published at least 20 articles that meet our requirements in the specific research approach.

Table 2 presents the number of publications that deal with each one of the selected VRP variants. Most papers, in their effort to address real-life problems, examine more than one variant of the problem. This is the reason why the cumulative relative percentage is more than 100%. Capacitated VRP is, by far, the most studied variant (82.89%) as it is the simplest variant and, therefore, can be easily combined with others. Papers that do not consider the CVRP deal instead with the Heterogeneous Fleet VRP (17.11%). Variants that make use of time windows are significantly studied as they adequately reflect real-life cases, and thus appear in almost half of the problems (46.39%). Respectively, the VRPPD is appeared in the one-fifth of the reviewed papers, due to its high correlation with real-life distribution cases. The GVRP seems to attract the attention of researchers during the last 6 years, due to the current need for minimizing CO2 emissions and fuel consumption and the use of electric vehicles.

Due to the fact that many companies have multiple warehouses that need to be considered for the distribution process, as well as, that more often in today's competitive environment, companies collaborate and cooperate in the distribution process for reducing operating cost, made the MDVRP and the Collaborative VRP among the most studied variants of the VRP. Also, compared to other classification and reviews, like those of (Eksioglu et al. 2009; Braekers et al. 2016), which are among the most analyzed, there are no data relative to the MEVRP. This variant has gained the interest of researchers and practitioners in the last few years, due to the need of companies to optimize the routing of vehicles in every stage of the supply chain.

Also, the VRP with two and three-dimensional loading constraints present an increased interest since 2013. This variant has been favored by the evolution of computer science and has given researchers the opportunity to consider simultaneously two complex problems, the routing of vehicles and the packing. Respectively, the DVRP and the TDVRP have taken advantage of new technologies, which offer real-time and big data. Both can significantly enhance the efforts of planners not only to create an initial and reliable plan of routes but also to make better decisions when needed, in less time. On the other hand, variants such as the OVRP, the SDVRP, and the MTVRP, seem to have a relatively low, but constant interest from researchers over the last decade, due to their correlation with real-life logistics cases, that do not frequently occur.

Finally, some variants of the VRP seem to receive the least attention from the research community. More specifically, the Periodic VRP and the ConVRP have relative percentages of less than 1.95% over the years. That is mainly due to the fact that few companies can plan their routes over a period of time in today's dynamic environment, as well as concerning the ConVRP, it is a relatively new variant of the VRP. Also, the TTRP is appeared in only 4 articles out of 263 extracted, and though trailers are used in some cases, such as in milk collection, it is a commonly neglected variant of the VRP in the last decade.

Table 2 VRP variants over years

VRP variants	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Total	Relative percentage
CVRP	18	11	12	15	19	34	24	24	18	31	12	218	82.89
VRPTW	7	5	7	7	10	16	12	12	13	22	11	122	46.39
VRPPD	3	1	3	6	4	10	6	5	3	8	4	53	20.15
HFVRP	3	2	1	3	7	4	6	2	4	11	2	45	17.11
MDVRP	1	1	2	3	4	5	3	1	3	3	3	29	11.03
GVRP				1	3	2	7	6	1	8	2	30	11.41
DVRP	1	1	2		3	4	2	1	1	5	1	21	7.98
3D-VRP				2	2	4	3		3	1	2	17	6.46
OVRP	4	1		1	1	1	1		1	1	1	12	4.56
SDVRP		1			2	1	2	1		3		10	3.80
TDVRP		1	1	1			2	4		1		10	3.80
MEVRP				2		1	1		1	4		9	3.42
MTVRP	1	1				1	1	1		3	1	9	3.42
PVRP		2								2	1	5	1.90
ConVRP			1			1			1	1		4	1.52
TTRP	2	1							1			4	1.52

In Table 3, the amount of papers that propose or develop each one of the algorithms of the classification shown in Sect. 3, is also presented. It should be pointed out that hybrid algorithms were presented as a separate category, including algorithms that were explicitly stated as "hybrid" in the studied papers. Metaheuristic algorithms dominate the field of proposed algorithms with 252 cases, followed by Classical Heuristics (122) and Hybrid algorithms (53). Exact algorithms (32) are developed less often due to their computational complexity and their limitation of applying successfully only to small-scale problems. It is an expected outcome that heuristic and metaheuristic algorithms are used more often than the rest, mainly because the VRP is an NP-Hard Problem. It should be noted that the sum of the number of publications does not equal to 263, which is the number of the studied papers because many of the examined papers either propose hybrid algorithms (53 articles) which by definition include more than one method or combine multiple algorithms.

In a more detailed analysis, construction algorithms seem to appear more frequently as they are applied both for solving the problem and for the creation of the initial solution used by metaheuristic algorithms. Local improvement heuristics are also widely used due to their ease of implementation and their ability to improve solutions fast. The first metaheuristics proposed for the VRP, clearly surpassing other algorithms in terms of solution quality, were Simulated Annealing and Tabu Search, which are still studied by researchers. However, GA's have attracted the interest of researchers in the last decade, as they are the second most frequently applied metaheuristic. In total, Evolutionary algorithms, which contain GA's and MA's, are developed and applied more often than swarm-based algorithms (ACO and PSO). As for the local search metaheuristics, researchers equally apply and develop these algorithms, except the GLS and the GRASP, which are less studied. Metaheuristic algorithms have the ability to offer good quality solutions or even optimum results when tested on benchmark instances. Simultaneously, their computational speed improves as technological advances. These two factors guarantee the research interest in these algorithms in the future.

As already mentioned above, the VRP variants are rarely studied individually. In most cases, researchers tackle a combination of these variants simultaneously to a better approximate real-life case. The CVRP, the HFVRP, and the VRPTW are among the most examined variants as shown in Fig. 1, combined with almost all the other variants. The only exception is the combination of the CVRP with HFVRP, as these two variants present different and mutually exclusive initial parameters relating to the capacity of the vehicles used. The CVRP is combined most with other variants due to the assumption that all vehicles are identical, which simplifies the problem significantly. As for the rest variants, multiple combinations between the VRPTW, the VRPPD, the HFVRP, the MDVRP, and the GVRP are observed and formed by researchers.

In Table 4, the correlation between VRP variants and their algorithms is being presented. A large number of papers suggest hybrid resolving algorithms for almost all variants of VRP, indicating a trend in the research community towards these algorithms. Construction and local improvement heuristics are involved in the solution of all VRP variants. As for the VRPTW, while TS and SA used to

Table 3 Applied algorithms per year

Applied method	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Totals
Exact	2	2	1	5	2	2	2	4	4	6	2	32
Heuristics (122)												
Construction (Constrn.)	8	6	5	4	7	9	9	3	7	10	2	70
Two-phase	1					1	1			1		4
Local improvements (Local imp.)	6	1	4	5	2	12	5	2	2	9		48
Metaheuristics (252)												
Local search (145)												
Simulated annealing (SA)	1			2	2	6	3	3	1	1	1	20
Tabu search (TS)	4	2	1	1	4	1	1	5	2	3	1	25
Variable neighborhood search (VNS)	2	1	2	1	5	5	3	3	4	10	4	40
Iterated local search (ILS)	2		1	1	2	6	1	1	1	3	2	20
Adaptive large neighborhood search and large neighborhood search ((A)LNS)	1	1	1		1	5	9	2	1	5	2	28
Guided local search (GLS)	1											1
Greedy randomized adaptive search procedure (GRASP)						2		1				3
Other local search algorithms (LSA)	1	1	1			1		2	1		1	8
Population search (107)												
Genetic algorithms (GA)	3	1	2	3	4	6		3	4	5	2	33
Memetic algorithm (MA)	1					1	1		1	2	1	7
Other evolutionary algorithms (EA)	2		1	1	1	4	2	1	3	2	1	18
Ant colony optimization (ACO)	1	2	1	1	2	2	4	2	2	2	2	21
Particle swarm optimization (PSO)		1	2	2		2	1	3	2	2		15
Other swarm intelligence algorithms (SIA)					1	2	1	2	1	3	1	11
Scatter search (SS)	1				1							2
Hybrid	2	1	3	4	4	11	5	4	7	8	4	53

Table 4 Correlation between VRP variants and algorithms

VRP variants	Exact	Heuristics			Local search metaheuristics								Population search metaheuristics							Hybrid
		Constrn.	Two-Phase	Local imp.	SA	TS	VNS	ILS	(A)LNS	GLS	GRASP	LSA	GA	MA	EA	ACO	PSO	SIA	SS	
CVRP	26	60	3	42	16	20	31	15	23	1	3	8	27	5	17	18	13	9	2	44
VRPTW	15	29	1	15	9	16	13	3	14		1	2	22	5	14	12	7	6	1	32
VRPPD	7	16	2	11	6	7	11	6	3		1	2	5		4	4	4			10
HFVRP	6	10	1	6	4	5	9	5	5				6	2	1	3	2	2		9
MDVRP	3	12		5	2		4	7	1		1	1	9			2	2	1		11
GVRP	5	6	1	3	2	4	5	2	9				2			1		1		5
DVRP	1	8		3		1	1	1	2		1		3	1	2	4	3	1		1
2D-VRP		4		5	3	1	6	2	2						1			1		2
OVRP	2	2		2	1	1	2	4		1		1			1		1	1		2
SDVRP	3	5		3			1	1	1											
TDVRP		4		1			2		1				2			2	1	1		1
MEVRP	4	3		1			1		2			1	1	2				1		2
MTVRP	2	3		2			2	1	2				1	1						2
PVRP	2				1	1										2				
ConVRP		2		2		2	2		1											
TTRP	1	1	1	1	1		1													1

be among the most common applied algorithms, a new direction towards Evolutionary Algorithms (mainly GA's) seems to have formed. In cases that only the CVRP and the VRPTW are considered, the chromosome's structure in GA's contributes to the faster execution of the crossover and mutation operators, as well as the storage of the population. More specifically, the chromosome is an array with length equal to the number of customers and contains all customers-nodes. The sequence of the elements-customers determines the order of visitations. In the last decade, the VRPTW is more frequently faced as multiobjective, and the simultaneous existence and development of multiobjective EA's leads in an increased number of articles solving the VRPTW with EA's.

The HFVRP is a significant variant for logistics and transportation companies, as most of them have a mixed fleet of vehicles. However, only 17.11% of articles consider the specific variant. The most common algorithms applied in the HFVRP are (i) GA's, (ii) the VNS, (iii) the (A)LNS algorithms, and (iv) the ILS algorithm. The three local search algorithms are applied in a single solution leading to shorter computational times. Instead, EA's which are frequently applied in this problem, need to storage solutions (which vehicle is used in each route), leading to increased computational times. However, the evolution process can contribute to a better solution in a reasonable time depending on the population size and the number of generations.

The Green, the Electric, the Hybrid VRP, as well as, the Pollution Routing Problem are considered as one category in our analysis. These variants have been proposed and appeared for the last 15 years and are thoroughly studied by researchers. In these first attempts for solutions reducing both CO_2 emissions and fuel consumption, (A)LNS algorithms are mostly applied due to their advantage of being applied in a single solution and their ease of implementation. More specifically, even simple "removal" and "reinsertion" operators can be very effective in any class of the VRP and, therefore, to the GVRP and the PRP. Finally, the fact that in this class of VRP variants, the fleet is mixed, leads to the conclusion that algorithms that can be efficient in the HFVRP can also be in the Green, the hybrid, and the Electric VRP, as the vehicles' capacities and costs differentiate in most of these variants as well.

Local based metaheuristics prevail population-based in the VRPPD. The fact that transportation companies must consider both delivering and returning quantities of goods leads to increased complexity. According to Avci and Topaloglu (2015), it is the last 15 years that population-based metaheuristics have been applied in the VRPPD. The advances in technology and computer science enhance these algorithms, which need a population set in order to operate.

In general, there are specific algorithms that are implemented in most VRP variants such as SA, TS, VNS, ILS, LNS, EA's, PSO, and ACO. These algorithms produce efficient results and, therefore, are proposed and implemented by researchers. Although metaheuristics have dominated the other methods, local improvement heuristics remain very popular and are used mainly as components of more sophisticated hybrid systems, while construction algorithms are mainly used for the creation of the initial solution or population, used as input in metaheuristics. Finally, a small part of the reviewed articles employs an exact method of problem-solving exclusively.

6 Applied algorithms in VRP variants

In this section, the papers that either propose novel algorithms and offer efficient results, either have been recognized by the research community, are presented. More specifically, we give insights to the algorithms proposed in these papers, in each one on the VRP variants selected in Sect. 2.

6.1 Capacitated VRP

CVRP is perhaps the simplest variant of the VRP, as the only constraint taken into consideration is the capacity of the vehicles, which is assumed to be identical in terms of actual capacity space and costs. In most cases, the CVRP is combined with other variants, with the most frequent being the VRPTW, which adds more constraints to the setting of the problem. The only papers that deal exclusively with the CVRP are Altabeeb et al. (2019) that propose a firefly algorithm for solving the CVRP, combined with a local search and a genetic operator, for searching a wider space and avoiding getting stuck in a local optimum. Also, Lysgaard and Wøhlk (2014) study the cumulative CVRP, in which the sum of arrival times at the customers aims to be minimized instead of the total distance. They propose a branch-and-cut-and-price algorithm for obtaining the optimum solutions of the problem.

6.2 VRP with time windows

The VRPTW is one of the most widely studied topics in vehicle routing, and therefore, multiple algorithms have been proposed for its solution. Ghoseiri and Ghannadpour (2010) treat the problem as multiobjective, where both the total traveled distance, and the number of vehicles must be minimized. They proposed a Genetic Algorithm that applies the Pareto ranking process in order to find the non-dominated solutions. Through this approach, possible biased solutions, either to the total number of vehicles or to the total traveled distance, are prevented.

Lei et al. (2011), in their research work, propose an adaptive large neighborhood heuristic. Initially, a construction heuristic is applied for providing an adequate solution. At each iteration, several heuristics remove customers and destroy the current solution before insertion heuristics repair the damaged solutions. The selection of the removal and insertion heuristic in each phase is made probabilistically, while their combination offers a wide exploration of the solution space. Vidal et al. (2013) addressed a wide range of large scale VRPTW, with route-duration constraints and additional attributes involving requirements for customer assignments to particular vehicle types, depots, or planning periods. For solving this large class of VRPTW, they proposed a new hybrid genetic search with advanced diversity control.

Yassen et al. (2015) proposed a harmony search (HS) metaheuristic with a local search (LS) algorithm with a proper balance between HS exploration and LS exploitation for solving the VRPTW. Nalepa and Blocho (2016) dealt with the unclear tuning of the numerous parameters, one of the main drawbacks of memetic algorithms for the VRPTW, and proposed an adaptive memetic algorithm. Parameters of the algorithm, such as the selection scheme, the population size, and the number of child solutions generated for each pair of parents, are adjusted dynamically during the search. Hu et al. (2018) examined a more realistic variation of VRPTW that involves demand and travel time uncertainty. To tackle large instances, they designed a two-stage method based on a modified variable neighborhood search heuristic. In the first phase, the total number of vehicles is minimized, while the second phase minimizes the total traveled distance.

6.3 VRP with pickups and deliveries

Transportation companies are not responsible just for delivering goods to customers, but in many cases, for picking goods as well. This need arises in reverse logistics and is tackled by multiple researchers, either by considering deliveries and pickups are executed at the same time (VRPSPD), either by considering the pickups are executed after the end of deliveries (VRPB). Çatay (2010) proposed an ACO algorithm which uses the nearest-neighbor heuristic (NNH) for the construction of the initial solution, and subsequently, a new savings-based visibility function is applied. Additionally, Goksal et al. (2013) developed a hybrid algorithm based on PSO and Variable Neighborhood Descent (VND) for solving the VRPSPD. The initial solution set is formed both with random solutions and with solutions constructed by the NNH. The PSO algorithm uses VND algorithms as a local search procedure for improving these solutions. Finally, Wang et al. (2015) combined the VRPSPD with the VRPTW and proposed a parallel SA method for solving this problem.

6.4 Heterogenous fleet VRP

The HFVRP is a generalization of the classical capacitated VRP by assuming that the fleet of vehicles is composed of different types of vehicles, each characterized by different capacities and costs. HFVRP is rarely examined standalone, and it is usually combined with other variants. Subramanian et al. (2012) proposed a hybrid algorithm consisting of an iterated local search based heuristic and set partitioning (SP) formulation for solving the HFVRP. The SP model is solved utilizing a Mixed Integer Programming solver that interactively calls the ILS heuristic during its execution. Also, Koç et al. (2015) tackled the HFVRP with time windows and introduced a hybrid evolutionary algorithm that combined two state-of-the-art metaheuristic concepts, adaptive large neighborhood search, and population-based search to achieve great results.

Finally, Belloso et al. (2019) analyzed the HFVRP with backhauls and proposed a solution based on a multi-start biased-randomized heuristic. This algorithm uses an iterative method that relies on solving smaller homogeneous instances of the problem and then uses these subsolutions as partial solutions for the original heterogeneous instance.

6.5 VRP with multiple depots and collaborative VRP

MDVRP is an extension of the classical VRP problem by adding multiple depots that can serve the customers. Yu et al. (2011) added a virtual central depot, thus converting MDVRP to VRP with the virtual depot as the original. For its solution, they proposed an improved ant colony optimization process with coarse-grain parallel strategy, ant-weight strategy, and mutation operation. Juan et al. (2015) presented a hybrid approach that combined biased randomization, employed to assign customers to depots, and for improving routing solutions, with the iterated local search metaheuristic. Their approach is easy to implement and can be parallelized naturally.

The research of genetic algorithms (GA's) for solving the MDVRP by Karakatič and Podgorelec (2015) is also worth mentioning. They claimed that GA's are on par with other algorithms and are very efficient when addressing the MDVRP, with the main advantage of a GA being the linear scaling with the growing problem size, and thus is preferred for solving large NP problems over exact and other heuristic algorithms.

Wang et al. (2020) studied the collaborative multiple depots VRP with time window assignments, where the distribution centers of multiple service providers collaborate so that to improve the efficiency of their logistics operations and make sure that customers are served on time, while the operations costs are reduced. Wang et al. (2020) proposed a hybrid heuristic that combines a customer clustering algorithm (K-means clustering), Clark-Wright saving algorithm, and the extended NSGA-II algorithm, which is a multiobjective evolutionary algorithm. The two objectives considered by the researchers are the minimization of the total operating cost and the number of vehicles needed for the deliveries.

6.6 Green VRP

From this class of problems, which contains the Green, the Hybrid, the Electric, and the Pollution, the Hybrid VRP seems to attract the most attention from researchers. It consists of a set of customers, a fleet of alternative fuel vehicles (electrical and hybrid), and a set of refueling stations with the objective of minimizing the total traveled distance while also making use of the refueling stations so as to restore their autonomy. Schneider et al. (2014) tackled the mixed fleet VRP with time windows in which both electric cars and internal combustion cars are used. As a solution method, they presented a hybrid heuristic that combines a variable neighborhood search algorithm with a tabu search heuristic. Goeke and Schneider (2015) dealt with the same problem and developed an adaptive large neighborhood search, enhanced by a local search for intensification. Hiermann et al. (2016) solved the same problem utilizing branch-and-price as well as proposing a hybrid heuristic, which combines an ALNwith an embedded local search and labeling procedure for intensification.

Yu et al. (2017) also focused on the hybrid VRP in which all the vehicles are plugged in hybrid electrical vehicles (PHEV), and they proposed a simulated annealing algorithm with a restart strategy. Last but not least, Andelmin and Bartolini (2019) also dealt with alternative fuel vehicles and their refueling stations and offered a multigraph reformulation of the GVRP in which refueling stations are not explicitly modeled. They exploited this reformulation by tailoring classical local search operators to work directly on it, and by combining these operators to develop a multi-start algorithm.

6.7 Open VRP

OVRP is another well known combinatorial optimization problem that addresses the service of a set of customers using a fleet of non-depot returning vehicles. Repoussis et al. (2010) developed a population-based hybrid metaheuristic consisting of the basic solution framework of evolutionary algorithms and memory-based trajectory local search algorithms, such as tabu search and guided local search to drive the local search process and to explore the solution space. Salari et al. (2010) presented a heuristic improvement procedure based on integer linear programming techniques. Given an initial feasible solution to be possibly improved, the method then destroys and repairs this solution by solving an ILP model, in the attempt of finding a new, improved feasible solution. MirHassani and Abolghasemi (2011) proposed a particle swarm optimization algorithm as well as a particular decoding method for assigning customers to routes, and one point moves for improving the found solutions.

6.8 Dynamic and stochastic VRP

In most VRP's the data is assumed to be known before the start of the routes and not being amenable to change. However, real-world routing problems are dynamic, as unforeseen events can constantly occur. Hong (2012) tackled the dynamic VRP with time windows (DVRPTW), which is modeled as a series of static VRPTW. Each phase has an event-trigger mechanism, which in the specific case, is a new request arrival during the operation. The author proposed a large neighborhood search (LNS) that utilizes the remove and reinsert procedure. The newly arrived request is considered as a removed node, which is being reinserted into the current solution. Mavrovouniotis and Yang (2015), in their article, proposed an ant colony optimization algorithm with immigrant schemes, in which three different cases are investigated, random, elitism, and memory-based. These three immigrant schemes determine the way to introduce new solutions (called immigrants) and replace a small portion of the current population. Finally, Baradaran et al. (2019) addressed the heterogeneous fleet VRP with multiple hard prioritized time windows and proposed an artificial bee colony algorithm (which belongs in the class of swarm intelligent algorithms) in order to face three different models. The first model considers travel times and transportation costs deterministic, the second considers the fixed and variable costs as stochastic, while the third model considers the travel times and costs as normal random variables (Stochastic VRP).

6.9 Multi-trip VRP

A variant of the classical VRP is the problem that deals with multiple uses of vehicles, that arises when customers have either great demands or when they are close to each other. Azi et al. (2010), tackle the MTVRP along with the VRPTW, through a branch-and-price approach, in which a column generation approach is also integrated. This was the first attempt to solve the MTVRP with an exact algorithm. François et al. (2016) developed and tested two Adaptive Large Neighborhood Search (ALNS) algorithms in the MTVRP, which does not consider duration tour constraints.

6.10 Multi-echelon VRP

It is the last few years that researchers deal with the MEVRP, as well as the VRPSF and the 2EVRP, which belong in this class. More specifically, Baldacci et al. (2013) propose an exact algorithm for the two-echelon capacitated VRP (2E-CVRP), which is transformed into a multi depot CVRP with side constraints, while the routing and the handling costs aim to be minimized. In the paper of Breunig et al. (2019), the electric two-echelon VRP is faced, in which both conventional and electric vehicles are used. They propose two algorithms, an LNS-based metaheuristic and an exact algorithm for optimizing charging visitations, as well as, the routing procedures in both levels.

6.11 Time-dependent VRP

The travel time between two points-customers depends on traffic congestion, which in turn is affected by multiple factors, such as unforeseen events, the time of the day, and the weather. Balseiro et al. (2011), solve the TDVRPTW where vehicles must deliver goods to a set of customers concerning their time windows, while travel time between two points, depends on the time of departure. They proposed an ACO algorithm hybridized with insertion heuristics. More specifically, the algorithm is based on the Multiple Ant Colony System framework, which coordinates two colonies, one for reducing the number of routes and one for optimizing the feasible solutions found by minimizing the total time. Since ants produce solutions with unrouted customers, insertion heuristics are further developed for incorporating customers into the solution. Andres Figliozzi (2012), faces the same VRP variants and presents an Iterative Route Construction and Improvement (IRCI) algorithm. The construction phase includes a sequential heuristic, in which an auxiliary route building heuristic is reiterated during its execution of the construction algorithm. Since the set of the initial solutions have been generated, the improvement algorithm, based on the ruin and recreate approach presented by Schrimpf et al. (2000), is implemented in a subset of the routes.

6.12 Two dimensional and three dimensional VRP

In the specific category of the VRP, the dimension of vehicles is considered as a loading constrain. (Leung et al. 2013) addressed the heterogeneous fleet VRP with two-dimensional loading constraints, where vehicles have different capacities, fixed and variable operating costs, and dimensions (width and length), which determine the loading constraints. For these types of problems, both packing and routing algorithms are needed, and therefore, Leung et al. (2013) proposed a simulated annealing algorithm with local search heuristics for the routing of vehicles and six packing algorithms for the two-dimensional loading constraints.

Zachariadis et al. (2016) also focus their research on the VRP with two-dimensional constraints, paired with simultaneous pickups and deliveries, while vehicles are identical. This problem is highly complicated since delivery goods are unloaded, while pickup goods are loaded to the vehicle. However, the algorithm proposed in this publication, which is a combination of a construction heuristic algorithm with local search procedures, manages to offer good quality solutions in reasonable computational times.

6.13 Consistent VRP

The consistent VRP has attracted the least attention from researchers. This is due to the fact that most logistics companies, (i) do not have stable deliveries over a period of time, neither can plan their routes for multiple days, (ii) do not focus on creating consistent routes so that frequent customers being delivered by the same driver, approximately at the same time over the planning period, while it is a relatively new variant of the problem, proposed by Groër et al. (2009). However, Tarantilis et al. (2012) addressed the specific problem by proposing savings and insertion based construction heuristics paired with a Tabu Search algorithm, while Xu and Cai (2018) proposed a Variable Neighborhood Search algorithm for addressing the ConVRP.

6.14 Split delivery VRP

In the Split Delivery VRP, the assumption that each customer is served by a single vehicle and only once is relaxed. Archetti et al. (2014) proposed two branch-and-cut algorithms for solving this variant of the VRP and tested it with up to 100 customers and with a time limit of 2 h. Han and Chu (2016) also studied this variant, coupled with minimum delivery amounts, and proposed a multi-start two-phased variable neighborhood descent heuristic algorithm. More specifically, a construction algorithm generates the initial solution, which is then improved by a VND procedure. The algorithm was tested in 128 cases and managed to find 81 best-known solutions and 43 new optimum solutions.

6.15 Periodic VRP

Yu and Yang (2011) state that there is little literature to use heuristics for periodic VRP with time windows. This statement is reinforced by our research, as no heuristic algorithm was proposed for solving the PVRP. More specifically, Yu and Yang (2011) proposed an improved ant colony optimization algorithm with multi-dimension pheromone information for solving the periodic VRP with time windows. On the other hand, Baldacci et al. (2011) and Rothenbächer (2019), both proposed exact algorithms for solving the problem.

6.16 Truck and trailer VRP

The Track and Trailer Routing Problem has not attracted the interest of researchers. In these few articles that study this variant of the VRP, Lin et al. (2010) developed and proposed a simulated annealing heuristic-based algorithm, and was tested not only existing benchmark problems but also in newly generated problems. Also, Rothenbächer et al. (2018) proposed an exact algorithm for the TTRP with time windows, and the computational results indicate that it outperforms other approaches facing this problem.

7 Concluding remarks

This paper presents the results of an extensive literature review of the VRP for logistics distribution, which means that it is mainly applied in freight transportation cases and companies. The literature review has resulted from a well-defined methodological approach and research protocol. An initial group of 334 papers extracted from the Scopus database published between 2010 and the first quarter of 2020. The articles were further shorted to a group of 263 relevant papers after applying deselection criteria. Emphasis was given in the applied algorithms proposed and developed for the VRP variants for the distribution of goods. Therefore, papers that are irrelevant from the freight transportation perspective were excluded from the analysis.

The articles were classified according to the VRP variants and the applied method proposed for their solution in order to identify the trends in each case, as well as to present their correlation. A trend towards Evolutionary Algorithms seems to be formed, as they are applied in many variants of the problem and offer very efficient results. Simultaneously, local search metaheuristics remain popular among researchers, while they can be easily combined with other algorithms, offering efficient solutions. Finally, hybrid algorithms are applied more and more frequently in many variants of the VRP, as from the algorithms combined, the advantages of each algorithm are exploited.

Concluding, it should be noted that logistics and distribution companies, have to fulfill restrictions of their customers and the external environment dictate, for optimizing their operations. In the last few years, environmental regulations have emerged and are studied by researchers. However, only a few algorithms have been applied to the relevant VRP variants. This will inevitably lead to increased interest in the variants of the VRP, that are related to environmental issues, such as the Green, the Hybrid, the Electric VRP, and the PRP. Simultaneously, in a competitive environment such as today's, where customers are increasingly demanding, the overall distribution process needs to be optimized. Therefore, the research interest about the multi-echelon VRP, which contains multiple layers of distribution and routing, may be increased in the following years. These two statements are reinforced by the fact that they are being studied more intensively from 2013 and onwards. Also, the interest in the collaborative VRP may increase in the future since significant benefits, in a network of logistics companies, are created. The collaboration between multiple logistics companies is a challenge, but an opportunity as well, for optimizing their deliveries and their operating costs. Finally, a topic for further investigation and research is that a minimum number of articles treat simultaneously a combination of different variants of the VRP (as is usual in the complexity of real-life scheduling problems) with most researchers limiting their study to 3 variants of the VRP. Only Penna et al. (2019) were found to tackle a broad range of variants simultaneously, whose hybrid Variable Neighborhood algorithm manages to treat 6 variants of the problem. It becomes clear, therefore, that the research on the VRP variants needs to be furthered as technology advances and new trends and algorithms emerge.

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References

Altabeeb AM, Mohsen AM, Ghallab A (2019) An improved hybrid firefly algorithm for capacitated vehicle routing problem. Appl Soft Comput 84:105728. https://doi.org/10.1016/j.asoc.2019.105728

Andelmin J, Bartolini E (2019) A multi-start local search heuristic for the Green Vehicle Routing Problem based on a multigraph reformulation. Comput Oper Res 109:43–63. https://doi.org/10.1016/j.cor.2019.04.018

Andres Figliozzi M (2012) The time dependent vehicle routing problem with time windows: benchmark problems, an efficient solution algorithm, and solution characteristics. Transp Res Part E Logist Transp Rev 48:616–636. https://doi.org/10.1016/j.tre.2011.11.006

Archetti C, Savelsbergh MWP, Speranza MG (2008) To split or not to split: that is the question. Transp Res Part E Logist Transp Rev 44:114–123. https://doi.org/10.1016/j.tre.2006.04.003

Archetti C, Bianchessi N, Speranza MG (2014) Branch-and-cut algorithms for the split delivery vehicle routing problem. Eur J Oper Res 238:685–698. https://doi.org/10.1016/j.ejor.2014.04.026

Avci M, Topaloglu S (2015) An adaptive local search algorithm for vehicle routing problem with simultaneous and mixed pickups and deliveries. Comput Ind Eng 83:15–29. https://doi.org/10.1016/j.cie.2015.02.002

Azi N, Gendreau M, Potvin J-Y (2010) An exact algorithm for a vehicle routing problem with time windows and multiple use of vehicles. Eur J Oper Res 202:756–763. https://doi.org/10.1016/j.ejor.2009.06.034

Baldacci R, Bartolini E, Mingozzi A, Valletta A (2011) An exact algorithm for the period routing problem. Oper Res 59:228–241. https://doi.org/10.1287/opre.1100.0875

Baldacci R, Mingozzi A, Roberti R, Calvo RW (2013) An exact algorithm for the two-echelon capacitated vehicle routing problem. Oper Res 61:298–314. https://doi.org/10.1287/opre.1120.1153

Balseiro SR, Loiseau I, Ramonet J (2011) An ant colony algorithm hybridized with insertion heuristics for the time dependent vehicle routing problem with time windows. Comput Oper Res 38:954–966. https://doi.org/10.1016/j.cor.2010.10.011

Baradaran V, Shafaei A, Hosseinian AH (2019) Stochastic vehicle routing problem with heterogeneous vehicles and multiple prioritized time windows: mathematical modeling and solution approach. Comput Ind Eng 131:187–199. https://doi.org/10.1016/j.cie.2019.03.047

Bektas T, Laporte G (2011) The pollution-routing problem. Transp Res Part B Methodol 45:1232–1250. https://doi.org/10.1016/j.trb.2011.02.004

Belloso J, Juan AA, Faulin J (2019) An iterative biased-randomized heuristic for the fleet size and mix vehicle-routing problem with backhauls. Int Trans Oper Res 26:289–301. https://doi.org/10.1111/itor.12379

Belmecheri F, Prins C, Yalaoui F, Amodeo L (2013) Particle swarm optimization algorithm for a vehicle routing problem with heterogeneous fleet, mixed backhauls, and time windows. J Intell Manuf 24:775–789. https://doi.org/10.1007/s10845-012-0627-8

Braekers K, Ramaekers K, Van Nieuwenhuyse I (2016) The vehicle routing problem: state of the art classification and review. Comput Ind Eng 99:300–313. https://doi.org/10.1016/j.cie.2015.12.007

Brandão JCS, Mercer A (1998) The multi-trip vehicle routing problem. J Oper Res Soc 49:799–805. https://doi.org/10.1057/palgrave.jors.2600595

Breunig U, Baldacci R, Hartl RF, Vidal T (2019) The electric two-echelon vehicle routing problem. Comput Oper Res 103:198–210. https://doi.org/10.1016/j.cor.2018.11.005

Caceres Cruz J, Arias P, Guimarans D et al (2014) Rich vehicle routing problem: survey. ACM Comput Surv 47:1–28. https://doi.org/10.1145/2666003

Çatay B (2010) A new saving-based ant algorithm for the vehicle routing problem with simultaneous pickup and delivery. Expert Syst Appl 37:6809–6817. https://doi.org/10.1016/j.eswa.2010.03.045

César H, De Oliveira B (2010) A hybrid search method for the vehicle routing problem with time windows. Ann Oper Res 180:125–144. https://doi.org/10.1007/s10479-008-0487-y

Coene S, Arnout A, Spieksma FCR (2010) On a periodic vehicle routing problem. J Oper Res Soc 61:1719–1728. https://doi.org/10.1057/jors.2009.154

Crainic TG, Perboli G, Mancini S, Tadei R (2010) Two-echelon vehicle routing problem: a satellite location analysis. Procedia Soc Behav Sci 2:5944–5955. https://doi.org/10.1016/j.sbspro.2010.04.009

Dantzig GB, Ramser JH (1959) The truck dispatching problem. Manag Sci 6:80–91. https://doi.org/10.1287/mnsc.6.1.80

Eksioglu B, Vural AV, Reisman A (2009) The vehicle routing problem: a taxonomic review. Comput Ind Eng 57:1472–1483. https://doi.org/10.1016/j.cie.2009.05.009

Feillet D, Garaix T, Lehuédé F et al (2014) A new consistent vehicle routing problem for the transportation of people with disabilities. Networks 63:211–224. https://doi.org/10.1002/net.21538

Flatberg T, Hasle G, Kloster O et al (2007) Dynamic and stochastic vehicle routing in practice. In: Zeimpekis V, Tarantilis CD, Giaglis GM, Minis I (eds) Dynamic fleet management: concepts, systems, algorithms & case studies. Springer US, Boston, pp 41–63

François V, Arda Y, Crama Y, Laporte G (2016) Large neighborhood search for multi-trip vehicle routing. Eur J Oper Res 255:422–441. https://doi.org/10.1016/j.ejor.2016.04.065

Gayialis SP, Konstantakopoulos GD, Tatsiopoulos IP (2019) Vehicle routing problem for urban freight transportation: a review of the recent literature. In: Sifaleras A, Petridis K (eds) Operational research in the digital era—ICT challenges. Springer, Cham, pp 89–104

Ghoseiri K, Ghannadpour SF (2010) Multi-objective vehicle routing problem with time windows using goal programming and genetic algorithm. Appl Soft Comput 10:1096–1107. https://doi.org/10.1016/j.asoc.2010.04.001

Goeke D, Schneider M (2015) Routing a mixed fleet of electric and conventional vehicles. Eur J Oper Res 245:81–99. https://doi.org/10.1016/j.ejor.2015.01.049

Goetschalckx M, Jacobs-Blecha C (1989) The vehicle routing problem with backhauls. Eur J Oper Res 42:39–51. https://doi.org/10.1016/0377-2217(89)90057-X

Goksal FP, Karaoglan I, Altiparmak F (2013) A hybrid discrete particle swarm optimization for vehicle routing problem with simultaneous pickup and delivery. Comput Ind Eng 65:39–53. https://doi.org/10.1016/j.cie.2012.01.005

Grangier P, Gendreau M, Lehuédé F, Rousseau L-M (2016) An adaptive large neighborhood search for the two-echelon multiple-trip vehicle routing problem with satellite synchronization. Eur J Oper Res 254:80–91. https://doi.org/10.1016/j.ejor.2016.03.040

Groër C, Golden B, Wasil E (2009) The consistent vehicle routing problem. Manuf Serv Oper Manag 11:630–643. https://doi.org/10.1287/msom.1080.0243
Han AF-W, Chu Y-C (2016) A multi-start heuristic approach for the split-delivery vehicle routing problem with minimum delivery amounts. Transp Res Part E Logist Transp Rev 88:11–31. https://doi.org/10.1016/j.tre.2016.01.014
Hiermann G, Puchinger J, Ropke S, Hartl RF (2016) The electric fleet size and mix vehicle routing problem with time windows and recharging stations. Eur J Oper Res 252:995–1018. https://doi.org/10.1016/j.ejor.2016.01.038
Hong L (2012) An improved LNS algorithm for real-time vehicle routing problem with time windows. Comput Oper Res 39:151–163. https://doi.org/10.1016/j.cor.2011.03.006
Hu C, Lu J, Liu X, Zhang G (2018) Robust vehicle routing problem with hard time windows under demand and travel time uncertainty. Comput Oper Res 94:139–153. https://doi.org/10.1016/j.cor.2018.02.006
Juan AA, Pascual I, Guimarans D, Barrios B (2015) Combining biased randomization with iterated local search for solving the multidepot vehicle routing problem. Int Trans Oper Res 22:647–667. https://doi.org/10.1111/itor.12101
Kaboudani Y, Ghodsypour SH, Kia H, Shahmardan A (2018) Vehicle routing and scheduling in cross docks with forward and reverse logistics. Oper Res Int J. https://doi.org/10.1007/s12351-018-0396-z
Karakatič S, Podgorelec V (2015) A survey of genetic algorithms for solving multi depot vehicle routing problem. Appl Soft Comput 27:519–532. https://doi.org/10.1016/j.asoc.2014.11.005
Kim G, Ong Y, Heng CK et al (2015) City vehicle routing problem (City VRP): a review. IEEE Trans Intell Transp Syst 16:1654–1666. https://doi.org/10.1109/TITS.2015.2395536
Koç Ç, Bektaş T, Jabali O, Laporte G (2015) A hybrid evolutionary algorithm for heterogeneous fleet vehicle routing problems with time windows. Comput Oper Res 64:11–27. https://doi.org/10.1016/j.cor.2015.05.004
Labadie N, Prins C, Prodhon C (2016) Metaheuristics for vehicle routing problems. Wiley, Hoboken
Lahyani R, Khemakhem M, Semet F (2015) Rich vehicle routing problems: from a taxonomy to a definition. Eur J Oper Res 241:1–14. https://doi.org/10.1016/j.ejor.2014.07.048
Lei H, Laporte G, Guo B (2011) The capacitated vehicle routing problem with stochastic demands and time windows. Comput Oper Res 38:1775–1783. https://doi.org/10.1016/j.cor.2011.02.007
Leung SCH, Zhang Z, Zhang D et al (2013) A meta-heuristic algorithm for heterogeneous fleet vehicle routing problems with two-dimensional loading constraints. Eur J Oper Res 225:199–210. https://doi.org/10.1016/j.ejor.2012.09.023
Lin S-W, Yu VF, Chou S-Y (2010) A note on the truck and trailer routing problem. Expert Syst Appl 37:899–903. https://doi.org/10.1016/j.eswa.2009.06.077
Lin C, Choy KL, Ho GTS et al (2014) Survey of green vehicle routing problem: past and future trends. Expert Syst Appl 41:1118–1138
Lysgaard J, Wøhlk S (2014) A branch-and-cut-and-price algorithm for the cumulative capacitated vehicle routing problem. Eur J Oper Res 236:800–810. https://doi.org/10.1016/j.ejor.2013.08.032
Mancini S (2017) The hybrid vehicle routing problem. Transp Res Part C Emerg Technol 78:1–12. https://doi.org/10.1016/j.trc.2017.02.004
Mańdziuk J, Nejman C (2015) UCT-based approach to capacitated vehicle routing problem. In: Rutkowski L, Korytkowski M, Scherer R et al (eds) Artificial intelligence and soft computing. Springer, Cham, pp 679–690
Marinakis Y, Migdalas A (2007) Annotated bibliography in vehicle routing. Oper Res Int J 7:27–46. https://doi.org/10.1007/BF02941184
Mavrovouniotis M, Yang S (2015) Ant algorithms with immigrants schemes for the dynamic vehicle routing problem. Inf Sci (NY) 294:456–477. https://doi.org/10.1016/j.ins.2014.10.002
Mekamcha K, Souier M, Bessenouci HN, Bennekrouf M (2019) Two metaheuristics approaches for solving the traveling salesman problem: an Algerian waste collection case. Oper Res Int J. https://doi.org/10.1007/s12351-019-00529-6
MirHassani SA, Abolghasemi N (2011) A particle swarm optimization algorithm for open vehicle routing problem. Expert Syst Appl 38:11547–11551. https://doi.org/10.1016/j.eswa.2011.03.032
Montané FAT, Galvão RD (2006) A tabu search algorithm for the vehicle routing problem with simultaneous pick-up and delivery service. Comput Oper Res 33:595–619. https://doi.org/10.1016/j.cor.2004.07.009

Nalepa J, Blocho M (2016) Adaptive memetic algorithm for minimizing distance in the vehicle routing problem with time windows. Soft Comput 20:2309–2327. https://doi.org/10.1007/s00500-015-1642-4

Penna PHV, Subramanian A, Ochi LS et al (2019) A hybrid heuristic for a broad class of vehicle routing problems with heterogeneous fleet. Ann Oper Res 273:5–74. https://doi.org/10.1007/s10479-017-2642-9

Perboli G, Rosano M (2019) Parcel delivery in urban areas: opportunities and threats for the mix of traditional and green business models. Transp Res Part C Emerg Technol 99:19–36. https://doi.org/10.1016/j.trc.2019.01.006

Pillac V, Gendreau M, Guéret C, Medaglia AL (2013) A review of dynamic vehicle routing problems. Eur J Oper Res 225:1–11. https://doi.org/10.1016/j.ejor.2012.08.015

Prins C (2009) Two memetic algorithms for heterogeneous fleet vehicle routing problems. Eng Appl Artif Intell 22:916–928. https://doi.org/10.1016/j.engappai.2008.10.006

Quak HJ, de Koster MBM (2009) Delivering goods in urban areas: how to deal with urban policy restrictions and the environment. Transp Sci 43:211–227. https://doi.org/10.1287/trsc.1080.0235

Rabbouch B, Saâdaoui F, Mraihi R (2019) Efficient implementation of the genetic algorithm to solve rich vehicle routing problems. Oper Res Int J. https://doi.org/10.1007/s12351-019-00521-0

Rajabi-Bahaabadi M, Shariat-Mohaymany A, Babaei M, Vigo D (2019) Reliable vehicle routing problem in stochastic networks with correlated travel times. Oper Res Int J. https://doi.org/10.1007/s12351-019-00452-w

Renaud J, Laporte G, Boctor FF (1996) A tabu search heuristic for the multi-depot vehicle routing problem. Comput Oper Res 23:229–235. https://doi.org/10.1016/0305-0548(95)O0026-P

Repoussis PP, Tarantilis CD, Bräysy O, Ioannou G (2010) A hybrid evolution strategy for the open vehicle routing problem. Comput Oper Res 37:443–455. https://doi.org/10.1016/j.cor.2008.11.003

Rothenbächer A-K (2019) Branch-and-price-and-cut for the periodic vehicle routing problem with flexible schedule structures. Transp Sci 53:850–866. https://doi.org/10.1287/trsc.2018.0855

Rothenbächer A-K, Drexl M, Irnich S (2018) Branch-and-price-and-cut for the truck-and-trailer routing problem with time windows. Transp Sci 52:1174–1190. https://doi.org/10.1287/trsc.2017.0765

Salari M, Toth P, Tramontani A (2010) An ILP improvement procedure for the open vehicle routing problem. Comput Oper Res 37:2106–2120. https://doi.org/10.1016/j.cor.2010.02.010

Schneider M, Stenger A, Goeke D (2014) The electric vehicle-routing problem with time windows and recharging stations. Transp Sci 48:500–520. https://doi.org/10.1287/trsc.2013.0490

Schrimpf G, Schneider J, Stamm-wilbrandt H, Dueck G (2000) Record breaking optimization results using the ruin and recreate principle. J Comput Phys 171:139–171. https://doi.org/10.1006/jcph.1999.6413

Silva MM, Subramanian A, Ochi LS (2015) An iterated local search heuristic for the split delivery vehicle routing problem. Comput Oper Res 53:234–249. https://doi.org/10.1016/j.cor.2014.08.005

Sitek P (2014) A hybrid approach to the two-echelon capacitated vehicle routing problem (2E-CVRP). In: Szewczyk R, Zieliński C, Kaliczyńska M (eds) Recent advances in automation, robotics and measuring techniques. Springer, Cham, pp 251–263

Subramanian A, Penna PHV, Uchoa E, Ochi LS (2012) A hybrid algorithm for the heterogeneous fleet vehicle routing problem. Eur J Oper Res 221:285–295. https://doi.org/10.1016/j.ejor.2012.03.016

Tarantilis CD, Stavropoulou F, Repoussis PP (2012) A template-based tabu search algorithm for the consistent vehicle routing problem. Expert Syst Appl 39:4233–4239. https://doi.org/10.1016/j.eswa.2011.09.111

Usberti FL, França PM, França ALM (2013) GRASP with evolutionary path-relinking for the capacitated arc routing problem. Comput Oper Res 40:3206–3217. https://doi.org/10.1016/j.cor.2011.10.014

Vidal T, Crainic TG, Gendreau M, Prins C (2013) A hybrid genetic algorithm with adaptive diversity management for a large class of vehicle routing problems with time-windows. Comput Oper Res 40:475–489. https://doi.org/10.1016/j.cor.2012.07.018

Wang C, Mu D, Zhao F, Sutherland JW (2015) A parallel simulated annealing method for the vehicle routing problem with simultaneous pickup–delivery and time windows. Comput Ind Eng 83:111–122. https://doi.org/10.1016/j.cie.2015.02.005

Wang Y, Ma X, Li Z et al (2017) Profit distribution in collaborative multiple centers vehicle routing problem. J Clean Prod 144:203–219. https://doi.org/10.1016/j.jclepro.2017.01.001

Wang Y, Zhang S, Guan X et al (2020) Collaborative multi-depot logistics network design with time window assignment. Expert Syst Appl 140:112910. https://doi.org/10.1016/j.eswa.2019.112910

Xu Z, Cai Y (2018) Variable neighborhood search for consistent vehicle routing problem. Expert Syst Appl 113:66–76. https://doi.org/10.1016/j.eswa.2018.07.007
Yassen ET, Ayob M, Nazri MZA, Sabar NR (2015) Meta-harmony search algorithm for the vehicle routing problem with time windows. Inf Sci (NY) 325:140–158. https://doi.org/10.1016/j.ins.2015.07.009
Yu B, Yang ZZ (2011) An ant colony optimization model: the period vehicle routing problem with time windows. Transp Res Part E Logist Transp Rev 47:166–181. https://doi.org/10.1016/j.tre.2010.09.010
Yu G, Yang Y (2019) Dynamic routing with real-time traffic information. Oper Res Int J 19:1033–1058. https://doi.org/10.1007/s12351-017-0314-9
Yu B, Yang ZZ, Xie JX (2011) A parallel improved ant colony optimization for multi-depot vehicle routing problem. J Oper Res Soc 62:183–188. https://doi.org/10.1057/jors.2009.161
Yu VF, Redi AANP, Yang C-L et al (2017) Symbiotic organisms search and two solution representations for solving the capacitated vehicle routing problem. Appl Soft Comput 52:657–672. https://doi.org/10.1016/j.asoc.2016.10.006
Zachariadis EE, Kiranoudis CT (2010) An open vehicle routing problem metaheuristic for examining wide solution neighborhoods. Comput Oper Res 37:712–723. https://doi.org/10.1016/j.cor.2009.06.021
Zachariadis EE, Tarantilis CD, Kiranoudis CT (2016) The vehicle routing problem with simultaneous pick-ups and deliveries and two-dimensional loading constraints. Eur J Oper Res 251:369–386. https://doi.org/10.1016/j.ejor.2015.11.018

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