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Recent dynamic vehicle routing problems: A survey

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ABSTRACT

Technological advances in the last two decades have aroused great interest in the class of dynamic vehicle routing problems (DVRPs), which is reflected in the significant growth of the number of articles published in this period. Our work presents a comprehensive review of the DVRP literature of the last seven years (2015–2021) focusing mainly on applications and solution methods. Consequently, we provide a taxonomy of the problem and a taxonomy of the related solution methods. The papers considered for this review are discussed, analyzed in detail and classified according to the proposed taxonomies. The results of the analysis reveal that 65% of the articles deal with dynamic and stochastic problems (DS) and 35% with dynamic and deterministic problems (DD). With respect to applications, 40% of articles correspond to the transportation of goods, 17.5% to services, 17.5% to the transport of people and 25% to generic applications. Among the solution methods, heuristics and metaheuristics stand out. We discussed the application opportunities associated with DVRPs in recent business models and new concepts of logistical operations. An important part of these new applications that we found in our review is in the segment of business-to-consumer crowd-sourced services, such as peer-to-peer ride-sharing and online food ordering services. In our review many of the applications fall into the stochastic and dynamic category. This means that for many of these applications, companies usually possess historical data about the dynamic and uncertainty sources of their routing problems. Finally, we present the main solution streams associated with DVRPs.

1. Introduction

The Vehicle Routing Problem (VRP) was introduced in the literature by Dantzig and Ramser (1959), to describe the problem of finding a set of least-cost routes for a fleet of vehicles to satisfy the total demand of a set of customers geographically dispersed in a network. Historically, the input data of the problem is obtained *a priori* (i.e., all information is assumed to be known, and it is collected before solving the problem), and it is static (i.e., data do not change over time). In real-world operations, however, the data may be highly dynamic, and not known in advance. In response to this real-world challenge, the Dynamic VRP (DVRP) emerged in the late 1970s, with the works of Speidel (1976), Wilson and Colvin (1977) and Psaraftis (1980). However, due to the lack of technological support (e.g. Global Positioning System), computational power, business models, and real-time applications (e.g. UberEATS), this area was not attractive to researchers. Nowadays, with the abrupt evolution of sophisticated information and computer systems, the processing of large quantities of data, as well as the collection of real-time data, are facilitated (Ritzinger et al., 2015). Innovative services and business opportunities have been emerging, such as ride-sharing, ride-hailing, and crowd-sourcing. Simultaneously, customers have imposed new requirements, such as attended home delivery and same-day delivery. Therefore, it is not surprising that the literature on DVRP has developed substantially, particularly since the beginning of the century. Using our literature review methodology, we identified 80 additional papers that have been published since 2015.

The evolution of DVRP literature also justifies the vast number of reviews on this problem (Ritzinger et al., 2015; Dial, 1995; Gendreau and Potvin, 1998; Larsen et al., 2002; Brotcorne et al., 2003; Ghiani et al., 2003; Hanshar and Ombuki-Berman, 2007; Ichoua1 et al., 2007; Larsen et al., 2007; Larsen et al., 2008; Berbeglia et al., 2010; Pillac et al., 2013; Bektas et al., 2014; Psaraftis et al., 2015). Among these reviews, the latter ones are of particular interest and deserve to be highlighted. Pillac et al. (2013) provide a classification of VRP into four

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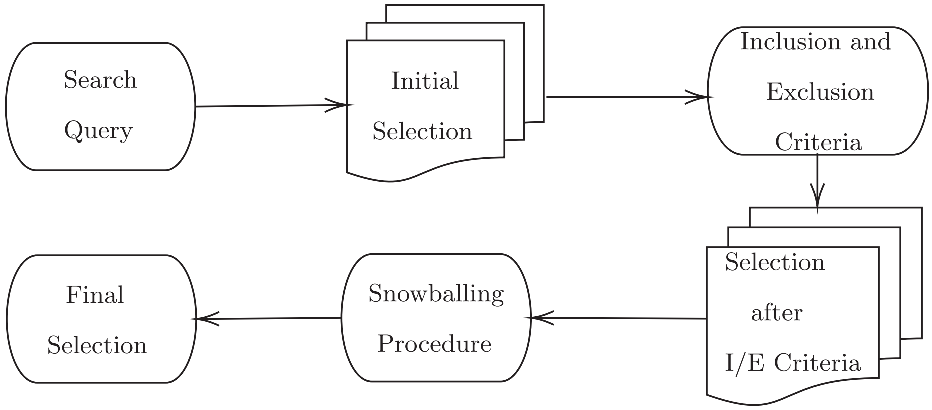

Fig. 1. General description of the material collection procedure.

categories, according to the evolution and quality of information. These categories are summarized as follows:

- Static and deterministic VRP: All information on the problem components *(input)* is known in advance and does not change during route execution.
- Static and stochastic VRP: The problem components *(input)* are partially known, and they are represented with random parameters, where the *real values* are known during the execution of the route. Additionally, the routes are designed before their execution and then minor changes are accepted.
- Dynamic and deterministic VRP: Partial or all information on the problem components *(input)* is unknown, and it is only disclosed during the execution or design of the routes. No component of the problem is represented with random variables.
- Dynamic and stochastic VRP: Partial or all information on the problem components *(input)* is unknown, and it is only disclosed during the execution or design of the routes. There is at least one component that is represented with a random variable.

Bektas et al. (2014) extended the work of Pillac et al. (2013) providing a more detailed analysis of more than 160 papers and identifying the advances and trends of DVRP. The last survey of DVRP was presented in Psaraftis et al. (2015) in 2015, which proposes a taxonomy for the problem. This taxonomy classifies a DVRP into 11 categories, as follows: *(i)* type of problem, *(ii)* logistical context, *(iii)* transportation mode, *(iv)* objective function, *(v)* fleet size, *(vi)* time constraints, *(vii)* vehicle capacity, *(viii)* ability to reject customers, *(ix)* nature of dynamic element, *(x)* nature of stochasticity, and *(xi)* solution methods.

The present paper aims to update the review on the DVRP literature. According to a very recent review on crowd-sourcing literature carried out by Alnaggar et al. (2019), the first academic paper published in this field was conducted by Archetti et al. (2016). This paper was only published in 2016, and as such, the review by Psaraftis et al. (2015) misses all the academic papers related to crowd-sourcing, one of the new transportation services that rely heavily on dynamic information. Therefore, the first motivation of our paper is to capture all the works that tackle this new transportation service. The second motivation relates to the characteristic of the taxonomy provided by Psaraftis et al. (2015). Although the authors proposed a comprehensive classification of DVRP, they do not provide a more in-depth analysis of the solution methods used to handle the dynamic nature of the problem. In fact, they briefly describe a set of DVRP papers under a somewhat narrow range of possible methods. In the present paper, we aim to deepen the classification of DVRP by not only looking to the solution method itself but including also the mode of data collection (online, offline, or hybrid). The third motivation of our paper is also related to the extension of the previous taxonomy, but focused on the application of the DVRP. As mentioned, innovative services have emerged due to the existence of new technologies, which have also lead to new applications of the DVRP. Hence, we aim to introduce a new category in the taxonomy provided by Psaraftis et al. (2015), considering its relevance nowadays. Finally, the fourth and last motivation of our paper is the obvious need to update the literature, since the number of DVRP papers published in the last seven years has increased significantly. For instance, Psaraftis et al. (2015) have reviewed 117 DVRP papers published in the literature up to 2014, whereas we found **80 papers** during the short period of 2015–2021.

Having defined the motivations for an updated review of the DVRP literature, the main contributions of our paper are as follows. Firstly, this review paper aims to extend the first taxonomy proposed for DVRP by detailing relevant characteristics of the problem, solution methods, and applications. In fact, inspired by the work of Oyola et al. (2016, 2016), we propose a two-part taxonomy for the DVRP - one for the problem and one for the solution method. Secondly, reviewing papers published in the last seven years allows for covering new applications of the DVRP, such as crowd-sourcing, which ultimately leads to positioning the DVRP literature in the context of new services and industry 4.0. The appendices A (Table 5) and B (Table 5) provide the classification of each paper reviewed according to the taxonomy proposed in this work.

The remainder of this paper is organized as follows. Section 2 presents the methodology used for the review. Section 3 describes the material evaluation in the perspective of the DVRP problem while Section 4 describes the material evaluation focusing on solution methods of DVRP. Finally, Section 5 analyses future works, application opportunities, and main solution streams associated with DVRPs found in our review.

2. Research method

The research method used for the present literature review follows the methodology proposed by Seuring et al. (2005). This methodology is based on four steps: *(i)* material collection, *(ii)* descriptive analytics, *(iii)* category selection, and *(iv)* material evaluation. Each of these steps is summarized next, whereas the last and most important step of this review is detailed in Sections 3 and 4.

2.1. Material collection

The collection and selection of DVRP papers used in the literature review follow the procedure depicted in Fig. 1.

The papers were searched in the online libraries *Scopus* and *Web of Science*. The search query included “dynamic routing AND vehicle”, “dynamic traveling”, “dynamic vehicle routing”, “vehicle routing AND real time”, “real time AND traveling salesman”, “real time AND traveling salesperson”. The search query covered the titles, abstracts and keywords of the papers.

Fig. 2. Number of publications per journal.

The initial selection of articles resulted in 819 papers from *Web of Science* and 1351 papers from *Scopus*. Among these, we found that several papers have classified the problem under study as dynamic but we could not find enough information in the respective model or solution method that deals with it accordingly. Therefore, we have applied Inclusion and Exclusion Criteria to discriminate the papers that properly define and solve the dynamic problem from the others. The inclusion criteria used at this stage were:

1. Articles published in journals since 2015;
2. Articles that have, at least, one element with a dynamic nature;
3. Articles that are in the first quartile of Scimago's journal ranking in the categories "Management Science and Operations Research" and "Transportation".

The exclusion criteria were:

1. Articles that deviate from the VRP topic, such as e-commerce, articles that propose frameworks, and articles focused on technological devices or conceptual approaches;
2. Master and PhD dissertations, survey papers, publications in conferences, and papers written in other languages than English.

After applying the inclusion and exclusion criteria, the total number of DVRP papers selected for the review was reduced to 68. Afterwards, we applied the Snowballing Procedure to complement the previous list of selected papers. This procedure consists of reviewing the references and citations of the articles on our list, to identify additional works and consequently decrease the number of lost articles of great interest (Wohlin, 2014). Snowballing was mainly applied to the work of Pillac et al. (2013). This procedure enabled us to add 9 articles to our list. The final selection of papers allowed us to collect 80 DVRP papers to be considered in the present review.

2.2. Descriptive analytics

The descriptive analytics aims to provide a first insight into the topic of DVRP. In particular, we aim to analyze the main journals where the DVRP literature has been published over the last years. As a result, it will be possible to gather information about the main focus of the overall literature. Fig. 2 presents the distribution of DVRP papers by journal, published between 2015 and 2021.

Fig. 2 shows that the journal with most DVRP papers published in the last seven years is *Transportation Science*, a journal that mainly focuses on the theoretical background, mathematical models and advanced methodologies applied to transportation problems. It can also be observed that many papers were published in journals that cover the development of computerized tools to support decision-making, such as *Computers and Industrial Engineering, Computers and Operations Research* and *Transportation Research Part C: Emerging Technologies*. Finally, journals that focus on the development of new and relevant methodologies, such as the *European Journal of Operational Research* and *Transportation Research Part B: Methodological*, are also a place for several DVRP publications reviewed in this article.

2.3. Category selection

The taxonomy proposed in this paper includes all the categories proposed by Psaraftis et al. (2015): type of problem, logistical context, transportation mode, objective function, fleet size, time constraints, vehicle capacity constraints, ability to reject customers, nature of dynamic element and nature of stochasticity. In addition, we introduce the following three new categories: (i) application, (ii) solution methods and (iii) mode.

The reasons that motivated these categories are the following:

- Type of problem: this category allows differentiation between static and stochastic versions of dynamic problems, that is, if some problem component is random or not. This classification will provide a relationship with other criteria of the taxonomy.
- Logistical context: this category provides additional information on the nature of the routing problem. It specifies if the problem is the common one way routing with only delivery or only pickup, if both delivery and pickup services occur, which can be provided in one- or two-way routing, or if another problem is integrated with routing (e.g., location, inventory, etc.).
- Transportation mode: the type of vehicle tackled in the problem may be related to both the logistical context and the application of the problem. The transportation mode comprises road, maritime and air.
- Objective function: this category is of utmost importance as it dictates the goal of the problem, often guiding solution approaches that rely on the specific structure of the problem.
- Fleet size: this category classifies the fleet in terms of the number of vehicles. It is an important criterion, especially if the number of vehicles is somehow connected with the dynamic or stochastic nature of the problem.
- Time constraints: constraints related to time, such as time windows and service time, among others, are of particular interest in dynamic problems where the temporal aspect is related to the dynamic or stochastic nature of the problem. Moreover, the time constraints can be hard, in the sense that cannot be violated, or soft, which implies some penalty if violated.

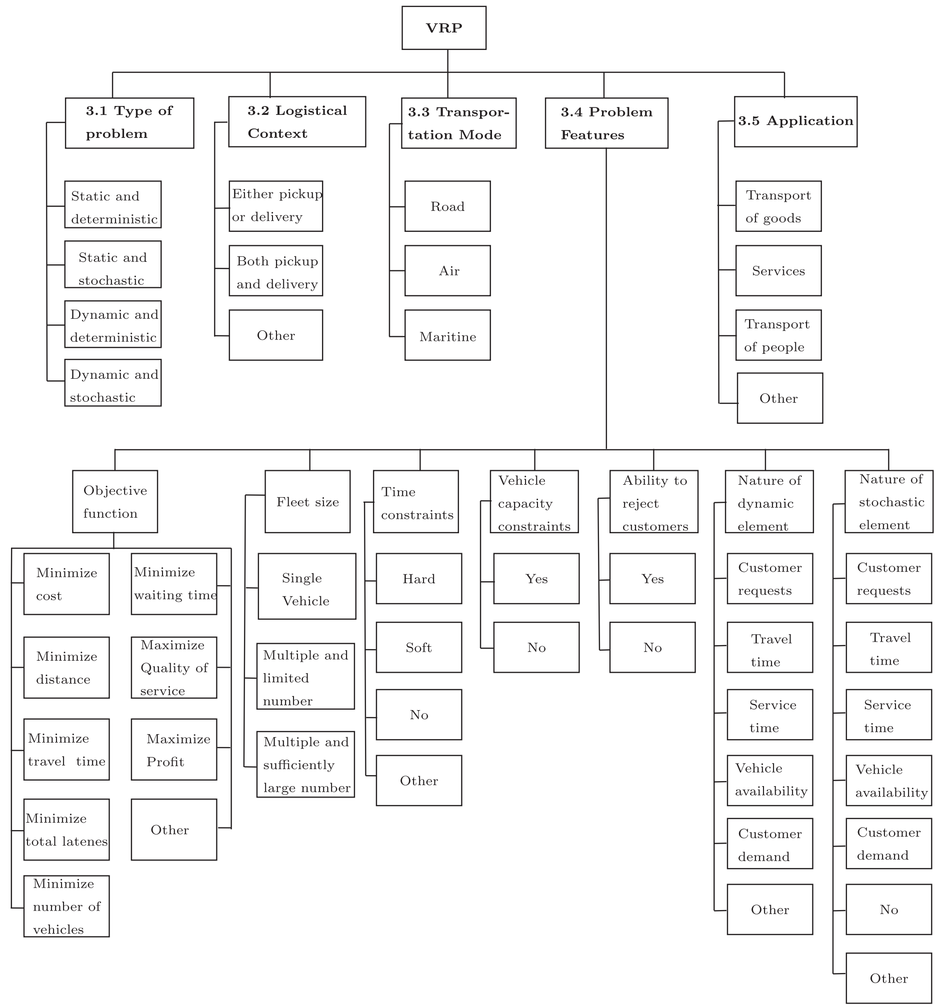

Fig. 3. Taxonomy of the problem.

- Vehicle capacity constraints: it classifies a problem if it considers capacitated or uncapacitated vehicles. In practice, this criterion is related to the dimensions of the loads to deliver/pickup.
- Ability to reject customers: this is one of the main distinctive categories between dynamic and static VRPs, as in the most traditional VRPs all customers must be visited and rejection is not allowed. In dynamic VRPs, however, attending to all customers demand may not be feasible due to the existence of dynamic elements, such as the arrival of several clients at the same time.
- Nature of dynamic element: this category is the core of the dynamic VRP, identifying which aspect or aspects of the problem make it different from the common static VRP. The dynamic element has a strong relationship with other categories of the taxonomy, either concerning the problem features or the solution methods.
- Nature of stochasticity: the presence of stochastic elements, and their identification, is important for two reasons. Firstly, because it allows the easy classification of problems in the first category of the taxonomy - the type of problem. Secondly, because it allows establishing connections with the dynamic elements of the problem. Ultimately, this category may guide the type of solution method applied to solve the dynamic VRP.
- Application: nowadays we came across various online business strategies (e.g., meal delivery, crowdsouring, etc.), which a few years ago were not so relevant. A clear example of this is the segment of online food ordering and delivery services that can be found in various cities around the world. Another example is peer-to-peer ride-sharing that has experienced significant growth over the last decade. This category is important in identifying research opportunities associated with DVRPs.
- Solution methods: using exact and heuristics methods is determined by the difference in obtaining optimal solutions or sub-optimal solutions and the computation time required to do so. The size of the problem also influences the selection of the solution method. Consequently, it is crucial to analyze the diversity of solution methods for the DVRP. This category was already proposed in the taxonomy of Psaraftis et al. (2015), but we introduce a longer classification of solution methods. Therefore, we consider in our taxonomy Exact algorithms and Approximate dynamic programming (ADP) as individual categories.
- Mode: the selection of an offline, online or hybrid method has a direct impact on computational performance. In online methods, the calculation is conducted on-the-fly as new information arrives. In contrast, the algorithms in offline mode compute a policy of how to construct routes before executing the plan. Finally, a hybrid approach combines both offline and online solution methods.

After defining all the categories, the extended taxonomy was divided in two parts, following the work of Oyola et al. (2016, 2016). The first part of the taxonomy covers the classification of the dynamic problem, and the second part covers the classification of the solution method. The taxonomy is depicted in Figs. 3 and 4, respectively.

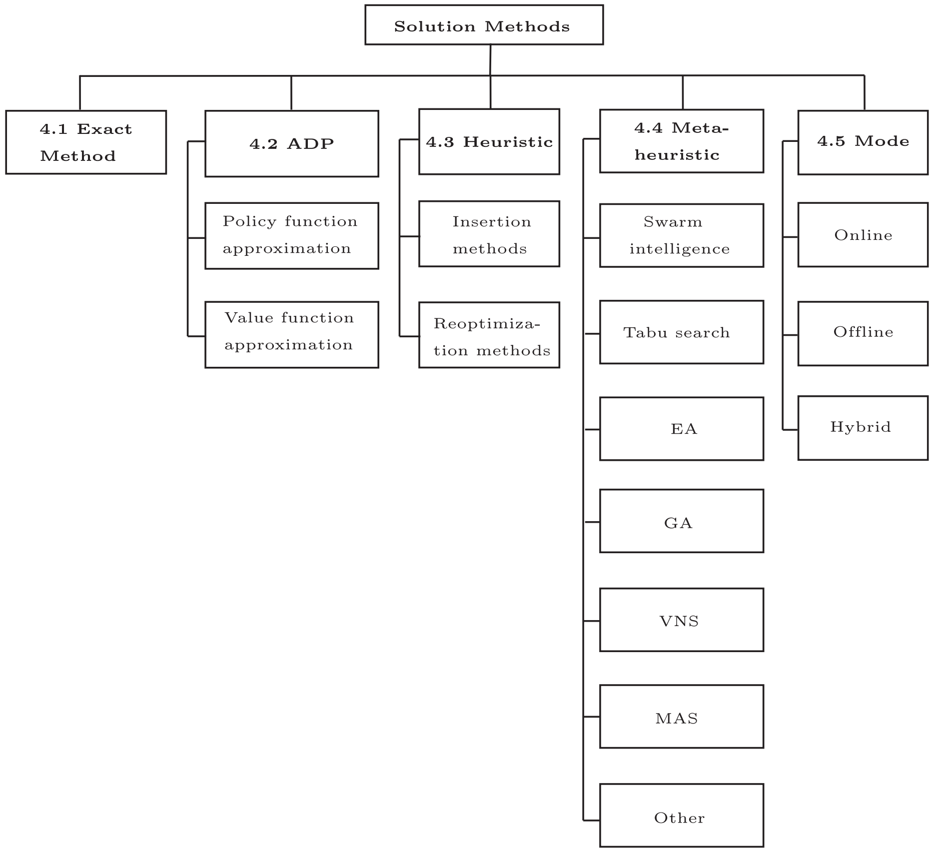

Fig. 4. Taxonomy of Solution Methods.

3. Material evaluation - problem perspective

In this section, the DVRP papers selected for the review are classified in terms of characteristics of the problem. Details are presented in Appendix A.

3.1. Type of the problem

According to Psaraftis (1980), vehicle routing problems have two dimensions: evolution and quality of information. The evolution of information refers to changes in the available information during route execution (dynamic or static). Quality of information refers to the possibility of having uncertainty in the available information (deterministic or stochastic).

The dynamic vehicle routing problems can be classified as follows: dynamic and deterministic (DD) and dynamic and stochastic (DS). In our review, we found that 28 papers belong to type DD and 52 belong to type DS. The following sections describe some papers of each type of problem.

3.1.1. Dynamic and deterministic (DD)

In this class of problems, the parameters are deterministic before and during the solution of the problem (the stochastic information is absent). Routes are continually redefined as realizations of data are revealed, requiring real-time technological support between the vehicle and dispatcher in route construction. Therefore, the exact methods only guarantee an optimal solution for the current state, therefore they do not guarantee that the solution is optimal once new data is revealed (Pillac et al., 2013). Contexts where the DD problem appears are real-time routing based on using mobile apps, real-time routing where interruptions occur unexpectedly (such as mechanical failures) and real-time routing that considers traffic congestion. Below, we present some examples of DD in these contexts.

Santos and Xavier (2015) deal with a dial-a-ride dynamic problem with money as an incentive. In this problem, passengers want to share their travel with other passengers. An app is used to share the location, destination, departure time, arrival time, and the maximum cost the passenger is willing to pay in a shared trip. On the car owners' side, there is an app that can specify the origin, destination, departure time, maximum accepted delay, location, start time, and end of the service. Each driver defines a cost per unit of distance traveled. The goal of the problem is to compute routes and match requests to vehicles allowing sharing. A set of restrictions must be respected: maximum vehicle capacity, maximum travel cost for each passenger, and maximum delay. This problem is dynamic because requests arrive online and routes may change to fulfill new requests. The problem is deterministic because all input parameters and incoming online information are not stochastic.

Monroy-Licht et al. (2016) introduce the rescheduling arc routing problem. This dynamic routing and scheduling problem considers adjustments to an initial routing itinerary when one or more vehicle failures occur during the execution stage, and the original plan must be modified. The objective is to minimize operational and schedule disruption costs. The problem is dynamic because the vehicles may not always be available to make routes; and it is deterministic because no stochastic parameters are found in the problem.

Ng et al. (2017) present an Online VRP (OVRP) where the objective is to determine optimal vehicle routing so that the total travel time considering travel conditions in real time is minimized. An image processing tool is used to estimate the traffic congestion in regions where vehicles are scheduled to pass, and this real time information is used in the online re-optimization of the vehicle's routes. The idea behind using this tool is to alleviate the risk of late deliveries by incorporating real time traffic density estimation in the vehicle scheduling.

Table 1
The P or D class (sample references).

Sarasola et al. (2015), Kim et al. (2016),
Mavrovouniotis et al. (2017), Jia et al. (2018),
Macharet et al. (2017), ssMaghfiroh and Hanaoka (2018),
Yu and Yang (2017), Christiansen et al. (2017)

Table 2
The P and D class (sample references).

Tirado and Hvattum (2016), Fikar et al. (2017),
Bertsimas et al. (2019), Cheng et al. (2016),
Fikar (2018), Aragão et al. (2019),
Hu et al. (2017), Voccia et al. (2019),

Table 3
Other class (sample references).

Ulmer (2017a), Ulmer and Thomas (2018),
Zhang et al. (2015), Brinkmann et al. (2019),
Agharkar et al. (2015), Vitello et al. (2017),
Güner et al. (2017), Chai et al. (2017)

3.1.2. Dynamic and stochastic (DS)

Unlike the previous category, in this class of problems exploitable stochastic knowledge is available on the dynamically revealed information (Pillac et al., 2013). DS can be seen as an extension of DD, where additional stochastic knowledge is dynamically available. This allows for anticipating future events through probability distributions of random variables or historic information. As before, routes can be redefined with the help of technology support. Contexts where DS problems appear in the literature include same day delivery (e.g, Voccia et al., 2019; Ulmer, 2017a; Ulmer and Thomas, 2018), courier and parcel services (e.g, Steever et al., 2019; Sarasola et al., 2015), traffic congestion (e.g, Vitello et al., 2017; Chai et al., 2017; Luo et al., 2018), and e-commerce (e.g, Ulmer and Streng, 2019; Angelelli et al., 2016). Below, we present three examples of DS problems.

Ulmer et al. (2018a) deal with the dynamic vehicle routing problem with a stochastic service request (VRPSSR). The problem considers two types of customer requests: early request customers (ERC) and late request customers (LRC). An uncapacitated vehicle must serve customers in a given service area, within a time limit, before returning to the depot. ERCs are known a priori, whereas LRCs are only known when vehicles are en-route. The decision to attend or reject these requests is made when the vehicle arrives at a customer. The goal is to maximize the number of solicitations served. To achieve this goal, the dispatcher must presuppose his/her time ahead of future requests. In the same line, Ulmer et al. (2018b) study a multi-period dynamic optimization problem with stochastic service request (MDRPSR). In this problem, a single vehicle serves customer requests in a set of periods. During each period, new customer requests arrive, which may be dynamically integrated in the current route or postponed to the next period. The goal of this problem is to find a policy that maximizes the expected number of services for all periods.

An unusual example where the quantity of products in the supermarkets decreases according to a stochastic process is presented by Angelelli et al. (2016). The authors analyze a variant of the traveling purchaser problem (TPP) called stochastic and dynamic TPP (SDTPP). The SDTPP considers a list of n products to buy, the demand of each product, and a set of m geographically dispersed supermarkets offering the products at different prices. The travel buyer aims to minimize both the travel cost and the purchase cost while meeting the demand for each product.

3.2. Logistical context

The logistical context refers to the main variants of the problem, namely if it handles only deliveries (or only pickups) or if it handles both pickups and deliveries. We note that the majority of the reviewed papers tackled the most common logistics aspect of performing only pickups or only deliveries. Few authors deal with the hybrid version of performing both pickup and delivery. This may be due to the additional challenges that the hybrid version bring to the mathematical formulation of the DVRP and respective algorithms to solve the problem.

3.2.1. Either pickup or delivery (P/D)

The traditional VRP is concerned with the deliveries of goods from a depot to a set of customers (Wassan and Nagy, 2014) while in the vehicle routing problem with pickup, the goods are transported from customers to the depot. In the literature we can also refer to these problems as: one-to-many and many-to-one problems (Toth and Vigo, 2014). The difference between them in dynamic problems lies in the possibility of being able or not to meet an order. In one-to-many problems, it is much more difficult to attend a new delivery (unless returning to the depot is allowed) than in many-to-one problems, since in the latter case, an order can be added during the execution of the route. Thus, the former type of problems may be more difficult to solve dynamically than the latter (Toth and Vigo, 2014). Among the papers reviewed in this work, 41 papers fall into the category of P/D type of problems. Table 1 shows some P/D examples.

3.2.2. Both pickup and delivery (PD)

The vehicle routing problem with deliveries and pickups (VRPDP) extends the VRP by having goods transported from a depot to customers but also from customers to the depot (Wassan and Nagy, 2014). In our review, 18 papers belong to this category. Some examples are shown in Table 2.

3.2.3. Other

Besides routing decisions, some works also include location and/or inventory decisions, such as the traveling salesman problem, DARP and the location-routing problem, among others (Psaraftis et al., 2015). In our review, 21 papers fall into this category. Table 3 shows some examples of such problems.

3.3. Transportation mode

The transportation mode refers to the means by which goods or people are carried. These are divided into three basic types: road, air and maritime. In our review, papers where the mode is not specified (the mode of transport can be applied in any category) are classified as road. In this review, 75 papers fall into the category of road mode, 2 in the maritime mode and 4 in the air mode. Among these, the work of Ulmer et al. (2018c) belongs to both road and air transportation modes.

3.3.1. Road

The works investigated in the context of road transportation cover diverse situations, such as:

- Disaster response operations: Maghfiroh and Hanaoka (2018).
- City logistics: Mavrovouniotis et al. (2017), Yu and Yang (2017).
- Logistic Dispatching: Jia et al. (2018).
- Logistic service providers: Ulmer et al. (2018a), Ulmer et al. (2019).
- Automated guided vehicles logistics: Macharet et al. (2017).

3.3.2. Air

Among the works reviewed, those that fall into the category of air transportation are: Ulmer and Streng (2019), Alinaghian et al. (2019), Grippa et al. (2018) and Ulmer and Thomas (2018).

In Ulmer and Streng (2019), the potential of combining parcel

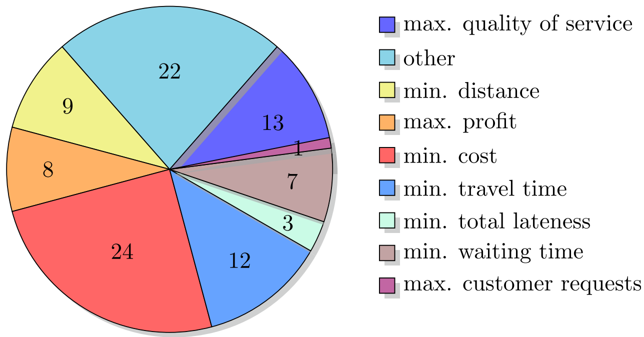

Fig. 5. Distribution of papers according to the objective function (some papers present several objective functions).

pickup stations and autonomous vehicles (e.g. drones) for same-day delivery is studied. This problem considers a set of pickup stations, a depot, a fleet of autonomous vehicles and a set of customers. Orders appear dynamically and are assigned to a specific pickup station. Then, goods are shipped directly using autonomous vehicles from the depot to a customer's preferred station or to a station in their neighborhood. Note that instead of sending the goods to the customer's home, they are sent to a station nearby. According to the authors, this has advantages such as automating delivery between depot and pickup station which facilitates the use of autonomous vehicles.

Alinaghian et al. (2019) present a mathematical model for the location of temporary relief centers and dynamic routing of aerial rescue vehicles during emergency events. In their model, the vehicles deliver basic supplies for rescue operations and the main objective is to locate temporary relief centers so that all affected areas are covered by, at least, one temporary relief center. The demand for relief supplies is stochastic, given that the information about the location and number of victims are inaccurate.

A problem of dimensioning and control of a fleet of autonomous aerial vehicles that deliver goods from depot to customers is studied in Grippa et al. (2018). Customer requests arrive according to a stochastic space–time process. This problem can be seen as a dynamic traveling repair-person problem (DTRP) (Bertsimas and van Ryzin, 1991) or a dynamic pickup and delivery problem (DPDP) (Swihart and Papastavrou, 1999). Several request assignment policies are proposed and computational simulations are presented.

Similarly, Ulmer and Thomas (2018) present a dynamic vehicle routing problem with a heterogeneous fleet. Customer requests are attended by a fleet of regular transportation vehicles or by drones within a time interval. To decide whether an order is delivered by a drone or by a vehicle, the authors present a policy function approximation based on geographical districting.

3.3.3. Maritime

Among the papers reviewed, only Tirado and Hvattum (2016) and Christiansen et al. (2017) investigate the dynamic VRP for maritime transportation.

Tirado and Hvattum (2016) present a problem based on maritime industrial transport. The shipping company has a heterogeneous fleet of vessels and each vessel is associated with a service speed, capacity and current location. At the beginning, some positions are known, the state of all vessels are empty and they are located in the same port. Known cargoes should be loaded and unloaded on vessels respecting hard time windows and capacity constraints. Each route between ports is associated with a cost given by the vessel and the cost of entering in a port with that specific vessel. The problem is dynamic because cargo requests can appear while vessels are performing transportation services and information about new cargoes can appear at any time. If this happens, vessel routes and schedules should be updated to ensure that all cargoes are transported at the lowest possible cost.

Christiansen et al. (2017) deal with a problem of routing and scheduling a fleet of fuel supply vessels used to service customer ships anchored outside a port. The authors present and compare two models for the problem: an arc-flow and a path-flow model. The routing and scheduling of the supply vessel fleet are planned following a variable horizon planning time. The plan may undergo changes when new information is available (e.g. new orders).

3.4. Problem features

A major criterion in the taxonomy concerns the problem features which cover i) objective function, ii) fleet size, iii) time constraints, iv) vehicle capacity constraints, v) ability to reject customers, vi) nature of the dynamic element, and vii) nature of the stochasticity.

3.4.1. Objective function

Dynamic routing can introduce new objectives such as customer ranking, service time, expected reachability time, satisfaction level of the customers, number of requests served, or minimizing delays. In fact, response time is a natural characteristic of dynamic requests in DVRPs; a client may request to be attended as soon as possible, which means that the goal of the problem is to minimize the delay between the arrival of a request and its service (Pillac et al., 2013). Moreover, traditional static goals, such as the minimization of the total distance traveled or the overall duration of the schedule, may not make sense in dynamic environments because the routing process can be hard to define. Surprisingly, most of the reviewed DVRP papers use similar objective functions to that of the classic VRP, such as minimization of total distance, travel time or travel costs, as shown in Fig. 5. Normally, we could expect to find per unit time objectives in DVRP such as: average per unit time serviced customers, average per unit time quality of service, average per unit time profit, average per unit time cost; or include objectives related to probabilities such as minimum probability of reject customers. This observation is in-line with the discussion in the review of Psaraftis et al. (2015) as well. Nevertheless, Fig. 5 shows that works dealing with the minimization of cost constitutes a significant part of the DVRP literature reviewed in our work.

Among the 80 reviewed papers, about 20% cover more than one objective function (e.g., Amrouss et al., 2017; Güner et al., 2017; Yu et al., 2015; Aragão et al., 2019; Alinaghian et al., 2019; Jung et al., 2015). In addition, some works propose unusual objectives, such as the works of Ferrucci and Bock (2015), Steever et al. (2019) and Schyns (2015).

Ferrucci and Bock (2015) consider a model to control vehicle en-route diversion. This situation occurs when a vehicle, while traveling to attend a customer's demand, receives a new order to attend the next one, resulting in an alteration of the previously planned route. The objective function of this problem is to minimize the total customer inconvenience, which is represented by a function of request response times. To control the number of diversions in the solution, the authors propose an approach based on a general penalty cost that is included as part of the objective function.

Steever et al. (2019) address the virtual food court delivery problem (VFCDP). In this problem, multiple restaurants can be included in a simple customer order, unlike standard business models (e.g. Grubhub and UberEat). Three customer-focused objectives are explored. The first seeks to maximize the total earliness to all customers, while also penalizing lateness to customers. If a delivery is made after the maximum time allowed for each client, a penalty per unit of time is added to the objective function. The second objective minimizes the total time that prepared meals wait in the restaurant.

Schyns (2015) studies a dynamic capacitated vehicle routing problem with time windows, (partial) split delivery and heterogeneous fleet (DVRPTWSD). This problem is based on the refueling of airplanes using trucks in an airport. Trucks must deliver fuel for the airplanes within a predefined time window which corresponds to the time interval that an

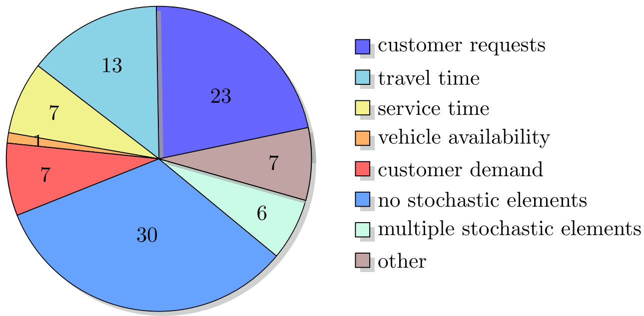

Fig. 6. Distribution of papers according to the nature of stochasticity (some papers present several stochastic elements).

airplane is on the ground. The objective of the proposed approaches is to optimize the responsiveness, which means completing the delivery as quickly as possible within the time window, so that the vehicle can restart its activity as soon as possible.

The third objective minimizes the total time between the pickup and the delivery points.

Other examples of papers within each objective function category are shown below.

1. To be minimized
   -Minimize cost: Vodopivec and Miller-Hooks (2017).
   -Minimize distance: Zhang et al. (2015).
   -Minimize travel time: Hyland and Mahmassani (2018).
   -Minimize total lateness: Ferrucci and Bock (2016).
   -Minimize waiting time: Dunnett et al. (2018)
2. To be maximized
   -Maximize Quality of Service: Brinkmann et al. (2019).
   -Maximize profit: Bian and Liu (2018).
   -Maximize attended requests: Santos and Xavier (2015).
3. Other: Steever et al. (2019), Ulmer and Streng (2019), Ulmer et al. (2018b).

3.4.2. Fleet size and time constraints

In our review, we found three scenarios of fleet types which are common in the literature (sample references are shown).

- Single Vehicle (1): Mavrovouniotis et al. (2017).
- Multiple and a limited number of vehicles (Many): Jia et al. (2018).
- Multiple and a sufficiently large number of vehicles (INF): Sarasola et al. (2015).

The distribution of papers according to the fleet size is as follows: 52 papers considered multiple and a limited number of vehicles, meaning that many authors address realistic problems where the number of vehicles is naturally limited; 7 papers considered multiple and a sufficiently large number of vehicles; and 21 papers considered problems with a single vehicle.

Regarding the subcategory of time constraints, we divided them into four types (sample references are shown):

- Hard time windows: Hu et al. (2017).
- Soft time windows: Jung et al. (2015).
- No time windows: Novaes et al. (2015).
- Other: Dunnett et al. (2018).

A constraint is called hard if it must be satisfied, while it is called soft if it can be violated (Hashimoto et al., 2006). The violation of a soft time window is penalized in the objective function. Note that the combination of hard time windows, no possibility of customer rejection and a finite number of vehicles may render problem instances infeasible (Psaraftis et al., 2015). In this sense, problems with soft time windows seem more realistic than those with hard time windows. Most of the dynamic problems consider soft time restrictions as it is truly difficult to ensure hard time restrictions unless the problem accepts an infinite number of vehicles. The distribution of papers according to time constraints is as follows: 19 papers use hard time windows, 17 papers use soft time windows, 19 use other time constraints, and 25 have no time constraints.

3.4.3. Vehicle capacity constraints and ability to reject customers

Some real problems can be modeled with unlimited capacity restriction, such as the case of the document courier service, where the transported goods are very small in relation to the capacity of the vehicle that transports them. These problems are considered to be uncapacitated. In this case, the vehicle's capacity can be considered as infinite. However, in many other applications, a capacity constraint should be used to correctly model the problem. We found 32 papers dealing with problems with capacity constraints (e.g., Ng et al., 2017; Onieva et al., 2017; Hu et al., 2017), and 48 papers dealing with uncapacited vehicle problems (e.g., Amrouss et al., 2017; Vodopivec and Miller-Hooks, 2017; Hyland and Mahmassani, 2018).

Regarding the ability to reject customers, in dynamic problems it makes sense to reject some customers as a result of hard time window constraints coupled with a limited number of vehicles or vehicles with capacity restrictions. Thus, there is a natural connection between hard time windows and the impossibility to reject clients, since these two simultaneous situations can make many instances of the problem in hand unfeasible. In our review, we found 25 papers considering problems where it is possible to reject customers (e.g., Fikar, 2018; Bian and Liu, 2018; Jung et al., 2015) and 55 papers that do not cover such a possibility (e.g., Ulmer et al., 2018b; Steever et al., 2019; Zhang et al., 2015).

Among the reviewed papers, we also found that when the possibility of rejecting customers is not present, most of the papers do not consider vehicle capacity constraints. This observation allows us to argue that most of the authors are interested in avoiding to deal with unfeasible solutions for the dynamic instances.

3.4.4. Nature of stochasticity

We note that the elements of a stochastic nature continue to be the same as observed by Psaraftis et al. (2015). Fig. 6 shows the number of reviewed articles and their division according to the nature of stochasticity. Most of the articles do not have elements of a stochastic nature (e.g., Bertsimas et al. (2019)). On the other hand, the most common stochastic elements are customer requests, travel time and service time. Some references are presented below.

- Customer Requests: Ulmer and Streng (2019).
- Travel Time: Köster et al. (2018).
- Service Time: Yu and Yang (2017).
- Vehicle Availability: Sabar et al. (2019).
- Customer Demand: Goodson et al. (2016).
- Other: Macharet et al. (2017).

Vehicle speed is an important aspect in dynamic problems, clearly related with travel times. For example, in urban areas vehicle speeds change due to current traffic and this generates problems in logistics transport operations. If the stochastic and time-dependent speeds of the vehicles are not considered, time windows are usually lost, which may jeopardize the services. The work of Schilde et al. (2014) published in 2014 is one of the few papers addressing this issue. This study considers the effect of exploiting stochastic information about vehicle speeds, using stochastic solution approaches for the dynamic dial-a-ride problem. The experiments, using test instances based on a real-world road network, show that in certain conditions, exploiting historical information about vehicle speeds leads to significant improvements over

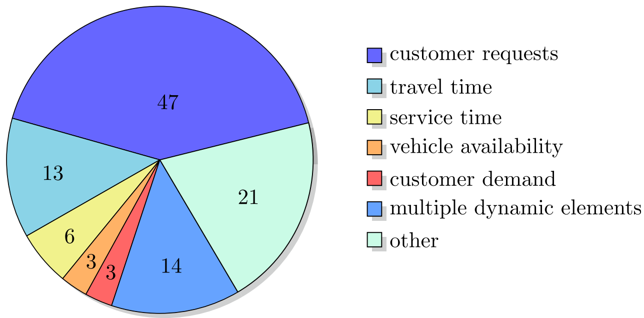

Fig. 7. Distribution of papers according to the dynamic nature of the elements (some papers present several dynamic elements).

deterministic approaches. However, in our review, no paper has considered the vehicle speed as a stochastic parameter. Only Ulmer and Streng (2019) provide a sensitivity analysis on the vehicle speed to examine how travel times of autonomous vehicles are influenced by this parameter. In their work, three different speed scenarios are analyzed, namely one with regular speed, one reduced by one third and one reduced by a half.

In our review, six articles have more than one element of stochasticity, namely Binart et al. (2016), Novaes et al. (2015), Baykasoğlu and Kaplanoğlu (2015), Bian and Liu (2018), Köster et al. (2018), Yu and Yang (2017). All these works use two elements of a stochastic nature, with the exception of Baykasoğlu and Kaplanoğlu (2015) where customer requests, travel times and service times are stochastic.

The categories *vehicle capacity constraints* and *ability to reject customers* are closely related to the stochastic nature of the problem. If we consider a problem setting where there are capacity restrictions in the vehicles and it is always possible to reject customers, we notice that few authors consider stochastic elements (e.g., Maghfiroh and Hanaoka, 2018; Ulmer and Thomas, 2018; Sayarshad and Chow, 2015). In the above situation, stochastic elements such as service time and travel time were not investigated by any author.

A second interesting relationship is found between the categories *fleet size*, *time constraints*, and the stochastic nature of the problem. For the case where soft time constraints and limited number of vehicles are considered, only one work addresses stochastic customer requests (Hyland and Mahmassani, 2018) and no other considers customer demands, service time or travel time as stochastic elements. On the other hand, if we consider the unrealistic situation where time constraints are hard and the fleet is multiple and sufficiently large, we note that no author conducted a study with any stochastic element. This suggests the tendency of the authors to deal with problems that are increasingly closer to reality.

Finally, a third relation exists between the objective function and the stochastic nature of the problem. For example, we note that many works dealing with stochastic travel time or stochastic service time, tend to associate the objective function to these stochastic elements (e.g., minimizing travel time Chai et al., 2017; Köster et al., 2018; Maghfiroh and Hanaoka, 2018; Yu and Yang, 2017).

3.4.5. Nature of dynamic element

In our review, we have not observed evolution in the nature of dynamic elements over the last seven years. Thus, many of the dynamic elements continue to be based on the stochastic elements. The dynamic elements commonly used in DVRP are:

- Customer requests: Sarasola et al. (2015)
- Travel Time: Kim et al. (2016)
- Service Time: Bian and Liu (2018)
- Vehicle availability: Monroy-Licht et al. (2016)
- Customer Demand: Klapp et al. (2018) and Alinaghian et al. (2019).
- Other: Ulmer et al. (2018a), Zhang et al. (2018), Ulmer et al. (2019) and Goodson et al. (2016).

In Fig. 7, we can see that the most common element of dynamism is customer requests and travel time. We found 14 articles with more than one element of a dynamism, some of these articles are: Ulmer and Streng (2019), Binart et al. (2016), Alinaghian et al. (2019), Novaes et al. (2015), Yu et al. (2015), Vodopivec and Miller-Hooks (2017) and Sabar et al. (2019) (for more details, see Appendix A). Moreover, we found other types of less common dynamic elements. An interesting example is provided in Agharkar et al. (2015), for which the dynamic element comprises moving targets. The goal of the dynamic VRP is to intercept as many targets as possible before they escape a radial system. This problem can be applied in the context of robotic patrolling, which is a very innovative field of application and for which dynamic approaches seem well suited.

Considering the ability to reject customers and vehicle capacity, approximately 10% of the papers investigate the case where the dynamic element is customer request (e.g., Ulmer and Thomas, 2018; Fikar, 2018; Sayarshad and Chow, 2015; Jung et al., 2015; Jia et al., 2018; Maghfiroh and Hanaoka, 2018; Santos and Xavier, 2015) However, if the dynamic element is one of the following: customer demand, vehicle availability, service time, or travel time, no work was addressed in such setting. In this work if the demand is unitary we call it customer request otherwise customer demand.

Considering that the fleet size is limited and time constraints are soft, the most investigated dynamic element is customer request (e.g., Hu et al., 2017; Bian and Liu, 2018; Christiansen et al., 2017; Ulmer et al., 2017b; Sayarshad and Chow, 2015; Vodopivec and Miller-Hooks, 2017), but other dynamic elements also considered, for example, travel time (e.g., Zhang et al., 2015; Agharkar et al., 2015; Ng et al., 2017; Aragão et al., 2019; Güner et al., 2017), service time (e.g., Zhang et al., 2018; Ulmer et al., 2018a; Mavrovouniotis et al., 2017; Hyland and Mahmassani, 2018; Hyland and Mahmassani, 2018; Vodopivec and Miller-Hooks, 2017), and customer demand (e.g., Ulmer et al., 2021; Ulmer et al., 2018c; Klapp et al., 2018; Klapp et al., 2018; Angelelli et al., 2016).

Finally, the relationship between dynamic elements and objective function is noteworthy. For example, when the objective function is cost minimization (the most common objective function in our review), the problem tends to consider the customer request as the dynamic element (e.g., Schyns, 2015; Ferrucci and Bock, 2016; Cheng et al., 2016; Fikar, 2018; Hung and Michailidis, 2015; Novaes et al., 2015).

3.5. Application

The development of technologies such as geographic information systems, tracking technologies, mobile communication, web services, cloud computing, and the arrival of 5G technology has allowed the emergence of new dynamic and smart transportation services, as well as new applications and business models. We refer the interested reader to the work of Perallos et al. (2015) for more details on Intelligent Transport Systems (ITS).

In general, dynamic vehicle routing manifests itself in a wide range of commercial and non-commercial sectors. For example, it has many applications on emergency services, such as rapid and massive evacuation of people in urban centers after a natural disaster, or medical transportation of sick or injured people. Another applications ranges from the distribution of consumer goods (wholesale and retail) to the package delivery services, express delivery and postal mail, and even related with planning of third-party logistics operations. Finally, the traditional dynamic VRP also has applications in reverse logistics and waste collection, along with optimization of the transportation network. More recently, dynamic VRPs have also been applied in several emerging business models. Services such as ride-sharing (Bertsimas et al., 2019; Jung et al., 2015), food delivery (Fikar et al., 2017; Steever

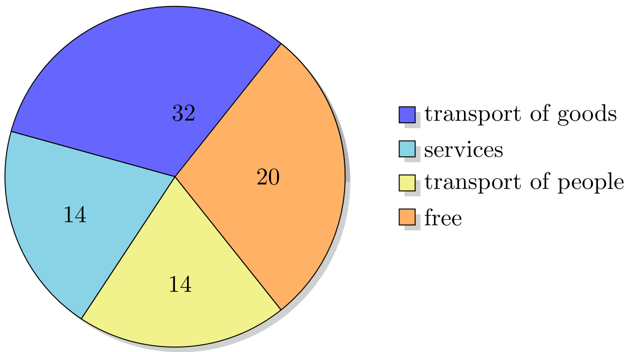

Fig. 8. Distribution of papers according to the Application.

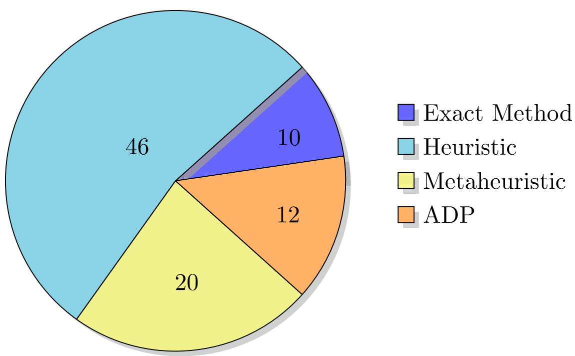

Fig. 9. Distribution of papers according to the method (some papers present several types of solution method).

et al., 2019) and medical transfer services, such as Uber Health, have been addressed considering dynamic elements in routing problems. Other innovative applications were also benefited by dynamic routing problems such as bike sharing services (Brinkmann et al., 2019), traffic optimization (Vitello et al., 2017; Chai et al., 2017; Luo et al., 2018), same-day delivery with drones (Ulmer and Thomas, 2018) and crowd-sourced deliveries (Alnaggar et al., 2019).

Fig. 8 presents the number of articles according to the application. Note that the most common application is on the transport of goods. Finally, we present applications that have been studied from the perspective of dynamic routing problems.

1. Transportation of goods
   -Crowdsourcing: Arslan et al. (2019)
   -Courier services: Steever et al. (2019), Sarasola et al. (2015).
   -E-grocery: Fikar (2018).
   -Food delivery services: Fikar et al. (2017), Steever et al. (2019).
   -Drug Delivery: Onieva et al. (2017).
   -E-commerce: Ulmer and Streng (2019).
2. Services
   -Logistic service providers: Ulmer (2018b), Ulmer et al. (2017b).
   -Emergency services: Maghfiroh and Hanaoka (2018), Alinaghian et al. (2019).
3. Transport of people
   -Dial-a-ride: Vodopivec and Miller-Hooks (2017).
   -Ride-sharing services: Bertsimas et al. (2019), Jung et al. (2015).
   -Traffic optimization: Vitello et al. (2017), Chai et al. (2017) and Luo et al. (2018).
4. Free:
   -Bian and Liu (2018), Sarasola et al. (2015), Klapp et al. (2018).

Among the innovative applications, ride-sharing and crowdsourcing fit perfectly the concept of “sharing economy”. Dynamic ride-sharing offers an alternative to private car usage, because it is less costly, and also more convenient than the public transport service (Stiglic et al., 2016). The ride-sharing service permits drivers to use their free vehicle capacity to transport passengers. In Dynamic ride-sharing it is critical to match the appropriate riders to form the shared ride, so many researchers focus on developing algorithms for ride matching (Lokhandwala and Cai, 2018) (e.g., Wang et al., 2018; Stiglic et al., 2016; Nourinejad and Roorda, 2016; Schreieck et al., 2016; Nourinejad and Roorda, 2016). Shortest-time dynamic route choice and VRP are more general problems that are not specific to ridesharing (Qin et al., 2021). In our review we are interested in investigations that propose models to optimize the combination passenger-vehicle matching and vehicle routing, such is the case of Santos and Xavier (2015), Bertsimas et al. (2019), and Jung et al. (2015). Santos and Xavier (2015) studies the combined ride-sharing problem performed by both taxis and car owners. Bertsimas et al. (2019) investigates the dynamic setting in a case-study comprising thousands of common taxis in the New York city, whereas Jung et al. (2015) addresses the challenges of electric vehicles of a taxi fleet. To know more about dynamic ride-sharing focused on optimization techniques and practical applications we encourage readers to view the surveys presented by Agatz et al. (2012), Martins et al. (2021) and Furuhata et al. (2013). Crowdsourcing comprises last-mile deliveries to customers performed by ordinary people in their own vehicles departing from stores or warehouses. This service allows the independent driver to use the free capacity in its vehicle to accommodate loads to deliver to customers located nearby the driver’s destination or along its route. The work of Arslan et al. (2019) is the only reviewed paper that applies the DVRP in the context of crowdsourcing. In this work, the driver sets the number of stops it is willing to perform en-route and the authors demonstrate that higher number of stops increases the cost savings.

4. Material evaluation - solution method perspective

The main techniques used for solving Dynamic Vehicle Routing Problems in our review are listed in this section. Nearly all of them are classified as heuristics or hybrid methods, mainly because there is no exact algorithm that can find optimal tours within reasonable computing time for large or practical instances size. The exact methods observed in this review are used to optimize a subset of the decision variables of the optimization problem. We also note that some authors use exact methods only to solve small instances of DVRPs. Fig. 9 presents the number of articles according to the solution method used. Note that some authors propose more than one type of solution method in the same paper (e.g., Steever et al., 2019; Brinkmann et al., 2019; Christiansen et al., 2017; Bertsimas et al., 2019).

4.1. Heuristics

Heuristics are largely employed in solving dynamic problems, since generally they are fast and provide simple rules to generate solutions of good quality. We review the main heuristics techniques used in solving DVRP problems.

4.1.1. Insertion methods

The insertion methods fall into the class of constructive heuristics in which a feasible solution is constructed by adding nodes to a partial tour one at a time and stopping when the final solution is found (Steven Orla Kimbrough, 2016). For example, for the TSP, the essential idea of the insertion method is to start with two randomly selected nodes creating a subtour; then, at each step, a node, that does not belong to the subtour, is selected and inserted into it. Insertion methods are widely used to address the curse of dimensionality in approximate dynamic programming. In our review, some works (Ulmer, 2018b; Ulmer, 2017a; Ulmer and Thomas, 2018) adopt insertion methods for this purpose. Another example of insertion heuristic is proposed in Fikar (2018). This is used to address a real time distribution problem of e-groceries. To deal with the problem, a decision support system is developed. Order picking is defined using different policies such as First-expired-first-out, last-expired-first-out and random picking. The insertion heuristic is used to define scheduling and routing of pickups and deliveries. Every minute the insertion heuristic evaluates all new requests (that consists of a pickup and delivery) to all the positions in the vehicle route. The option that minimizes the distance or maximizes delivery quality is chosen.

4.1.2. Reoptimization methods

Reoptimization methods can be classified into Myopic and Look-ahead. Myopic solution methods are approaches that focus only on optimizing the current state of the problem, as defined by Powell et al. (2012). Ulmer (2017b) also presents a similar definition, in which he defines myopic approaches as methods that consider only immediate reward. Therefore, every time new information arrives, the problem is solved again considering its new current state. Usually, this method is more used in dynamic and deterministic problems, in which reaction is the main focus, rather than anticipation. However, myopic policies may also have tunable parameters to avoid greediness and produce good results over time (Powell et al., 2012).

An example is presented in Steever et al. (2019). They propose methods embedded in myopic reoptimiziation to address the dynamic courier routing for a food delivery service. Firstly, a mixed-integer programming model is proposed. The model must be resolved periodically to deal with the dynamic elements (e.g., when a new order is placed). Auction-based heuristics (myopic and proactive) are also suggested to efficiently solve the problem. Basically, the auction-based myopic heuristic considers one courier at a time and assigns a new order to the courier that presents the maximum objective function. The auction-based proactive heuristic includes measures of equity and dispersion to assess and improve the system's preparedness for future demands. A simulation framework is developed to compare the proposed methods and obtain managerial insights. The authors compare three strategies: myopic (the courier with the maximum bid value wins the auction, and is assigned the newly arrived customer), mixed and proactive. In the computational experiment, the proactive auction-based heuristic provided better results than the other methods.

According to Powell et al. (2012), lookahead methods optimize not only the current state, but more than one period into the future. Therefore, the future can be approximated deterministically over a defined planning horizon and scenarios could be used in order to model future values of uncertain parameters (e.g., orders, demands and travel times). This method can become easily intractable when considering a multistage structure of recourse decisions or several scenarios, therefore authors usually use the method considering a two-stage structure with here-and-now variables (decisions that are taken before uncertainty is revealed) and wait-and-see (recourse) decision variables. In the operations research community lookahead methods are also known as rolling-horizon approaches. Two studies that use lookahead reoptimization are described below.

Köster et al. (2018) examine the dynamic vehicle routing problem with stochastic changes in travel time matrices. This problem arises in the context of traffic pollution and the service of delivery companies, in which the objective is to minimize travel time and at the same time avoid areas that may be affected by contaminating emissions. Based on potential trajectories of emission values, emission samples are generated and average travel times are calculated according to the samples. A commercial solver is used to solve the routing problem with the updated travel times. The procedure is repeated at each point of time until the end of the time horizon. To deal with the problem, three static routing heuristics with different initial distributions are analyzed. The first static policy does not rely on any information and determines the routing based on the travel times when no hotspot is active. The second policy determines the routing based on the current travel time matrix. The third static policy is the same heuristic present by Huang et al. (2017), which integrates the forecasted travel times. In addition, an anticipatory dynamic routing policy is used to analyze the impact of dynamic updates of routing and forecasts. Computational experiments show that the average improvements of dynamic policy over the static benchmark policy are 6.8% decrease in travel time and even 54.6% reduction traveling through polluted areas. Computational experiments show the superiority of the anticipatory method over myopic policies.

Kim et al. (2016) address a DVRP with stochastic travel times and traffic congestion using a rollout lookahead method. The one-step look-ahead rollout approach uses the Bellman equation and makes decisions about the next vehicle's destination, considering uncertainty of traffic condition. A Monte Carlo simulation is used to generate scenarios for the rollout algorithm. Computational experiments indicate an improvement of 7% of the dynamic approach over the static solution.

4.2. Exact methods

Mixed-integer linear programming models are widely used to formulate discrete and combinatorial optimization problems. Optimization problems are usually formulated through MILP models and solved using branch-and-bound, branch-and-cut and branch-and-price solution methods. Pure deterministic MILP are often used to solve dynamic and deterministic vehicle routing problems mainly through myopic reoptimization. As a consequence, exact methods only provide an optimal solution for the current state, but do not guarantee that the solution will remain optimal once new data becomes available (Pillac et al., 2013). The methods classified in this section solve small instances or are used in conjunction with heuristics to obtain good quality solutions from DVRPs.

An example of mixed-integer linear programming for DVRP is the one used by Monroy-Licht et al. (2016). They apply mixed-integer programming to model policies for the dynamic rescheduling arc routing problem. In the problem, the itineraries of the vehicles are readjusted every time there are failures in the vehicles during the execution of the routes. The objective is to minimize operating and interruption costs in the schedule. The authors propose a two-phase algorithm to solve the problem. They consider a small problem to solve where some decision variables are fixed, and then the smaller problem is solved to optimality using the proposed formulation.

Hu et al. (2017) investigate the economic and environmental performance of multi-capacity rail-guided vehicles (RGVs) working on a linear track automated freight handling system (AFHS). In this problem, air cargo enters and leaves the system dynamically in time. The problem can be seen as a capacitated pickup and delivery problem. It is modeled as a MILP with the objective to minimize energy consumption. Two routing approaches are applied to compute the total energy cost: a rolling-horizon approach and a rule-based approach. Rules-based approaches were reported in Lee (1999), Roodbergen and Vis (2009). The MILP model is combined with a rolling-horizon approach do deal with the problem. The simulations show that, compared to the rule-based approach, the rolling-horizon approach is capable of reducing the energy cost by up to 15%.

Amrouss et al. (2017) address the log-truck scheduling problem (LTSP) through a mathematical programming model. An approach that re-optimizes transport planes in real time (when an unforeseen event is revealed) was proposed. This approach is built on a time–space network representation which is used in the mathematical programming model. The model takes the time–space network as input and is reoptimized. Computational experiments showed that the mathematical model was solved in a few seconds, showing its potential of being used in real time practical applications.

4.3. Approximate dynamic programming (ADP)

In this section we review works presenting solution methods using Approximate Dynamic Programming (ADP), and the two main techniques used, policy function approximation and value function

Table 4
Legend of Table 5.

Key	Meaning	Key	Meaning
1	single	DS	Dynamic and stochastic
Many	Multiple, limited number of vehicles	DD	Dynamic and deterministic
INF	Multiple, sufficiently large number of vehicles Time Constraints	P/ D	Either pickup (P) or delivery (D
O	Other	PD	Both Pickup and Delivery

approximation.

4.3.1. Policy function approximation (PFA)

Policy function approximation is a method that returns an action given a state without necessarily solving an optimization problem (Powell et al., 2012). Policy function approximations can be categorized into three groups: lookup tables, parametric and non-parametric. Lookup table methods present a table that give an action for each discrete state. Parametric policies are those parameterized by a vector that gives an action based on vector values and the state. Non-parametric models rely on non-parametric statistics, in which specifying a parametric model is avoided. Below we describe some of the reviewed works that used PFA.

Ulmer and Thomas (2018) study the same-day delivery problem with heterogeneous fleets of drones and vehicles considering dynamic requests. A PFA is used in order to decide the transportation mode according to the delivery time. Computational results show that the method is able to increase the expected number of same-day delivery requests attended and that combining drones and vehicles may significantly reduce the required delivery resources.

Inspired by the above paper, Ulmer and Streng (2019) performed a study on the same-day delivery problem with pickup stations and autonomous vehicles. The problem is modeled using a Markov decision process and solved through a policy function approximation. Basically, the PFA decides which stations are going to deliver the product according to their current capacities. Computational studies confirm the superiority of the heuristic proposed over other benchmarks policies and provides managerial insights on the problem addressed.

4.3.2. Value function approximation (VFA)

Value function approximations are based on Bellman's equation in which the value function is approximated because of the curse of dimensionality. Therefore, reduction and aggregation methods are used to reduce the state, decision and transition spaces. Similar to policy function approximation, value function approximation can also be categorized into lookup tables, parametric and nonparametric policies. Below we describe some of the works that apply VFA to solve dynamic routing problems.

Ulmer et al. (2018b) study the dynamic multi-period vehicle routing problem under stochastic service requests and with the objective of maximizing the number of customers attended and the service quality. The problem is modeled as a Markov decision process and solved through an approximate dynamic programming method that estimates future rewards over the periods. Four policies are compared: VFA, single, PFA, and myopic. The VFA and single policies were reported in Ulmer et al. (2018a), and the PFA policy is related to the method presented in Angelelli et al. (2009). The single policy draws on VFA and allows intra-period anticipation, while acting multi periodically myopic. To analyze the policies' impact on the customer acceptance behavior, it was applied a purely myopic policy. In more than 90% of the instance settings, VFA achieves the best results. In the remaining cases, the best results are provided by the single policy.

Another related work is presented in Ulmer et al. (2018c). They explore preemptive depot returns for a stochastic dynamic one-to-many pickup and delivery problem (SDPD). To deal with this problem, an approach called anticipatory preemptive depot return (APDR) is introduced. APDR combines a procedure based on approximate dynamic programming and a routing heuristic. The ADP approximates the value of choosing any particular set of delivery requests, therefore it can capture the current value of a subset decision as its impact on future rewards. The benchmark heuristics used to test the quality of APDR were the ATB (time budgeting approach) proposed by Ulmer et al. (2018a), a myopic assignment strategy, a preemptive method, and an PAH (plan-at-home heuristic). ATB is based on approximate dynamic programming and PAH is an approach that does not account for the possibility of preemptive depot returns (the vehicle must return empty to the depot). Computational experiments show that APDR overcame the benchmark policies. It means that preemptive depot returns, and the APDR approach in particular, increase the number of deliveries per workday.

4.4. Metaheuristic

Sorensen and Glover (2013) define a metaheuristic as a high-level problem-independent algorithmic framework that provides a set of guidelines or strategies to develop heuristics for specific optimization problems. In this section, we review the main metaheuristics used to solve the DVRP.

4.4.1. Swarm intelligence

According to Mavrovouniotis et al. (2017) swarm intelligence (SI) is the property of a system whereby the collective behaviors of agents that interact locally with their environment cause coherent functional global patterns to emerge. SI is inspired from nature, especially biological systems such as ant colonies and flocks of birds, in which the agents have simple behaviors and are self-organized among them (Mavrovouniotis et al., 2017). The most popular algorithms of SI are ant colony optimization (ACO) (Colorni et al., 1992) and particle swarm optimization (PSO) (Kennedy et al., 1995).

Schyns (2015) introduces an algorithm based on ant colony optimizaton (ACO) to deal with a broad range of DVRPTWSD (see Section 3.4.1). Since the response capacity is the main objective in the DVRPTWSD, every time new information arrives the optimizer is called again. This procedure allows to immediately take into account any dynamic change in the problem. Experiments show that the proposed algorithm is flexible and achieves good solutions within a short time. Another work that uses the ACO approach to deal with DVRP is the one of Mavrovouniotis et al. (2017). They propose a memetic ACO algorithm to deal with both symmetric and asymmetric Dynamic Traveling Salesman Problems (DTSP). Unlike the classic TSP, in the DTSP the weights between cities can change. In the proposed approach, a local search operator is integrated into ACO. Basically, the best solution from ACO is passed to the local search operator, then it removes and inserts cities aiming to improve the solution quality. Computational experiments show the efficiency of the memetic ACO compared to other memetic algorithms. In the same line, a related study is the one by Ng et al. (2017). They develop a Multiple Colonies Artificial Bee Colony (MC-ABC) to solve an Online Vehicle Routing Problem (OVRP). The OVRP allows for dynamic vehicle rerouting under traffic congestion. The authors present two variations of the MC-ABC based on a reoptimization approach to solve the OVRP under time-dependent traffic congestion. Experiments show that MC-ABC algorithms present better results than original ABC for the OVRP.

In our review only the works of Jia et al. (2018), Okulewicz and Mańdziuk (2019), and Muñoz-Carpintero et al. (2015) report the use of PSO to deal with DVRP. The work of Muñoz-Carpintero et al. (2015) reports a hybrid between PSO + GA (see Section 4.4.6). Jia et al. (2018) address a dynamic capacitated vehicle routing problem using a system that consists of a set-based PSO algorithm (S-PSO-D) and a periodic reoptimization framework. Moreover, three techniques make this system efficient. A local refinement procedure is used to lightly modify the

Table 5
Taxonomy of problems: papers reviewed.

#	Reference	Type	Log. Context	Trans. Mode	Objective function	Fleet Size	Time Constraints	VCC	ARC	Dynamic Element	Stochastic Element
1	Ulmer et al. (2018b)	DS	P/D	Road	Max. quality of service (Max. # accepted requests)	1	Other (Max ride time)	No	Yes	Customer requests	Customer requests
2	Ulmer (2018b)	DS	P/D	Road	Max. quality of service (Max. # accepted requests)	1	Other (Max ride time)	No	Yes	Customer requests	Customer requests
3	Ulmer (2018b)	DS	P/D	Road	Max. quality of service (Max. # customer served)	1	Other (Max ride time)	No	Yes	Customer requests	Customer requests
4	Ulmer and Streng (2019)	DS	P/D	Air	Other (Min. average delivery time per customer)	Many	Other (Pickup time)	Yes	No	Customer requests, Other (Pickup time)	Customer requests
5	Ulmer (2017a)	DS	O	Road	Other (Min. expected sum of delay over all customers)	Many	Soft	No	No	Customer requests	Customer requests
6	Ulmer and Thomas (2018)	DS	O	Road, Air	Max. quality of service (Max. # customer served)	Many	Hard	Yes	Yes	Customer requests	Customer requests
7	Zhang et al. (2015)	DD	O	Road	Min. distance	1	No	No	No	Other (Edge blockages)	No
8	Binart et al. (2016)	DS	P/D	Road	Maximize Profit	Many	Other	No	Yes	Travel time, Service time	Travel time, Service time
9	Steever et al. (2019)	DS	PD	Road	Other (Min. lateness, Min. earliness, Min. total ready-to-delivery time)	Many	Soft	Yes	No	Customer requests	Customer requests
10	Brinkmann et al. (2019)	DS	O	Road	Max. quality of service	Many	No	Yes	No	Customer requests	Customer requests
11	Amrouss et al. (2017)	DD	PD	Road	Min. cost, Max. quality of service	Many	No	Yes	Yes	Other (Closures, demand/supply variations, breakdowns)	No
12	O'Neil and Hoffman (2019)	DD	PD	Road	Min. cost	1	No	No	No	Other	No
13	Agharkar et al. (2015)	DS	O	Road	Other (Capture fraction)	1	No	No	No	Other (Appears of the target in the region)	Other (Appears of the target in the region)
14	Schyns (2015)	DD	P/D	Road	Min. distance, Other (Min. lateness)	Many	Hard	Yes	No	Customer requests	No
15	Ferrucci and Bock (2016)	DS	P/D	Road	Max. quality of service	Many	Soft	No	No	Customer requests	Customer requests
16	Cheng et al. (2016)	DS	PD	Road	Min. waiting time, Other (Min. total service time)	Many	Hard	Yes	No	Customer requests	Customer requests
17	Ng et al. (2017)	DD	P/D	Road	Min. travel time	Many	No	Yes	No	Travel time	No
18	Monroy-Licht et al. (2016)	DD	P/D	Road	Min. cost, Other (operational and disruption cost)	Many	No	No	No	Vehicle availability	No
19	Alinaghian et al. (2019)	DD	P/D	Air	Min. total lateness, Min. waiting time	Many	No	Yes	No	Customer requests, Customer demand	No
20	Fikar (2018)	DS	PD	Road	Min. cost, Other (Max. remaining shelf lives of products)	Many	Hard	Yes	Yes	Customer requests	No
21	Aragão et al. (2019)	DS	PD	Road	Min. cost, Max. quality of service	Many	Other	No	No	Travel time	Travel time
22	Vitello et al. (2017)	DD	O	Road	Min. travel time	Many	No	No	No	Other (Traffic congestion)	No
23	Güner et al. (2017)	DS	O	Road	Min. cost, Max. quality of service	1	Hard	No	No	Other(Dynamic routing)	Travel time
24	Chai et al. (2017)	DS	O	Road	Min. travel time	Many	No	No	No	Travel time	Travel time
25	Hung and Michailidis (2015)	DD	P/D	Road	Max. throughput (efficiency)	Many	No	No	No	Customer requests	No
26	Novaes et al. (2015)	DS	P/D	Road	Min. cost	Many	Hard	No	No	Travel time, Service time	Travel time, Service time
27	Baykasoğlu and Kaplanoğlu (2015)	DS	P/D	Road	Min. cost	Many	No	No	Yes	Customer requests, Travel time, Service time	Customer requests, Travel time, Service time
28	Du et al. (2015)	DD	O	Road	Min. travel time	Many	No	No	No	Travel time	No
29	Luo et al. (2018)	DS	O	Road	Other (Energy Consumption)	Many	Other (Max. lenght)	No	No	Travel time	No
30	Onieva et al. (2017)	DD	P/D	Road	Other (Min. total time spent)	Many	No	Yes	No	Customer requests	No
31		DS	P/D	Road		Many	Soft	No	No	Customer requests	Customer requests

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Table 5 (*continued*)

#	Reference	Type	Log. Context	Trans. Mode	Objective function	Fleet Size	Time Constraints	VCC	ARC	Dynamic Element	Stochastic Element
	Ferrucci and Bock (2015)				Max. quality of service						
32	Dunnett et al. (2018)	DD	O	Road	Min. waiting time	Many	Other	No	No	Customer requests	No
33	Hu et al. (2017)	DD	PD	Road	Other (Energy Consumption)	1	Hard	Yes	No	Customer requests	No
34	Kim et al. (2016)	DS	P/D	Road	Min. cost	INF	No	Yes	No	Travel time	Travel time
35	Bian and Liu (2018)	DS	O	Road	Max. profit	1	Other (Max ride time)	No	Yes	Travel time, Service time	Travel time, Service time
36	Christiansen et al. (2017)	DD	P/D	Maritime	Min. cost	Many	Hard	Yes	No	Customer requests	No
37	Ulmer et al. (2017b)	DS	P/D	Road	Other (Max. # customer served)	1	No	No	Yes	Customer requests	Customer requests
38	Yu et al. (2015)	DD	O	Road	Min. cost, Min. travel time	INF	Other	No	No	Customer requests, Customer demand	No
39	Sayarshad and Chow (2015)	DS	O	Road	Max. profit (social welfare)	Many	No	Yes	Yes	Customer requests	Customer requests
40	Köster et al. (2018)	DS	P/D	Road	Min. travel time	Many	No	No	No	Travel time, Other	Travel time, Other (emissions)
41	Vodopivec and Miller-Hooks (2017)	DS	O	Road	Min. cost	1	Soft	No	No	Travel time, Vehicle availability	Travel time
42	Hyland and Mahmassani (2018)	DS	O	Road	Min. distance, Min. waiting time	Many	Soft	No	No	Customer requests	Customer requests
43	Jung et al. (2015)	DD	O	Road	Min. waiting time, Max. quality of service, Other	Many	Hard	Yes	Yes	Customer requests	No
44	Tirado and Hvattum (2016)	DS	PD	Maritime	Min. cost	Many	Hard	Yes	No	Customer requests	Other
45	Sarasola et al. (2015)	DS	P/D	Road	Min. cost, Min. total lateness	INF	Soft	Yes	No	Customer requests	Customer demand
46	Sabar et al. (2015)	DD	P/D	Road	Min. distance	Many	Soft	No	No	Customer requests	No
47	Mavrovouniotis et al. (2017)	DS	O	Road	Min. distance	1	Soft	No	No	Other	Travel time
48	Jia et al. (2018)	DD	P/D	Road	Min. travel time	Many	Soft	Yes	Yes	Customer requests	No
49	Fikar et al. (2017)	DD	PD	Road	Min. travel time, Max. quality of service	Many	Hard	Yes	No	Customer requests	No
50	Bouchra (2018)	DD	P/D	Road	Min. travel time, Max. quality of service	Many	Soft	Yes	Yes	Customer requests	No
51	Macharet et al. (2017)	DS	O	Road	Min. distance	Many	No	No	No	Other	Other (regions randomly placed according to an uniform distribution)
52	Maghfiroh and Hanaoka (2018)	DS	P/D	Road	Min. travel time	INF	Other	Yes	Yes	Customer requests	Customer demand
53	Yu and Yang (2017)	DS	P/D	Road	Min. travel time	INF	Other	No	No	Other	Travel time, Service time
54	Bertsimas et al. (2019)	DD	PD	Road	Max. profit	Many	Hard	No	Yes	Customer requests	No
55	Muñoz-Carpintero et al. (2015)	DS	P/D	Road	Other	Many	Other	Yes	No	Customer requests	Customer demand
56	Ulmer et al. (2018a)	DS	P/D	Road	Ohter	1	No	No	Yes	Other	Customer demand
57	Zhang et al. (2018)	DS	P/D	Road	Max. profit	1	Soft	No	No	Other	Service time
58	Ulmer et al. (2019)	DS	P/D	Road	Other (Max. # customers)	1	Other	No	Yes	Other	Customer demand
59	Goodson et al. (2016)	DS	P/D	Road	Max. profit	Many	Other	Yes	No	Other	Customer demand
60	Voccia et al. (2019)	DS	PD	Road	Other (Max. expected number of requests that can be delivered on time)	Many	Soft	No	Yes	Customer requests	Customer requests
61	Angelelli et al. (2016)	DS	P/D	Road	Min. cost, Other (Max. probability of satisfying product demand)	1	Other	No	No	Other (information about consumption events is made available at runtime)	Other
62	Sabar et al. (2019)	DS	P/D	Road	Min. distance	INF	No	Yes	No	Travel time, Service time	Vehicle availability
63	Okulewicz and Mańdziuk (2019)	DS	P/D	Road	Min. cost	Many	Hard	Yes	No	Customer requests	Customer demand
64	Klapp et al. (2018)	DS	P/D	Road	Min. cost	1	Soft	No	No	Custoomer demand	Customer requests

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Table 5 (*continued*)

#	Reference	Type	Log. Context	Trans. Mode	Objective function	Fleet Size	Time Constraints	VCC	ARC	Dynamic Element	Stochastic Element
65	Santos and Xavier (2015)	DD	PD	Road	Max. customer requests, Min. cost	Many	Hard	Yes	Yes	Customer requests	No
66	Grippa et al. (2018)	DS	PD	Air	Other	Many	Other	Yes	No	Customer requests	Travel time
67	Klapp et al. (2018)	DS	P/D	Road	Min. cost	1	No	No	Yes	Customer requests	Customer requests
68	Srour et al. (2018)	DS	PD	Road	Min. cost	INF	Soft	No	Yes	Service time	Service time
69	Bopardikar and Srivastava (2020)	DS	P/D	Road	Other	1	No	No	No	Customer requests	Customer requests
70	Ulmer et al. (2018c)	DS	P/D	Road	Other (Max expected number of SOs served over the horizon of the problem)	1	Other	No	Yes	Customer requests	Customer requests
71	Ulmer (2020)	DS	P/D	Road	Max. profit	Many	Hard	No	No	Other	Customer requests
72	Vinsensius et al. (2020)	DS	P/D	Road	Min. cost and max. Profit	Many	Hard	Yes	No	Customer requests and other	Customer requests
73	Ulmer et al. (2021)	DS	PD	Road	Min. waiting time	Many	Soft	No	No	Customer requests	Customer requests
74	Wang et al. (2021)	DD	P/D	Road	Min. distance and min. waiting time	Many	Hard	No	No	Customer requests	No
75	Drótos et al. (2021)	DD	PD	Road	min. total lateness	Many	Soft	Yes	No	Customer requests	No
76	Xu and Zhou (2020)	DD	O	Road	min. cost	1	No	No	No	Other	No
77	Alisoltani et al. (2021)	DD	PD	Road	min. distance, travel time and waiting time	Many	Hard	Yes	Yes	Other	No
78	Lee and Savelsbergh (2015)	DD	O	Road	min. cost	Many	Hard	No	No	Customer requests	No
79	Levin (2017)	DD	P/D	Road	min. travel time	Many	No	No	Yes	Other	No
80	Dayarian and Savelsbergh (2020)	DS	PD	Road	min. cost and total lateness	Many	Other	Yes	No	Customer requests	other

solutions in order to improve them. A region partition method improves the solution efficiency by dividing a large static CVRP into independent minor problems. Finally, an archive strategy is applied to seize the evolution experience of the previous optimizations. Computational experiments reveal that the proposed approach presents high performance in large instances. On the other hand, Okulewicz and Mańdziuk (2019) deals with the DVRP in a continuous search space. The work compares PSO and Diferential Evolution (DE) metaheuristics. The results obtained by both continuous algorithms outperform state-of-the-art algorithms utilizing a discrete problem representation.

4.4.2. Tabu search

The tabu search (Glover, 1986) explores part of the solution space by moving to the best neighbor of the current solution, even when this movement deteriorates the objective function (Gendreau et al., 1996). Recently considered candidate solutions are stored in a structure known as a tabu list. The idea is to avoid cycling, therefore solutions in a tabu list are made inaccessible for a number of iterations. This approach is one of the most successful in the literature to deal with VRP.

Ferrucci and Bock (2015) studied a problem called vehicle en-route diversion in DVRPs. This problem occurs when a vehicle goes to a customer location to serve a request and receives a new request that must be served next. This is possible due to current real-time communication technologies. In this study, real-time routing takes place by solving consecutive static problem instances. These instances appear in a predefined time interval. To solve the static problems, two approaches that use tabu search (TS) are introduced: the first approach is a pro-active approach that anticipates future requests and the second approach is deterministic and integrates newly arriving requests. These two previous approaches are capable of finding good quality solutions quickly in the static instances of the problem. By comparing the results with the lower bound values obtained by the approach of Westphal and Krumke (2007), it turns out that this Tabu Search approach solves static problem instances, which occur in the considered application, to optimality or near optimality.

Inspired by their previous work, Ferrucci and Bock (2016) propose a tabu search (TS) to deal with a Dynamic Vehicle Routing Problem with Soft Time Window constraints. The algorithm presents a pro-active routing approach that generates different profiles of requests in order to create stochastic knowledge for a dynamic vehicle problem. During the day, the approach repeatedly analyzes the characteristics of the requests and then selects a combination of profiles. To evaluate the performance of the applied Tabu Search, the authors consider real problem instances under restrictive time limits. The authors compare the attained results with lower bound values generated by the exact approach of Westphal and Krumke (2007). This evaluation reveals that the applied Tabu Search method yields near-optimal or even optimal solutions for all tested instances within 10 s.

4.4.3. Evolutionary algorithms and genetic algorithm

Evolutionary computing (EC) includes techniques based on population methods and biological concepts. An algorithm in this collection is known as an evolutionary algorithm (EA). Most EAs may be classified into generational algorithms, which update the entire population once per iteration, and steady-state algorithms, which update a few candidate solutions at a time (Luke, 2013). Genetic algorithms (GA) and evolutionary algorithms (EA) are good examples of EAs.

Onieva et al. (2017) present an Adaptive Multi-Crossover Evolutionary Algorithm (AMCEA) for a drug distribution problem. The proposed AMCEA is a variant of the classic Genetic Algorithm (GA) and it was introduced first by Osaba et al. (2014). An incident is the arrival of new information that was not present at the time of planning the routes. The dynamism introduced by an incident occurs in case a delivery for a pharmacy has suffered a problem, e.g., an incomplete delivery (Onieva et al., 2017). Every time an incident occurs, a new route is recalculated based on the incident priority (high or low). The problem is modeled as dynamic asymmetric capacitated VRP with variable service and travel times. The results obtained by the proposed AMCEA have been compared with the ones obtained by three different classical GAs. Results show good performance of the proposed algorithm in terms of

Table 6
Taxonomy of solution methods: papers reviewed.

#	Reference	Application	Method	Mode
1	Ulmer et al. (2018b)	Free	ADP	Offline
2	Ulmer (2018b)	Free	ADP	Hybrid
3	Ulmer (2018b)	Free	ADP, Heuristic, EM	Hybrid
4	Ulmer and Streng (2019)	Transport of goods	ADP	Offline
5	Ulmer (2017a)	Transport of goods	Heuristic	Online
6	Ulmer and Thomas (2018)	Transport of goods	Heuristic	Offline
7	Zhang et al. (2015)	Free	Heuristic	Online
8	Binart et al. (2016)	Services	ADP	Offline
9	Steever et al. (2019)	Transport of goods	Heuristic, EM	Online
10	Brinkmann et al. (2019)	Services	Heuristic, ADP	Online
11	Amrouss et al. (2017)	Transport of goods	EM	Online
12	O'Neil and Hoffman (2019)	Free	EM, CP model	Online
13	Agharkar et al. (2015)	Free	Heuristic	Offline
14	Schyns (2015)	Services	Metaheuristic, Other	Online
15	Ferrucci and Bock (2016)	Transport of goods	Heuristic, Metaheuristic (TS)	Online
16	Cheng et al. (2016)	Transport of goods (Express courirer)	Heuristic (pickup policy)	Offline
17	Ng et al. (2017)	Services	Metaheuristic (ABC), Heuristic (Local Search)	Online
18	Monroy-Licht et al. (2016)	Free	MIP with itereative reoptimization	Online
19	Alinaghian et al. (2019)	Services	Metaheuristic (GA, VNS, SS)	Online
20	Fikar (2018)	Transport of goods (e-grocery)	Heuristic	Hybrid
21	Aragão et al. (2019)	Transport of goods	Heuristic	Hybrid
22	Vitello et al. (2017)	Transport of people	Heuristic	Online
23	Güner et al. (2017)	Transport of goods	ADP	Online
24	Chai et al. (2017)	Transport of people	Heuristic (Dijkstra, signal control policies)	Online
25	Hung and Michailidis (2015)	Services	Heuristic	Offline
26	Novaes et al. (2015)	Transport of goods	Metaheuristic (GA)	Online
27	Baykasoğlu and Kaplanoğlu (2015)	Transport of goods	Heuristic	Online
28	Du et al. (2015)	Transport of people	Heuristic	Online
29	Luo et al. (2018)	Transport of people	Heuristic	Online
30	Onieva et al. (2017)	Transport of goods	Metaheuristic (EA)	Hybrid
31	Ferrucci and Bock (2015)	Transport of goods	Metaheuristic (TS)	Online
32	Dunnett et al. (2018)	Services	Heuristic (Dijkstra, dispatching rules)	Online
33	Hu et al. (2017)	Transport of goods	MIP with rolling horizon	Online
34	Kim et al. (2016)	Transport of goods	Metaheuristic (NNS)	Online
35	Bian and Liu (2018)	Free	Metaheuristic	Online
36	Christiansen et al. (2017)	Transport of goods	Heuristic, EM	Online
37	Ulmer et al. (2017b)	Free	Heuristic	Offline
38	Yu et al. (2015)	Transport of people	Metaheuristic	Online
39	Sayarshad and Chow (2015)	Transport of people	Heuristic	Online
40	Köster et al. (2018)	Transport of goods	Heuristic	Online
41	Vodopivec and Miller-Hooks (2017)	Transport of people	Heuristic	Online, Offline
42	Hyland and Mahmassani (2018)	Transport of people	Heuristic	Online
43	Jung et al. (2015)	Transport of people	Heuristic	Online
44	Tirado and Hvattum (2016)	Transport of goods	Heuristic	Hybrid
45	Sarasola et al. (2015)	Free	Metaheuristic (VNS)	Online
46	Sabar et al. (2015)	Free	Heuristic	Online
47	Mavrovouniotis et al. (2017)	Free	Metaheuristic (ACO)	Online
48	Jia et al. (2018)	Transport of goods	Metaheuristic (PSO)	Hybrid
49	Fikar et al. (2017)	Transport of goods	Heuristic	Online
50	Bouchra (2018)	Free	Metaheuristic (VNS + GA)	Hybrid
51	Macharet et al. (2017)	Free	Heuristic	Online, Offline
52	Maghfiroh and Hanaoka (2018)	Services	Metaheuristic (SA and VNS)	Online
53	Yu and Yang (2017)	Services	Heuristic, EM	Online
54	Bertsimas et al. (2019)	Services	Heuristic, EM	Hybrid
55	Muñoz-Carpintero et al. (2015)	Services	Metaheuristic (PSO + EA)	Online
56	Ulmer et al. (2018a)	Services	Heuristic, EM	Online
57	Zhang et al. (2018)	Transport of goods	Heuristic, MDP	Online, Offline, Hybrid
58	Ulmer et al. (2019)	Services	ADP, EM	Hybrid
59	Goodson et al. (2016)	Services	Heuristic	Online, Offline
60	Voccia et al. (2019)	Transport of goods	Heuristic	Online
61	Angelelli et al. (2016)	Transport of goods	Heuristic, EM	Online
62	Sabar et al. (2019)	Free	Metaheuristic (EA)	Online
63	Okulewicz and Mańdziuk (2019)	Free	Metaheuristic (PSO, GA, DE)	Online
64	Klapp et al. (2018)	Free	Heuristic	Online, Offline
65	Santos and Xavier (2015)	Transport of people	Metaheuristic (GRASP)	Online
66	Grippa et al. (2018)	Transport of goods	Heuristic	Online
67	Klapp et al. (2018)	Transport of goods	ADP	Hybrid
68	Srour et al. (2018)	Free	Heuristic	Online
69	Bopardikar and Srivastava (2020)	Free	Heuristic	Online
70	Ulmer et al. (2018c)	Transport of goods	ADP	Offline
71	Ulmer (2020)	Transport of goods	ADP	Online
72	Vinsensius et al. (2020)	Transport of goods	ADP	Online
73	Ulmer et al. (2021)	Transport of goods	Heuristic method	Offline
74	Wang et al. (2021)	Transport of goods	Heuristic method	Offline
75	Drótos et al. (2021)	Transport of goods	Heuristic method	Online
76		Free	Heuristic method	Online

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Table 6 (*continued*)

#	Reference	Application	Method	Mode
	Xu and Zhou (2020)			
77	Alisoltani et al. (2021)	Transport of people	Heuristic method and exact method	Online
78	Lee and Savelsbergh (2015)	Transport of people	Heuristic method	Online
79	Levin (2017)	Transport of people	Exact method	Offline
80	Dayarian and Savelsbergh (2020)	Transport of people	Metaheuristic	Online

Table 7
Acronymus and Abbreviations.

ADP	Approximate dynamic programming
ACO	Ant colony optimization
ABC	Artificial Bee Colony
ARC	Ability to Reject Customers
CP	Constraint Programming
DE	Diferential Evolution
DARP	Dial-a-Ride Problem
DOD	Degree of dynamism
EDOD	Effective degree of dynamism
EM	Exact Method
EA	Evolutionary algorithms
GRASP	Greedy randomized adaptive search procedure
GA	Genetic algorithms
ITS	Based geographic information systems
MP	Mathematical Programming
NNS	Nearest Neighbor Search
MILP	Mixed-integer linear programming
MAS	Multi agent systems
OEM	Original equipment manufacturer
PFA	Policy function approximation
PSO	Particle swarm optimization
SA	Simulated Annealing
SC	Scatter Search
SD	Static and deterministic
SS	Static and stochastic
TS	Tabu Search
VCC	Vehicle Capacity Constraints
VNS	Variable neighborhood search
VFA	Value function approximation
VSS	Value of stochastic solution
VPI	Value of perfect information
VRP	Vehicle routing problem
DVRP	Dynamic vehicle routing problem

solution quality and execution time.

Novaes et al. (2015) proposed a genetic algorithm (GA) with re-optimization to address an original equipment manufacturer (OEM) dynamic picking-up routing problem. In the problem, tasks assigned to regular vehicles may exceed a time limit due to traffic congestion. Therefore auxiliary vehicles can be dynamically assigned to some tasks and auxiliary routes are created. A simulation procedure is proposed to estimate the service level gains of the dynamic formulation over the static version.

4.4.4. VNS

The variable neighborhood search (VNS), by Mladenović and Hansen (1997), systematically changes neighborhood structures during the search of good quality or near-optimal solutions (Hansen et al., 2016). An example of VNS to deal with the DVRP is presented by Sarasola et al. (2015). They tackle the vehicle routing problem with stochastic demand and dynamic requests through a variable neighborhood search (VNS) algorithm. In the problem, stochastic demands are only revealed when the vehicle arrives at the customer location. The requests are dynamic, new orders from previously unknown customers can be received and scheduled over time. Computational experiments show that the proposed VNS overcame existing results.

4.4.5. MAS

The Multi agent systems (MAS) approach is one of the most mature concepts in the collective intelligence literature, where a set of proactive agents act individually to solve collaborative problems (Ayhan et al., 2013). The idea behind MAS is to form teams of intelligent autonomous agents to solve problems harmoniously and with a certain level of co-ordination, which allows each individual to collaborate proactively and efficiently using individual intelligence (Aydin, 2010).

Aragão et al. (2019) evaluated different collaboration strategies using MAS for dynamic vehicle routing in milk-run OEM operations. In this work, vehicles and carriers are intelligent autonomous agents, and therefore they interact autonomously to respond to unplanned events in cargo transportation operations. Computational results show the trade-off between operating costs and service level when using auxiliary vehicles, where the size of the auxiliary fleet shall be dependent on the demand attributed to regular vehicles. Another example is presented by Baykasoğlu and Kaplanoğlu (2015). The author proposed a MAS based load/truck planning model. This study is oriented to support the decisions made by a third-party logistics company during logistic operations processes. Normally, land transport services are subject to difficulties in taking decisions, specifically, in load/truck planning the customers are generally unpredictable and they are subject to sudden changes. The authors developed a multi-agent based dynamic load/truck control system to address the problem, in which orders and vehicles are expressed in terms of agent entities. The proposed MAS was able to dynamically respond to new orders while maintaining low transport operations costs.

4.4.6. Other

In this section, we present hybrid metaheuristics used to deal with the DVRP.

PSO + EA – Muñoz-Carpintero et al. (2015) presented a dynamic pickup and delivery problem formulated under a hybrid predictive control approach. The idea behind this problem is to support the dispatcher of a dial-a-ride service, so that it has fast and efficient solutions in real time. To deal with the problem, they proposed a solution method that combines particle swarm (PSO) and genetic algorithms (GA).

SA + VNS – Maghfiroh and Hanaoka (2018) presented a stochastic and dynamic VRP based on the last mile distribution for disaster response. A hybrid algorithm based on simulated annealing (SA) and VNS is proposed. The basic SA algorithm is modified and it has two stochastic processes: the solution acceptance criterion and the event scheduler architecture. The first one is used for solving stochastic problems, while the second one deals with dynamic demand requests. The VNS is used as a diversification and intensification strategy. Computational experiments show that the proposed method overcomes other metaheuristics (SA, VNS and ACO) in solving the problem.

VNS + GA – Bouchra (2018) examined the dynamic vehicle routing problem with soft time windows (D-VRPSTW). In the problem, requests can appear at any time during the execution of a route. An approach that hybridizes a genetic algorithm and a VNS is proposed. To deal with dynamic requests, time is discretized in time intervals, then the proposed algorithm is applied to resolve each interval as a partial static problem. A dynamic benchmark based on Solomon's static instances for VRPTW was used to validate the method. Results show that the proposed algorithm presents a similar performance to other algorithms of the literature.

4.5. Mode

In this work, we consider three execution modes of the algorithms: offline, online and hybrid. Each mode concept is explained in detail below.

Online solution methods are those that apply calculations on-the-fly as new information arrives, requiring the major computation time when dynamic events occurs (Ulmer et al., 2019; Ritzinger et al., 2015). It is also important to notice that online decisions usually rely on look-ahead or greedy solution strategies as pointed out by Ritzinger et al. (2015).

Ulmer et al. (2019) and Ritzinger et al. (2015) considered offline approaches (or preprocessed decisions) as methods that compute solutions before the execution of the plan occur, or the calculations required to select a decision are conducted before the policy execution. Methods such as policy function approximation and value function approximation are usually used in an offline manner by means of simulation. Ulmer and Thomas (2018) proposed an offline approach to deal with a same-day delivery problem considering heterogeneous fleets of drones and vehicles. The method is based on policy function approximation that decides if an order will be delivered by a drone or by a vehicle according to geographical districting.

A hybrid approach combines both offline and online solution methods. A good example of this strategy is presented by Ulmer et al. (2019), in which an offline value function approximation strategy is combined with an online rollout algorithm in order to produce a computationally tractable policy for a DVRP problem that presents temporal and spatial anticipation of requests.

Next, we present some representative works of each execution mode:

- Online methods: Ng et al. (2017), Steever et al. (2019) and Amrouss et al. (2017)
- Offline methods: Ulmer et al. (2018b), Ulmer and Thomas (2018) and Cheng et al. (2016)
- Hybrid methods: Ulmer (2018b), Ulmer et al. (2019)

5. Future work and opportunities

This section presents application opportunities and main solution streams associated with DVRPs found in our review.

5.1. Problem

In recent years, there have been new business models and new concepts of logistics operations, which pose new additional operational challenges to companies and create new applications associated with DVRP. Good examples of these applications are: online food ordering and delivery services, peer-to-peer ride-sharing, online retail services, e-commerce, last mile delivery services, traffic optimization and urban mobility. Some of these new services have a high market value and involve several competitors, forcing companies to provide a high level of service under profitable logistics operations. In this subsection we present the opportunities associated with the mentioned applications.

Today in the segment of online food ordering and delivery services there are different companies that compete for food delivery in large cities. This generates disputes over the high quality of service and low delivery prices. According to Morgan Stanley Research (2020), the online food delivery market could grow to $470 billion by 2025. Given the practical importance of the operational problem behind the business, there are few scientific papers that address it. Among the 5 articles that address the problem of meal delivery that we find in the literature, only (Ulmer et al., 2017a) explicitly considers sources of uncertainty and anticipatory decisions. Therefore, we believe that an important research opportunity in this segment lies in the value of recognizing uncertain information, such as meal preparation times, delivery orders (spatial and temporal), and courier availability. Each company seems to present different operations, fleet composition and courier contracts that can substantially change the problem, so future studies could consider heterogeneous fleets and the analysis of different delivery policies, problem assumptions, and objective functions.

Online retailers and e-commerce companies are undergoing a transformation in their logistics operations to address the expectations of new customers related to delivery services. Recent demands, such as same-day delivery, next-day delivery, and tight time slot preferences, pose operational challenges for these companies, especially due to short response time, and the uncertain and dynamic nature of the customers' orders. Some authors have addressed the same-day delivery (with drones), attended home delivery and dynamic time slot management problems in past years (e.g., Voccia et al., 2019; Klein et al., 2017; Yang and Strauss, 2017; Ulmer, 2017a; Ulmer and Thomas, 2018). Research on these problems appears to be more established than other recent problems. However, there are still challenges and opportunities posed by the authors, such as the development of better anticipatory approaches and value function approximations, the recognition of various types of delivery modes, the possibility of rejecting or postponing requests and incentives to customers to change their time windows.

Innovative solutions for the last mile delivery can also benefit companies by coupling with dynamic routing but, despite its pertinence, there is little research in this stream related to DVRPs. For instance, a company can create incentives in the checkout line for a customer to deliver grocery shopping to another consumer that ordered goods online. This innovative operation is subjected to several uncertain and dynamic elements over the day (e.g., online consumers' orders and physical customers that live near the online order destination) that should be considered in order to maintain a high service level at an acceptable cost. Therefore, decisions associated with routing that are related to the amount of incentive given to each delivery, or when to call a professional delivery service should be taken several times during a day and may be improved considering a dynamic setting.

The study of crowdsourced delivery problems is still new and presents several research opportunities. Arslan et al. (2019) is one of the few works that address a crowdsourced dynamic pickup and delivery problem. As a research opportunity, one possibility is the development of efficient solution methods to solve large problems and the evaluation of different operation strategies, such as the possibility of parcel transfer between drivers. Analysis of impacts of different payments, pricing, and incentives are also paths to be explored.

Dynamic optimization of traffic and urban mobility have been drawing researchers attention for a long time. Most of the recent work that addresses traffic optimization problems considers that a central planner or several agents trying to optimize their own routes in an urban area. In most of these works, the travel time is dynamic or uncertain and solving methods based on metaheuristics, parameterized rules and multi-agent simulation are used to solve the problems. The research opportunities indicated by recent works (Vitello et al., 2017; Chai et al., 2017; Luo et al., 2018) lie in the optimization of larger-scale road networks, the incorporation of forecasts and probabilistic information and the proposal of more efficient solution methods. On the other hand, urban mobility generally focuses on specific operational services such as bike-sharing (Brinkmann et al., 2019) or transit circulator services (Yu et al., 2015). The opportunities in this stream lie in the possibility of incorporating more details of operations and decisions (e.g., coordination of several buses) and an improvement of solution methods to solve larger instances of the problem.

Emergency and, more recently, humanitarian relief services have also been an increasing subject of researchers attention in recent years. Some recent works started studying how dynamism can be addressed in these critical situations. Here, most of the works consider dynamic and deterministic problems, in which the focus is to react to new information (usually location and demand of the emergencies) that arises over time. Usually, objective functions of these problems are slightly different, in which the service level, response time and minimum lateness are prioritized over economics metrics. A recent example, (Dunnett et al., 2018) addresses emergency services by having an event manager and resolving the static problems. Opportunities in this research stream are very similar to other areas such as the study of efficient solution methods to improve solution quality and incorporation of more realistic aspects of the problem. It is also important to notice that most of the works in this stream consider stochastic rather than dynamic VRPs.

Other research opportunities are related to two characteristics of the problem: objective function and vehicle speed. Most of the articles reviewed continue to use objective functions similar to classic VRPs. We encourage researchers to use new objective functions of a dynamic nature typical of DVRPs, such as average per unit time serviced customers, average per unit time quality or average per unit time cost. Vehicle speed is an important issue in the dynamic setting. We have found some papers that consider vehicle speed as a global parameter of the instance, meaning that it is treated as a fixed input (e.g, Ulmer et al., 2018b; Ulmer et al., 2018a; Ulmer, 2018b). Nevertheless, we did not find works that consider speed as a dynamic element that varies over time, nor that analyzes the impact of modifying the vehicle speed on the solutions. Thus, we believe that this current gap in the literature should be addressed in future research.

5.2. Solution methods

The scientific literature reviewed is divided into two main streams: reactive solution methods and methods that incorporate probabilistic information on future events. The first stream usually does not incorporate historical or probabilistic information about future uncertain events, instead it focuses on developing efficient methods that allow fast recourse and dynamic solutions. Typically, these pure reactive approaches are applied in the following circumstances: to recover or optimize operational activities after unexpected events, to address problems where it is impossible to predict future events, or tackle problems in which optimizing the current state is more critical than anticipating future states. The second stream uses methods to incorporate probabilistic information on future events. These methods address problems in two ways. The first one is using offline methods, such as approximate policies (policy function approximation) and approximate dynamic programming (value function approximation). The second is via online solution approaches, such as lookahead policies that acknowledge scenarios of future events. A combination of online and offline methods is also possible, as studied by some authors (Ulmer, 2018b; Ulmer, 2018b).

We believe that the research opportunities on reactive solution methods lie in the development of efficient solution methods to increase responsiveness, improve solution quality, or allow more complex systems to be considered. For example, the study of parallel algorithms and GPU programming to address DVRP is scarce in the literature and could bring more efficiency to the responsive solution. The literature indicates that several reactive problems were tackled using meta-heuristics. Thus studies on structured methods to incorporate or improve responsiveness in meta-heuristics could also be a research opportunity. We also believe that opportunities lie in the development of offline solution methods, such as policy or value function approximations, to increase the responsiveness of some pure reactive problems. Finally, in problems where viability or stability is highly desirable, the use of robust optimization, adaptative robust optimization and recovery robust optimization embedded in a rolling-horizon procedure might be interesting, since, to the best of our knowledge, robust optimization has never been used to address DVRPs.

Opportunities in the anticipatory stream are in two branches. The first branch consists of evaluating and comparing the solutions of the anticipatory approaches. Evaluating the value of an anticipatory approach over a pure reactive approach, or the value of incorporating probabilistic information from future events is highly valuable, but scarce in the literature of DVRPs. The second branch of opportunities in this stream lies in the study of value function approximation methods to address the problem, since they are less studied than policy function approximations and lookahead strategies. Furthermore, hybrid approaches are not very explored by the authors and could be a balanced alternative between reaction and anticipation.

It is also noteworthy that solution methods that incorporate anticipatory approaches and stochastic information are highly intractable. Therefore, studies towards the direction of efficient or approximate methods that incorporate stochastic information and anticipatory strategies could bring valuable contributions to the community. For instance, most of the metaheuristics found in this review are more focused on reaction, therefore the study of anticipatory approximations as the one presented in Bent and Hentenryck (2004) could show alternative ways to address large-scale problems. Finally, the comparison of reactive and anticipative reoptimization approaches for specific problems, as the one performed by Ulmer (2018b) could yield valuable insights in showing which strategy should be prioritized in solution methods for specific problems, according to different circumstances, degrees of dynamism and decision-makers' preferences.

Finally, this article supports a general conclusion of Psaraftis et al. (2015) that DVRP research has grown substantially in the past decade. Specifically, we provide evidence of the growth of research on DVRP in the last seven years. The vast majority of articles reviewed are adaptations of static approaches. We believe that there should be a different methodological basis for DVRP, and in this sense more work is needed in this area. Most objective functions are similar to the goals of static problems. Therefore, it would be good to focus on closer targets to dynamic problems. Examples of stochastic and dynamic problems (Psaraftis et al., 2015) are the average customers served per unit time, the average cost per unit time, the rejection average demand per unit time and others. The statistical results, presented in the previous sections, have the sole purpose of informing the current state of the art on DVRP and do not imply conclusions about the importance of the characteristics of the problems and solution methods. We believe there are many opportunities for future research on related topics such as Data mining, Big Data, Predictive modeling, Machine learning. Advances in these fields can open up new horizons and contribute to more efficient real-time route optimization.

Appendix A

Table 4 presents the legend of Table 5. For other acronyms please see Table 7 in Appendix C.

Appendix B

Table 6

Appendix C

Table 7

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