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# Unmanned aerial vehicles/drones in vehicle routing problems: a literature review

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**Abstract**

During recent years, advances in drone technologies have made them applicable in various fields of industry, and their popularity continues to grow. In this paper, the academic contributions on drones routing problems are analyzed between 2005 and 2019 to identify the main characteristics of these types of problems, as well as the research trends and recent improvements. The literature is classified according to the objectives optimized, solution methods, applications, constraints, and whether they use a complementary vehicle or not. Finally, a discussion for trends and future research is presented.

*Keywords:* UAV; drone; routing optimization; literature review

## 1. Introduction

### 1.1. Background

In general terms, a drone could be defined as a pilotless aircraft. However, many authors use the term “drone” to refer to the category that contains many types of pilotless aircraft guided remotely or autonomously. Several technical terms are also used when referring to “drones,” such as unmanned aerial vehicles (UAVs), unmanned aircraft systems (UAS), remotely piloted vehicles (RPV), remotely piloted aircrafts (RPA), and many others. Formally speaking, RPA or RPV refers to a pilotless aircraft directed by remote control (Granshaw, 2018), while the term UAV is defined

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as “a pilotless aircraft which is flown without a pilot-in-command on board and is either remotely and fully controlled from another place or programmed and fully autonomous” (ICAO, 2005). The UAS is defined as “an aircraft and its associated elements which are operated with no pilot on board” (ICAO, 2011).

Over the past years, several companies have shown interest in drone delivery. In 2013, Amazon announced that they will deliver packages directly to customers’ houses in 30 minutes through “Prime Air” using small drones (CBSNews.com, 2013). Since then, Amazon has improved its Prime Air delivery drone to a hybrid aircraft that is capable of vertical takeoff and landing as well as sustained forward flight, generating a robust and stable commercial aircraft that can fly up to 15 miles and deliver packages under five pounds to customers in less than 30 minutes (Vincent and Gartenberg, 2019).

Also, Google, UPS, and some European delivery services have been evaluating the potential use of drones for parcel delivery (Mack, 2018). As drones are not restricted by traditional infrastructure, they can be used for the last-mile delivery, urban and rural distribution, surveillance and intralogistics (DHL, 2014). Additionally, UAV systems are also being used in today’s world for geological and environmental 3D mapping for data collection (Sujit et al., 2012), as well as Wi-Fi connectivity such as the “Flying COW” by AT&T after Hurricane Maria hit Puerto Rico (Fitzpatrick, 2018).

The usage of drones, within the scenarios mentioned above, face issues addressed by routing problems. This route definition describes a transport network that needs to be planned and optimized, by considering that the vehicles (with different attributes or characteristics) have to move from an origin to a destination to accomplish a specific task (Murray, 2018). The variables within the solution models may be altered to drive the problem to optimize a specific issue and develop the most efficient route related to an explicit resource like time, distance, energy or cost. They are also able to face multiple challenges like the nodes visiting to organize pop-up orders, possible threats, or specific time windows at destination nodes.

In this paper, we develop a literature review of different routing models based on the usage of UAVs. To the best of our knowledge, only one literature review concerning unmanned vehicle routing has been published to date (Coutinho et al., 2018). However, these authors considered only the trajectory optimization problem. Therefore, a complete literature review is carried out in this paper, addressing different classification criteria for the UAV routing problems and/or path planning problems. In this paper, we will use the terms “drone” and “unmanned aerial vehicle” as an aircraft without a pilot on board, which can operate autonomously by a preprogrammed flight plan.

### *1.2. UAV routing problem*

The UAV routing problem concerns the assignment of UAVs to accomplish a predetermined task while optimizing cost, time, distance, or energy, among other objectives, considering restrictions such as the impact of the package weight, the effects of external and environmental conditions (i.e., wind and obstacles), the battery life of the UAVs, and the demand (nodes to be visited) requirements. The problem depends on the further logistics applications, as it will determine the kind of UAV used and the parameters or additional constraints to consider, such as the time windows, pick-up and delivery constraints, and battery or fuel limitations.

Depending on the application and the available resources, it may not be useful to visit each node by drone if the main objective is to reduce the time (Murray and Chu, 2015). Additionally, the nodes may have some requirements that may be infeasible to fulfill by a UAV, like the deliveries that exceed its capacity, the no-flying zone restrictions, the mandatory signature for receiving the parcel, or unsafe landing territory (Murray and Chu, 2015). Consequently, some applications require a mixed model that involves ground vehicles to support the UAV routes. Delivery by a UAV can be faster, with lower transportation costs and can easily avoid traditional roads, but they are limited by their battery life, distance, and parcel size. The truck is able to overcome the UAV's weaknesses, and their complementary capabilities are the basis of the "last-mile delivery with a drone" (Ha et al., 2017).

On the other hand, some applications are addressed for surveillance, reconnaissance, or data collection over terrain, and most of these models do not consider a ground vehicle to support the UAVs' path planning. These sensing systems are essential in today's world, as they can provide flexible aerial views over large areas (Scott et al., 2016).

### *1.3. Material collection*

In this paper, a systematic literature review of the different models studied and designed for the routing problems using UAVs is presented. The approaches were selected because they let us develop a specific characterization of the vehicle routing problems applied to "drones" and identify the investigation trends and the most recent improvements on the subject. A systematic review of literature is employed, instead of a narrative review, by being more explicit in the selection of the studies and employing rigorous and reproducible evaluation methods (Tavares et al., 2016).

The literature reviewed was limited to academic papers published in journals and relevant conference proceedings available in Scopus, Web of Science, and Science Direct since they are considered the largest abstract and citation database of peer-reviewed literature. Thesis and books were intentionally excluded from this research, but they could be included in future reviews. The current literature review was limited to papers published between 2005 and 2019; the intention of defining this wide year range was to identify trends related to this topic, as well as considering the technological advances of UAVs.

A critical issue during this literature review was the terminology used to describe a drone and the acronym used for the proposed model in each paper. Therefore, it was essential to define some keywords to address the search of the papers in each database. During the initial searches, the words used were related to "drones," "logistics," and "distribution," to identify some of the most referenced papers, the most common terminology for "drone" and the most frequent optimization problem to base on. Subsequently, the most repeated words and acronyms were as follows: "drone"; "UAV"; "VRP," that is, vehicle routing problem; "TSP," that is, traveling salesman problem; "FSTSP," that is, flying sidekick traveling salesman problem; and "PDSTSP," that is, parallel drone scheduling traveling salesman problem, so the logical structure of the search was a combination of words as follows in each database: Drone; Drone + FSTSP; Drone + PDSTSP; Drone + VRP; Drone + TSP; UAV + FSTSP; UAV + PDSTSP; UAV + VRP; and UAV + TSP.

The rest of the paper is organized as follows. Section 2 presents the descriptive analysis of the reviewed papers. Section 3 presents the classification and findings of the review. Section 4 is devoted

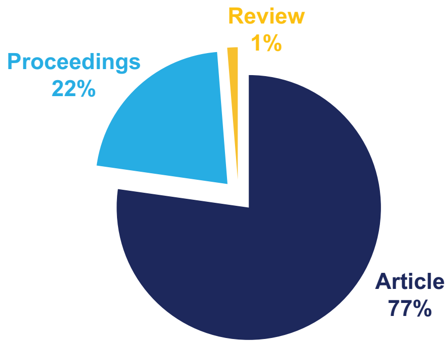


Fig. 1. Document type.

to discussing trends and possible research opportunities on this topic. Concluding remarks are presented in Section 5.

## 2. Descriptive analysis

This section describes the main results of the search by identifying and dividing the papers according to the following features:

- main journals in which the papers were published;
- the number of papers per year;
- usage of drones within the models;
- type of problem (limited to routing problems);
- the number of citations of the article from the database.

From the initial set of 135 research papers obtained following the search methodology, a total of 79 papers were finally short-listed after meticulous analysis and evaluation, related to the quality of the publication, the usage of the UAV in the problem described, and the relevance it has to the current review. From the reviewed publications, 61 were journal papers (77.2%), 17 were conference papers (21.5%), and 1 was a review paper (see Fig. 1). The literature shows a significant increase in the number of publications throughout the years, as shown in Fig. 2. The years with a higher number of relevant publications were 2017 and 2018, which demonstrate a meaningful growth in the knowledge, awareness, and popularity of the topic. On average, there were 5.26 relevant papers published per year between 2005 and 2019. In this research, papers published at the beginning of 2019 were included because of the relevance they had to the literature review. During the first three months of 2019, there were seven relevant publications, which indicate that the number of published papers will probably increase by the end of the year.

The journal that had the highest number of relevant publications is *Transportation Research Part C* with five published papers. However, the IEEE published 15 research papers in its journals and conference proceedings, including *IEEE/RSJ International Conference on Intelligent Robots and*

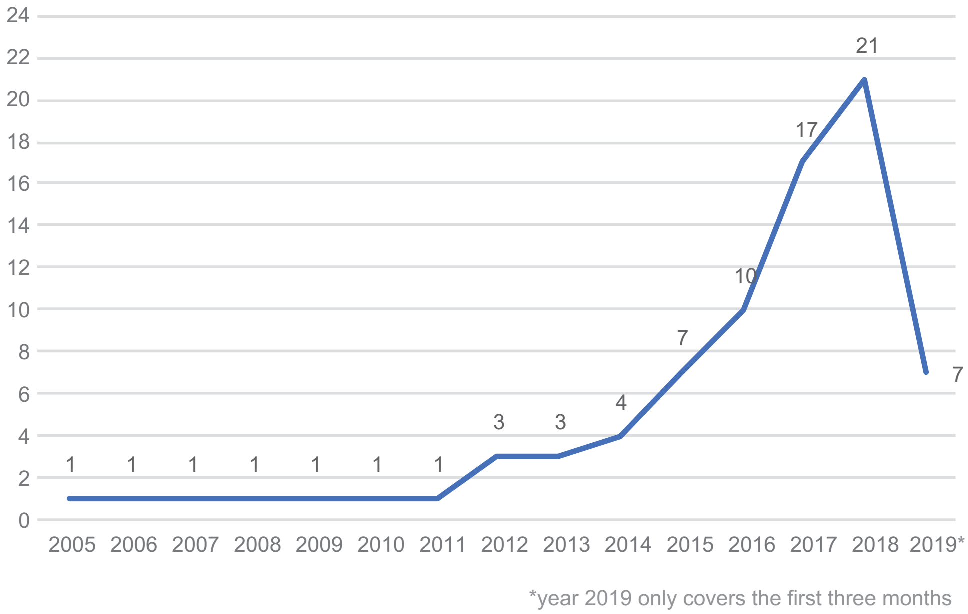


Fig. 2. Distribution of publications per year.

*Systems (IROS)* and *IEEE Transactions on Systems, Man, and Cybernetics*, respectively, with 3 and 2 papers, while the other 10 papers appeared in different IEEE journals. These were followed by *Networks: An International Journal* (four papers), *Computers & Industrial Engineering* (three papers), and *Journal of Intelligent and Robotic Systems* (three papers). Figure 3 shows the distribution of 42 short-listed papers published in the main journals; the other 37 papers were published in 37 different journals.

The affiliation of authors is another interesting element of analysis. From the 79 short-listed papers, 59 had their authors affiliated to academic institutions in a single country, from which the USA had the highest participation with 22 papers, representing 28% of the total, as shown in Fig. 4, followed by authors from different country affiliation. China accounts for eight publications followed by France and Turkey with five papers each. Concerning the papers written by authors from different countries' affiliations (20 in total), there were 10 papers with at least one author affiliated to an institution in the USA, from which three of them also had authors affiliated in South Korea (see Table 1). Also, five papers had at least one author affiliated to a Chinese institution, followed by five from France and four from Italy.

## *2.1. Category selection*

In this section, the results of the search are analyzed, and the description of the papers is made through a matrix that combines the most common characteristics of the proposed problem in each paper. Thus, papers are classified according to the following categories.

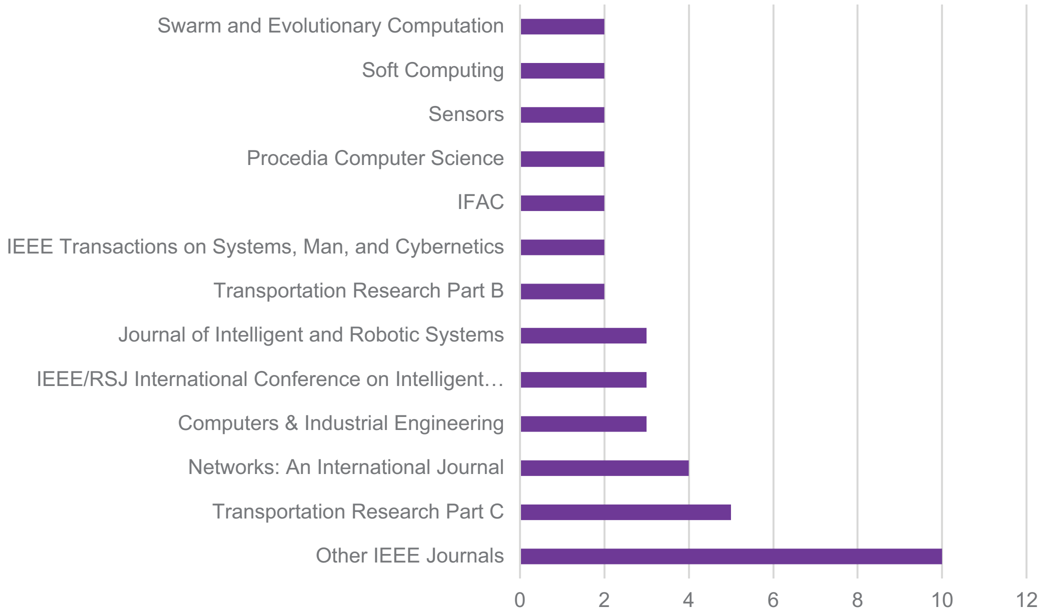


Fig. 3. Distribution of papers published in (main) journals.

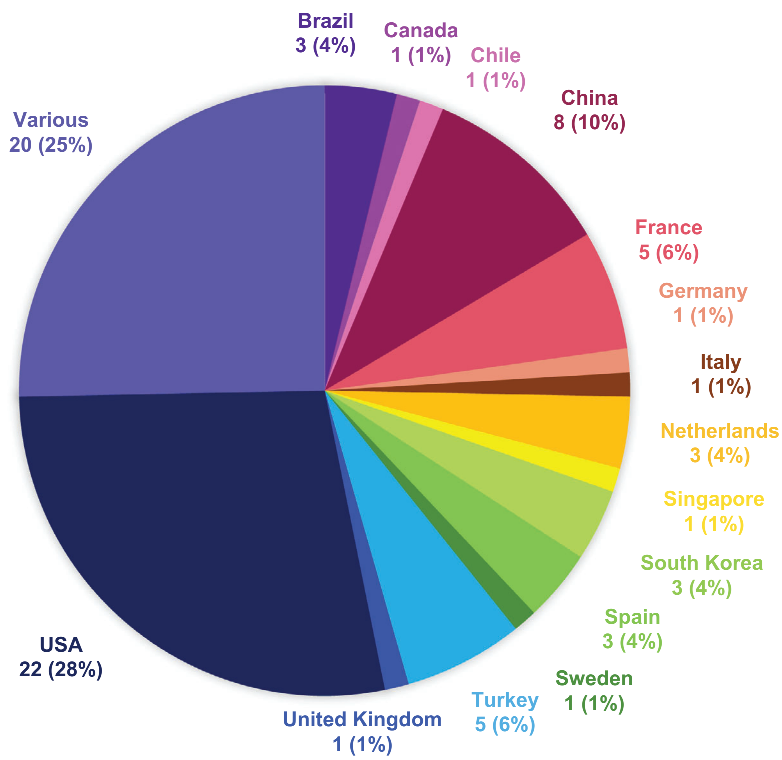


Fig. 4. Countries of authors' affiliation.

Table 1
Number of papers with authors of various country affiliations

| Countries | Number of articles |
|---|---|
| Italy and France | 3 |
| USA and South Korea | 3 |
| Canada and China | 2 |
| Germany and USA | 2 |
| Singapore and China | 1 |
| Belgium and Vietnam | 1 |
| China and Sweden | 1 |
| China and USA | 1 |
| Israel and USA | 1 |
| Italy, France and USA | 1 |
| Luxemburg and France | 1 |
| Portugal and USA | 1 |
| Singapore and USA | 1 |
| Vietnam and Australia | 1 |

- *Objective(s) of the proposed solution*: This category covered the objective functions that were optimized in short-listed papers, such as time, distance, cost, number of UAVs, energy, etc.
- *Logistics application*: This category included the logistics application described within the paper's problem, such as humanitarian approach, parcel delivery, information or surveillance, internal processes of a company, entertainment, and military.
- *Mixed model or not*: This category focused on the use of mixed vehicles to address the proposed problem, or if it just considered a drone-based model.
- *Type of solution method*: This category included the method to solve the problems, like a heuristic algorithm, metaheuristic, exact method, or policy.
- *Constraints*: This category covered the most common constraints addressed, such as time windows, external issues, battery/fuel constraints, and pick-up and delivery.

### 2.2. Material evaluation

Short-listed papers were evaluated and analyzed according to the standards of Section 2.1. Results are presented and discussed in the following section, to guide future research on the routing problems using drones.

## 3. Classification

### 3.1. Logistics applications

The proposed models within the reviewed publications depend on the application that inspired the research. With such a specific context, the authors include different constraints and assumptions.

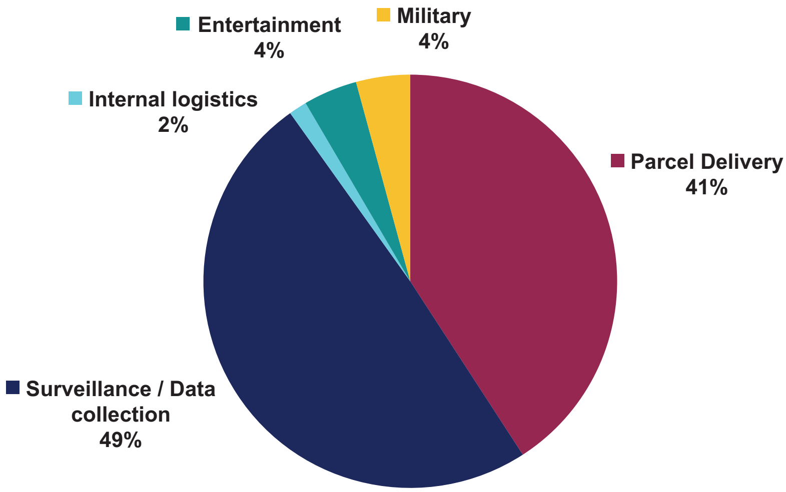


Fig. 5. Distribution of single application papers.

Also, some of the problems described within the papers were designed for a specific drone and its characteristics were considered as well. The logistics applications that stand out from the reviewed papers are the ones for parcel delivery and for surveillance and information collection. Besides, this review also found different applications in humanitarian logistics to respond as fast as possible in emergency scenarios including natural disasters, human-made disastrous incidents, or the delivery of medical supplies (Dorling et al., 2016; Zillies et al., 2016; Cannioto et al., 2017; Oruc and Kara, 2018; Chauhan et al., 2019). Furthermore, some publications also dealt with internal logistics processes of a company during the assembly of products (Olivares et al., 2015) or to gather information of air and soil for agricultural purposes (Tokekar et al., 2016). Likewise, some investigations focused on the usage of drones for the entertainment industry, specifically to film sports events such as car races or a live match transmission (Natalizio et al., 2013; Guerriero et al., 2014; Di Puglia et al., 2017). Some military applications were also found in which UAVs' path planning is required to attack targets, reduce threats, or for reconnaissance missions (Duan et al., 2009; Zhang et al., 2012; Ercan and Gencer, 2018; Rosalie et al., 2018; Zhou et al., 2018).

### *3.1.1. Single application versus multiple application approaches*

Among reviewed papers, 71 (90%) presented a single application approach: parcel delivery distribution, path planning for surveillance/reconnaissance or data collection, internal logistics routing processes, entertainment events, and military purposes. Figure 5 presents such a distribution of papers according to the type of application and Table 2 the detailed group of references. The application studied the most is path planning for surveillance or data collection with 35 papers, closely followed by the routing problem for parcel delivery with 29 publications. On the other hand, Table 3 presents the publications with multiple applications within the same given problem in the fields of (a) humanitarian logistics and parcel delivery, focused on the distribution of medical supplies, blood for transfusions, food, or different supplies for emergency scenarios; (b) humanitarian

Table 2
Articles with single applications

| Applications | Authors |
|---|---|
| Parcel delivery | Sundar and Rathinam (2014), Murray and Chu (2015), Savuran and Karakaya (2015), Sonmez et al. (2015), Boone et al. (2015), Wang et al. (2015, 2016), Furini et al. (2016), Ferrandez et al. (2016), ,Poikonen et al. (2017), Luo et al. (2017), Kim and Matson (2017), Modares et al. (2017), Chen et al. (2017), Agatz et al. (2018), Song et al. (2018), Ulmer and Thomas (2018), Chang and Lee (2018), Bouman et al. (2018), Mbiadou et al. (2018), Schermer et al. (2018), Ha et al. (2018), Ham (2018), Luo et al. (2018), Es Yurek and Ozmutlu (2018), Troudi et al. (2018), Freitas and VazPenna (2018), Kim and Moon (2019), and Jeong et al. (2019) |
| Surveillance/data collection | Russell and Lamont (2005), Shima et al. (2006), Kahveci et al. (2007), Lim et al. (2008, 2010), Karaman and Frazzoli (2011), Sujit et al. (2012), Ny et al. (2012), Guerrero and Bestaoui (2013), Gentilini et al. (2013), Evers et al. (2014), Bo et al. (2014), Avellar et al. (2015), Chow (2016), Manyam et al. (2016), Scott et al. (2016), Kim et al. (2017), Bouzid et al. (2017), Perez-Carabaza et al. (2017), Jang et al. (2017), Olivieri and Endler (2017), Greiff and Robertsson (2017), Phung et al. (2017), Alemayehu and Kim (2017), Coutinho et al. (2018), Li et al. (2018), Yue and Jiang (2018), Jeauneau et al. (2018), Hu et al. (2018), Dai et al. (2018), Yu et al. (2018), Ramirez Atencia et al. (2019), Ropero et al. (2019), Xie et al. (2019), and Zhen et al. (2019) |
| Entertainment | Natalizio et al. (2013), Guerriero et al. (2014), and Di Puglia et al. (2017) |
| Military | Zhou et al. (2018), Zhang et al. (2012), and Duan et al. (2009) |
| Internal logistics | Olivares et al. (2015) |

Table 3
Articles with multiple applications

| Applications | Authors |
|---|---|
| Humanitarian and delivery | Dorling et al. (2016), Zillies et al. (2016), and Chauhan et al. (2019). |
| Humanitarian and data collection | Cannioto et al. (2017) and Oruc and Kara (2018) |
| Data collection and military | Ercan and Gencer (2018) and Rosalie et al. (2018) |
| Data collection and internal logistics | Tokekar et al. (2016) |

logistics and data collection to reduce the response time after a (hypothetic) disaster (natural or human-made), by gathering information about the damages; (c) data collection and military approach to accomplish surveillance and reconnaissance missions and to avoid unexpected threats in a war context; and (d) data collection and internal logistics approaches to collect samples in ground and air for precision agriculture.

### 3.2. *Objective*

In this section, the variables considered in the literature are presented in Table 4. From the selected publications, 50 articles intended to optimize one objective, while 29 papers designed a model as a multiobjective problem or are geared to optimize several variables within the same given article while addressing them as different problems.

Table 4
Optimization objectives per contribution

| Authors | Cost | Energy/ fuel | No. of UAV | Time | Distance | Profit | No. of circuits | No. of nodes | Covered area/ demand | Client satisfaction |
|---|---|---|---|---|---|---|---|---|---|---|
| Murray and Chu (2015) | | | | X | | | | | | |
| Chang and Lee (2018) | | | | X | | | | | | |
| Ha et al. (2017) | X | | | | | | | | | |
| Ham (2018) | | | | X | | | | | | |
| Di Puglia Pugliese et al. (2017) | | | | | X | | | | | X |
| Wang et al. (2016) | | | | X | | | | | | |
| Poikonen et al. (2017) | | | | X | | | | | | |
| Luo et al. (2018) | | | | X | | | | | | |
| Dorling et al. (2016) | X | | | X | | | | | | |
| Es Yurek and Ozmutlu (2018) | | | | X | | | | | | |
| Zhou et al. (2018) | X | | X | X | | | | | | |
| Luo et al. (2017) | | | | X | | | | | | |
| Furini et al. (2016) | X | | | X | | | | | | |
| Mbiadou Saleu et al. (2018) | | | | X | | | | | | |
| Schermer et al. (2018) | | | | X | | | | | | |
| Kim and Matson (2017) | X | | | | | | | | | |
| Natalizio et al. (2013) | | | | | X | | | | | X |
| Agatz et al. (2016) | X | | | X | X | | | | | |
| De Freitas and VazPenna (2018) | | | | X | | | | | | |
| Modares et al. (2017) | X | X | | | X | | | | | |
| Kim et al. (2017) | | | | X | | | | | | |
| Ferrandez et al. (2016) | X | X | | X | | | | | | |
| Olivares et al. (2015) | | X | | | | | | | | |
| Hu et al. (2018) | | | | X | | | | | | |
| Troudi et al. (2018) | | X | X | | X | | | | | |
| Dai et al. (2018) | | X | | | | | | X | | |
| Bouzid et al. (2017) | | | | | X | | X | | | |
| Cannioto et al. (2017) | | | X | | X | | | | | |
| Zillies et al. (2016) | X | | | | | | | | | |
| Savuran, and Karakaya (2015) | | | | | X | | | X | | |

*Continued*

Table 4
Continued

| Authors | Cost | Energy/ fuel | No. of UAV | Time | Distance | Profit | No. of circuits | No. of nodes | Covered area/ demand | Client satisfaction |
|---|---|---|---|---|---|---|---|---|---|---|
| Scott et al. (2016) | | X | | | | | | | | |
| Avellar et al. (2015) | | | | X | | | | | | |
| Guerriero et al. (2014) | | | X | | X | | | | | X |
| Manyam et al. (2016) | | | | | X | | | | | |
| Guerrero and Bestaoui (2013) | | | | X | | | | | | |
| Xie et al. (2019) | X | | | | | | | | | |
| Yu et al. (2018) | | | | X | | | | | | |
| Jang et al. (2017) | | | | X | | | | | | |
| Olivieri and Endler (2017) | X | | | | | | | | | |
| Chen et al. (2017) | | | | | X | | | | | |
| Greiff and Robertsson (2017) | | | | | X | | | | | |
| Sonmez et al. (2015) | | | | | X | | | | | |
| Boone et al. (2015) | | | | | X | | | | | |
| Ercan and Gencer (2018) | X | | | X | | | | | | |
| Teo et al. (2015) | | | | X | | | | | | |
| Phung et al. (2017) | | | | | X | | | | | |
| Alemayehu and Kim (2017) | | | | X | | | | | | |
| Tokekar et al. (2016) | | | | X | | | | X | | |
| Sundar and Rathinam (2014) | X | X | | | | | | | | |
| Sujit et al. (2012) | X | | | | | | | | | |
| Gentilini et al. (2013) | | | | X | | | | | | |
| Zhang et al. (2012) | X | | | | | | | | | |
| Ny et al. (2012) | | | | | X | | | | | |
| Shima et al. (2006) | | | | X | | | | | | |
| Chauhan et al. (2019) | | | | | | | | | X | |
| Jeong et al. (2019) | | | | X | | | | | | |
| Oruc and Kara (2018) | | | | | | X | | | X | |
| Chow (2016) | X | X | | | | | | | | |
| Lu Zhen et al. (2019) | | | | X | | | | | | |
| Song et al. (2018) | | | | | X | | | | X | |
| Coutinho et al. (2018) | X | | | | | | | | | |
| Li et al. (2018) | X | | | | | | | | | |

*Continued*

Table 4
Continued

| Authors | Cost | Energy/ fuel | No. of UAV | Time | Distance | Profit | No. of circuits | No. of nodes | Covered area/ demand | Client satisfaction |
|---|---|---|---|---|---|---|---|---|---|---|
| Ramirez Atencia et al. (2019) | X | X | X | X | X | | | | | |
| Ulmer and Thomas (2018) | | | | | | X | | | X | X |
| Ropero et al. (2019) | | | | | X | | | | | |
| Yue and Jiang (2018) | | | | | X | | | | X | |
| Perez-Carabaza et al. (2017) | | | | X | | | | | | |
| Evers et al. (2014) | | | | | | X | | | X | |
| Rosalie et al. (2018) | | | | | | | | | X | |
| Jeauneau et al. (2018) | X | | | | X | | | | | |
| Russell and Lamont (2005) | | | | | X | | | | | |
| Lim et al. (2008) | | | | | X | | | | X | |
| Duan et al. (2009) | X | | | | X | | | | | |
| Kahveci et al. (2007) | | | | X | | | | | | |
| Lim et al. (2010) | | | | | X | | | | | |
| Kim and Moon (2019) | | | X | X | | | | | | |
| Bouman et al. (2018) | X | | | | | | | | | |
| Bo Shang et al. (2014) | | | | | X | | | | X | |
| Karaman and Frazzoli (2011) | X | | | | | | | | | |

### *3.2.1. Single-objective problems*

Among reviewed papers, 50 describe a problem in which a single objective is optimized: time (50% of papers), distance (20%), cost (22%), energy, or the covered area. Figure 6 shows the spread of articles that focused on a single objective. In regards to time optimization, different goals were identified depending on the context under study. Es Yurek and Ozmutlu (2018) addressed the problem to minimize the waiting time of trucks while the drone meets them. De Freitas and Penna (2018) aimed at minimizing the duration of servicing all customers, while Alemayehu and Kim (2017) proposed to reduce the data delivery latency, and Jeong et al. (2019) minimized the arrival time at the ending depot.

On the other hand, the cost optimization approach included problems to minimize the cost of inventory (Chow, 2016), as well as additional operating costs like traversing and battery charging (Li et al., 2018) for traffic monitoring with UAVs. Besides, other problems reduce possible threats, which are represented as costs (Duan et al., 2009). The distance optimization papers involve the path planning of the shortest route while avoiding obstacles (Greiff and Robertsson, 2017) to reduce time or energy due to a minimum distance (Boone et al., 2015; Ropero et al., 2019). Furthermore, some problems focused on identifying the shortest route distance, on obtaining highly effective

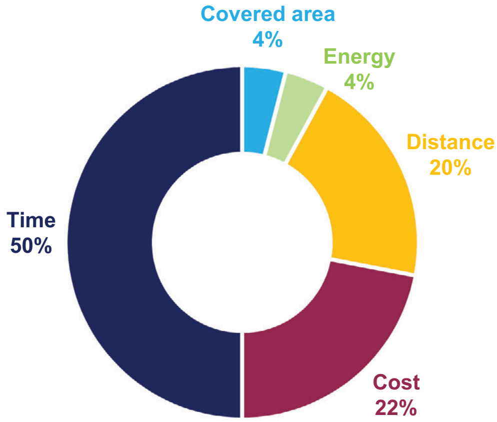


Fig. 6. Distribution of papers optimizing a single objective.

surveillance or inspection of the terrain (Russell and Lamont, 2005; Lim et al., 2010; Phung et al., 2017; Ropero et al., 2019).

The covered area optimization approaches were addressed to minimize the number of steps to visit the entire area (Rosalie et al., 2018), or to maximize the total area covered by the UAV routes, which is expressed as the clients' demand maximization (Chauhan et al., 2019). Authors dealing with energy optimization focused on the reduction of energy/battery used while carrying weight in a specific capacitated problem (Olivares et al., 2015) or dealing with the optimization of the energy consumption efficiency while visiting waypoints and capture pictures of a terrain (Scott et al., 2016).

### 3.2.2. *Multiobjective optimization problems*

In the reviewed literature, 29 papers deal with the optimization of two or more objectives. The paper distribution is shown in Fig. 7. From the total of papers, 72.4% studied a biobjective optimization problem, while 24.1% and 3.5%, respectively, studied three or five objectives simultaneously. Zhou et al. (2018) formulated an MILP in which the objective functions included the total number of UAVs, the total costs, and the total flight time of all UAVs. Di Puglia et al. (2017) minimized the total distance traveled by the drones and the viewers' satisfaction, within the same given mathematical formulation. Guerriero et al. (2014) optimized the distance, client satisfaction and number of UAVs, simultaneously, through an LP formulation. Ramirez Atencia et al. (2019) proposed a multiobjective model that minimizes time, distance, costs, energy, and the number of UAVs.

Some papers present different objectives within separate solution approaches. Dorling et al. (2016) proposed two VRPs: one that reduces the total costs and the other that minimizes the overall delivery time. Furini et al. (2016) designed two different approaches: one aims at minimizing time and another optimizing the total operational costs. Tokekar et al. (2016) presented two informative path planning approaches to minimize the sum of the travel and measurement times and to maximize the number of visited points by the UAV, respectively. Ferrandez et al. (2016) evaluated different optimization approaches through separate models under the same given scenario for the total delivery time

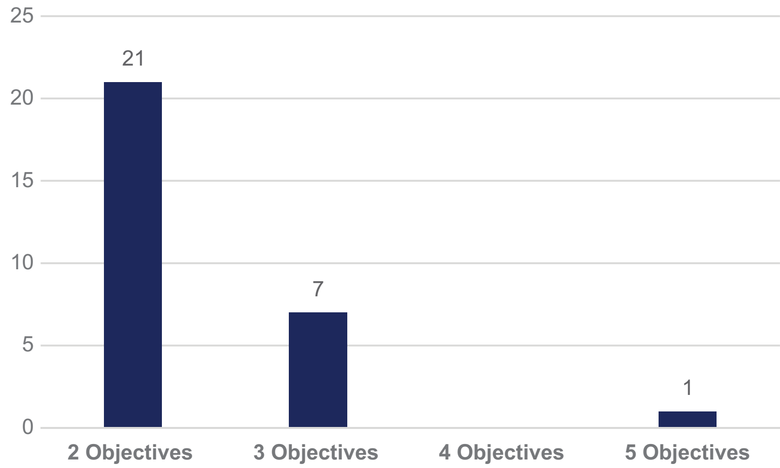


Fig. 7. Distribution of papers dealing with multiobjective objectives.

and energy reduction, and to find the optimal number and locations of truck stop/drone launch locations (min-cost function).

Another approach when dealing with multiple objectives is to split the problem under study into several subproblems so an efficient solution approach can be designed. Modares et al. (2017) formulated an energy-efficient coverage path planning problem through an NP-hard mixed integer quadratic constrained program (MIQCP). The authors decomposed the problem into two subproblems: a load-balancing MILP that aims to minimize the energy in terms of distance, and the minimum energy path planning problem, which is an MIQCP that minimizes the energy in terms of distance and costs.

### *3.3. Solution methods*

In this section, the classification of reviewed papers is presented according to the proposed solution approach for the routing problem with UAVs. Figure 8 shows the solution methods found in the literature. The distribution of the references is by type of solution method because some of the publications address several methods in the same contribution. The most employed solution approach is heuristic algorithms, which provide a solution in good computational time. Exact approaches are also widely used, as they provide an optimal solution. However, several papers addressed the problem with an exact mathematical formulation and then proposed a heuristic algorithm, metaheuristic, or tested different policies.

#### *3.3.1. Exact methods*

From the review, 48 applied exact methods, such as mixed integer linear programming (MILP), nonlinear programming (NLP), constraint programming (CP), binary programming (BP), dynamic programming (DP), branch-and-bound algorithm (B&B), quadratic programming (QP), robust

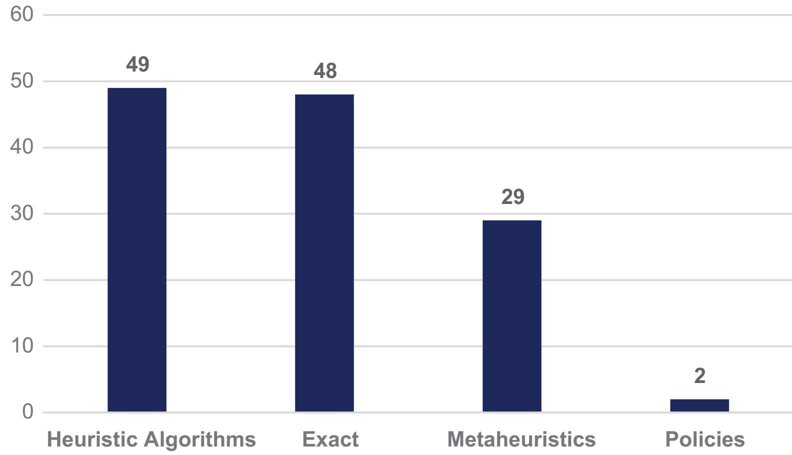


Fig. 8. Number of references by solution method.

optimization (RO), MIQCP, and Pareto optimality (PO). Figure 9 presents the percentages of these methods, while the list of detailed references is given in Table 5. MILP was used by 21 references, followed BP (nine papers), DP, and NLP (each with four papers).

Regarding the applications of the exact methods, Dai et al. (2018) designed a min–max energy path planning algorithm in two steps in which MILP is used to minimize energy, and then a genetic algorithm (GA) is implemented to plan the paths. Furini et al. (2016) proposed an MILP formulation and a branch-and-cut algorithm. Modares et al. (2017) addressed their problem by MILP implementation and then an MIQCP formulation. Scott et al. (2016), Zhen et al. (2019), Evers et al. (2014), and Bo et al. (2014) formulated integer linear models, and then developed a metaheuristic to find an effective solution and overcome the NP-hardness, or to reduce the computational time. Xie et al. (2019) proposed two approaches, including a grid-based approach and a DP-based approach to minimize costs. Ham (2018) implemented a CP formulation to address a multitruck, multidrone, and multidepot scheduling problem with time windows, drop–pickup, and multivisit, in which the objective is to minimize the maximum completion time.

### *3.3.2. Heuristic algorithms*

In the reviewed literature, 54 applications of heuristic algorithms were found: multistage (MS) methods, approximation algorithm (AA), motion planning (MP) algorithm, nearest neighbor (NN), 2-opt heuristics (OH), graph algorithm (GRA), ball movement interception (BMI), column generation (CG), greedy heuristics (GH), K-means (KM) algorithms, projective algorithms (PA), and algorithms and procedures, that is, *ad hoc* approaches (AP) that did not belong to any of the other categories. Figure 10 shows the distribution of the heuristic methods implemented in these 49 references. The most used heuristic method was the algorithms and procedures with 15 references, from which some of them were new heuristics proposed by the authors, followed by MS procedures and then the AAs, MP algorithms, and NN procedure. Table 6 shows the relationship between the heuristic methods and the authors.

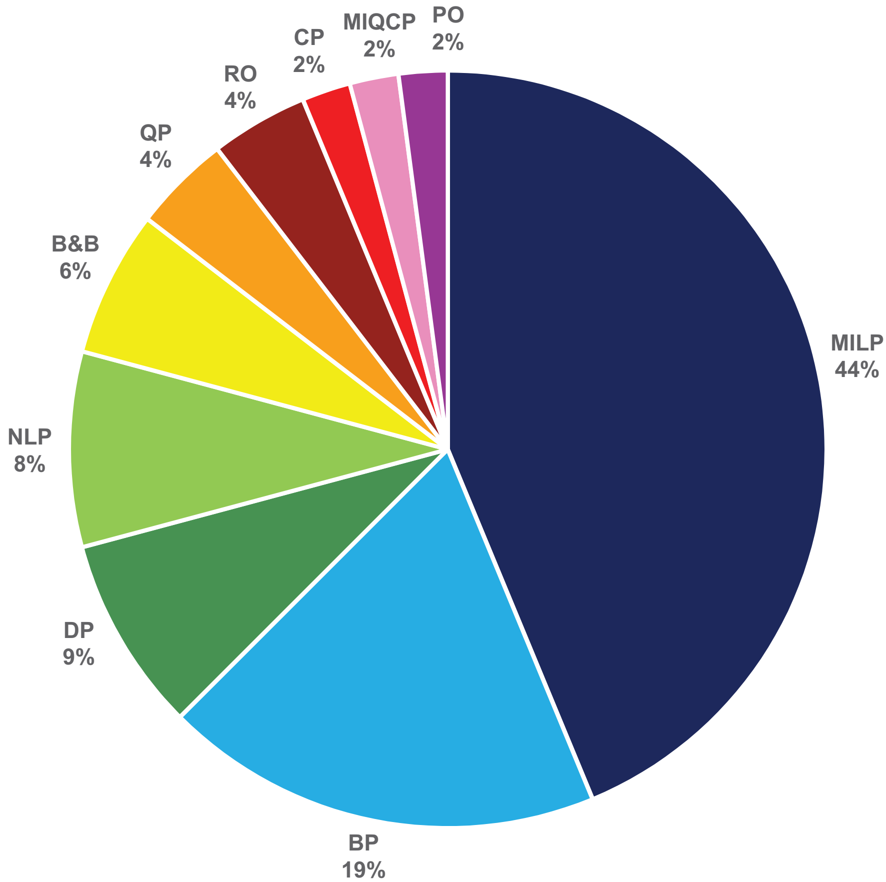


Fig. 9. Distribution of exact methods.

Regarding the use of these heuristic methods, Murray and Chu (2015) proposed two heuristic models to solve the FSTSP and PDSTSP in a practical size, which were later adapted by Ha et al. (2017). Additionally, Mbiadou et al. (2018) designed an iterative two-step heuristic to solve the PDSTSP problem as well. On the other hand, Schermer et al. (2018) proposed two heuristic algorithms with two stages (initialization and improvement) based on route-first cluster-second method, and a variation of the 2-opt and String mix operators to minimize the maximum completion time. Likewise, Ropero et al. (2019) developed a cooperative exploration routing algorithm split into five stages to solve their problem and minimize the distance. The MP heuristic methods include different algorithms. The rapidly exploring random trees approach was developed by Bouzid et al. (2017) to identify the shortest path. The grid-based algorithm was used by Xie et al. (2019) to find a near-optimal solution to reduce costs. The sampling-based algorithm was implemented by Jang et al. (2017) to find the minimum time path. The “A star” algorithm (A*) was used by Jeauneau et al. (2018) to identify a single-path plan to reduce costs. Finally, the probabilistic roadmap algorithm was implemented by Teo et al. (2015) for the path planning while reducing the time and by Zhang et al. (2012) for their proposed algorithm.

Table 5
Relationship between exact methods and authors

| Exact method | Authors |
|---|---|
| MILP | Karaman and Frazzoli (2011), Guerriero et al. (2014), Sundar and Rathinam (2014), Murray and Chu (2015), Teo et al. (2015), Avellar et al. (2015), Dorling et al. (2016), Furini et al. (2016), Modares et al. (2017), Ha et al. (2017), Di Puglia et al. (2017), Oruc and Kara (2018), Song et al. (2018), Li et al. (2018), Es Yurek and Ozmutlu (2018), Zhou et al. (2018), Mbiadou et al. (2018), Troudi et al. (2018), Dai et al. (2018), Kim and Moon (2019), and Jeong et al. (2019) |
| BP | Evers et al. (2014), Bo et al. (2014), Agatz et al. (2016), Scott et al. (2016), Luo et al. (2017), Coutinho et al. (2018), Yu et al. (2018), Chauhan et al. (2019), and Lu Zhen et al. (2019) |
| DP | Chow (2016), Ulmer and Thomas (2018), Bouman et al. (2018), and Xie et al. (2019) |
| NLP | Zhang et al. (2012), Zillies et al. (2016), Jang et al. (2017), and Chang and Lee (2018) |
| B&B | Shima et al. (2006), Gentilini et al. (2013), and Furini et al. (2016) |
| QP | Kahveci et al. (2007) and Greiff and Robertsson (2017) |
| RO | Wang et al. (2016) and Poikonen et al. (2017) |
| CP | Ham (2018) |
| MIQCP | Modares et al. (2017) |
| PO | Ramirez Atencia et al. (2019) |

#### *3.3.3. Metaheuristics*

The metaheuristic methods used within the literature were GA, ant colony (AC), local search (LS), simulated annealing (SA), adaptive large neighborhood search (ALNS), greedy randomized adaptive search procedure (GRASP), particle swarm optimization (PS), and tabu search (TS). Figure 11 shows the distribution by percentages of the use for these solution methods among the 30 references. It was also considered the proposed solutions based on these metaheuristics, and the variations or modifications presented in the papers. The most employed metaheuristic to solve a routing problem with UAVs was the GA with 14 references, followed by ACO with five papers, then LS in four papers, and SA and PS optimization in two references each. GRASP, ALNS, and TS were the least employed algorithms. Table 7 shows the classification of reviewed references according to the metaheuristic methods.

Regarding applications of metaheuristic methods, Greiff and Robertsson (2017) used the GA to solve the TSP, as well as a PA and a QP formulation to find the shortest path around obstacles. Savuran and Karakaya (2015) proposed an adaptation of the GA to minimize the nodes visited by the UAV. Chen et al. (2017) designed an improved GA and a PS optimization based AC optimization algorithm to solve the TSP for UAV path planning. Finally, Zhen et al. (2019) developed a TS metaheuristic to solve a variant of the VRP.

#### *3.3.4. Policy*

Two papers in the set of reviewed references were identified to fit within this category. The authors developed a DP exact method and an effective policy to solve the problem. Chow (2016) designed a stochastic dynamic arc inventory routing policy, while Ulmer and Thomas (2018) used a parametric policy function approximation to solve a same-day delivery problem with drones.

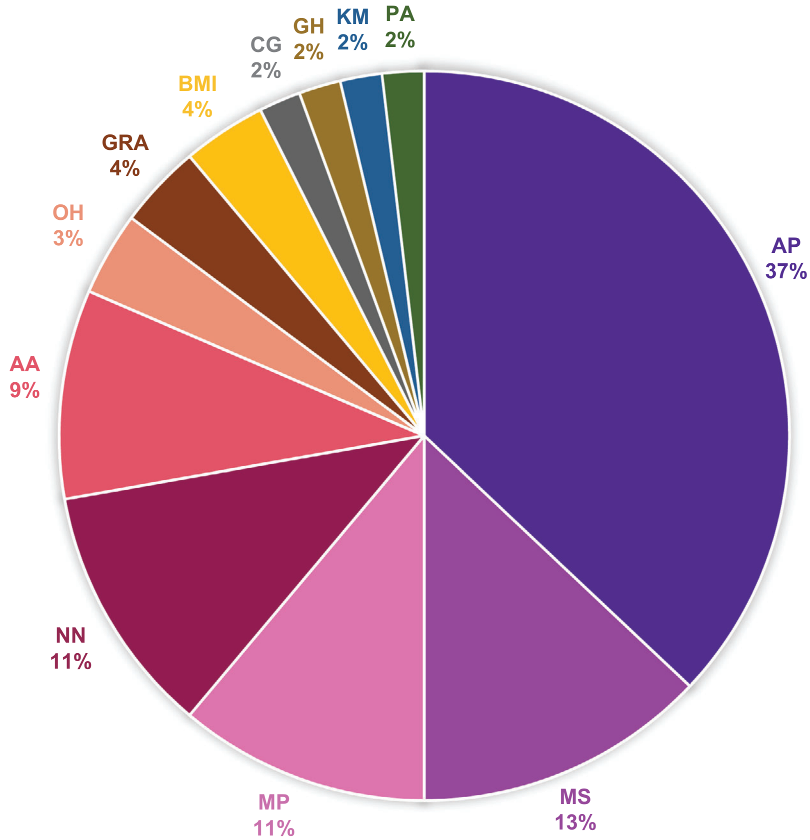


Fig. 10. Distribution of heuristic methods.

### 3.4. *Mixed approach*

In the literature reviewed, some "mixed approach" based on the "last-mile delivery with a drone" was found, which contemplates a carrier vehicle to support the UAV during the route. There were 55 papers addressing the routing problem by considering only the usage of drones and 25 publications that introduced a mixed approach to assist the UAVs' path plan. The "last-mile delivery with a drone" problem has some variations and adaptations depending on the application of the model and on the considerations or assumptions. Some of the models are designed for specific situations in which the drone can carry a single parcel at a time and its battery will only last to serve that single customer. Therefore, the drone has to meet at some point with a ground vehicle (usually described as a truck), in which the UAV can recharge its battery and load the next parcel to be delivered. In this type of model, all the nodes are eligible to be visited by both vehicles (drone and truck) and it is possible to carry all the parcels. This problem is called the "flying sidekick traveling salesman problem" first introduced by Murray and Chu (2015), and worked on later by Es Yurek and Ozmutlu (2018), Ha et al. (2017), and Agatz et al. (2016).

Table 6
Relationship between heuristic methods and authors

| Heuristic | Authors |
|---|---|
| AP | Sujit et al. (2012), Ny et al. (2012), Sundar and Rathinam (2014), Murray and Chu (2015), Furini et al. (2016), Manyam et al. (2016), Tokekar et al. (2016), Agatz et al. (2016), Olivieri and Endler (2017), Ha et al. (2017), Luo et al. (2017), Kim and Matson (2017), Kim et al. (2017), Oruc and Kara (2018), Yue and Jiang (2018), Rosalie et al. (2018), Hu et al. (2018), Yu et al. (2018), Kim and Moon (2019), and Jeong et al. (2019) |
| MS | Es Yurek and Ozmutlu (2018), Mbiadou Saleu et al. (2018), Schermer et al. (2018), Ercan and Gencer (2018), Song et al. (2018), Chauhan et al. (2019), and Ropero et al. (2019) |
| MP | Zhang et al. (2012), Teo et al. (2015), Jang et al. (2017), Bouzid et al. (2017), Jeauneau et al. (2018), and Xie et al. (2019) |
| NN | Modares et al. (2017), Alemayehu and Kim (2017), Furini et al. (2016), Natalizio et al. (2013), Guerriero et al. (2014), and Lim et al. (2010) |
| AA | Manyam et al. (2016), Ny et al. (2012), Sundar and Rathinam (2014), Tokekar et al. (2016), and Kim et al. (2017) |
| OH | Lim et al. (2010) and Boone et al. (2015) |
| GRA | Tokekar et al. (2016) and Teo et al. (2015) |
| BMI | Natalizio et al. (2013) and Guerriero et al. (2014) |
| CG | Zillies et al. (2016) |
| GH | Chauhan et al. (2019) |
| KM | Ferrandez et al. (2016) |
| PA | Greiff and Robertsson (2017) |

Table 7
Relationship between metaheuristic methods and authors

| Metaheuristic | Authors |
|---|---|
| GA | Russell and Lamont (2005), Guerrero and Bestaoui (2013), Bo et al. (2014), Olivares et al. (2015), Savuran and Karakaya (2015), Sonmez et al. (2015), Ferrandez et al. (2016), Scott et al. (2016), Bouzid et al. (2017), Chen et al. (2017), Greiff and Robertsson (2017), Luo et al. (2018), Dai et al. (2018), and Jeauneau et al. (2018) |
| AC | Lim et al. (2008), Duan et al. (2009), Perez-Carabaza et al. (2017), Chen et al. (2017), and Rosalie et al. (2018) |
| LS | Evers et al. (2014), Furini et al. (2016), Freitas and VazPenna (2018) and Li et al. (2018) |
| SA | Dorling et al. (2016) and Cannioto et al. (2017) |
| PS | Phung et al. (2017) and Chen et al. (2017) |
| GRASP | Ha et al. (2017) |
| ALNS | Zhou et al. (2018) |
| TS | Zhen et al. (2019) |

On the other hand, some studies considered that the UAVs are the only ones capable of reaching the customers and delivering the parcels. This model is ideal for reaching nodes located in areas of difficult ground access; therefore, drones are carried up to a certain point of the route in which they launch from the ground vehicle and continue the route in the airspace. Some of the models were designed with clusters and considered that drones return to the truck for battery recharge and

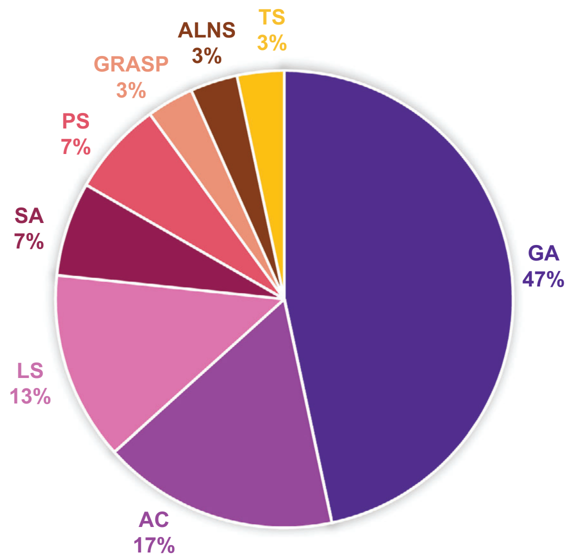


Fig. 11. Distribution of metaheuristic methods.

parcel reload if necessary. Few of these models are described in the works of Chang and Lee (2018), Luo et al. (2017), and Kim and Matson (2017).

Furthermore, other works have assumed that the UAVs can depart directly from the depot, deliver or pick up a parcel, and return to their starting point in which they may recharge their battery or reload a new parcel. In this type of models, the ground vehicles and the UAVs take different routes that may or may not start in the same depot, and both visit different customers. This kind of problem is ideal when the parcels to be delivered are different for each customer and some nodes are infeasible to be fulfilled by a drone. This problem is called the "parallel drone scheduling traveling salesman problem" first introduced by Murray and Chu (2015). Some further adaptations and studies are carried out by Mbiadou et al. (2018), Ulmer and Thomas (2018), Ham (2018), and Oruc and Kara (2018).

Table 8 shows the list of authors that proposed a model with a ground vehicle to support the UAVs during the routing, and the considerations they had while formulating the problem and creating the specific context.

In general, authors consider a specific carrier vehicle to assist the UAV depending on the context of the problem. Figure 12 shows the distribution of the carrier vehicles within the proposed mixed approaches, spread between trucks (*T*), unmanned ground vehicle (UGV), motorcycles (*M*), UAV that acts as a carrier, and public transportation (PT). Any other carrier that the authors refer to as "ground vehicle," "traditional delivery vehicle," and "carrier platform" are grouped in the category ground vehicle. The most used complementary vehicle for the mixed models was the trucks within 15 problems, followed by other types of ground vehicles (four references) and UGVs (three papers). Shima et al. (2006) formulated a problem in which a carrier exists to accomplish the tasks, so it was included as a mixed approach. However, the carrier is a UAV flying over an urban area that transports and dispenses micro-UAVs to fly over multiple points of interest for inspection from a

Table 8
List of authors with mixed approaches

| Authors | 1GV | 1D | C + D | CDC |
|---|---|---|---|---|
| Murray and Chu (2015) | X | X | X | X |
| Chang and Lee (2018) | X | | | X |
| Ha et al. (2017) | X | X | X | X |
| Ham (2018) | | | X | |
| Wang et al. (2016) | | | X | X |
| Poikonen et al. (2017) | | | X | X |
| Es Yurek and Ozmutlu (2018) | X | X | X | X |
| Luo et al. (2017) | X | X | | X |
| Mbiadou et al. (2018) | X | | X | |
| Schermer et al. (2018) | | | X | X |
| Kim and Matson (2017) | | | | X |
| Agatz et al. (2016) | X | X | X | X |
| Freitas and VazPenna (2018) | X | X | X | X |
| Ferrandez et al. (2016) | | | | X |
| Hu et al. (2018) | X | | | X |
| Savuran and Karakaya (2015) | X | X | | X |
| Yu et al. (2018) | | X | | X |
| Tokekar et al. (2016) | X | X | X | X |
| Shima et al. (2006) | N/A | | X | X |
| Jeong et al. (2019) | X | X | X | X |
| Oruc and Kara (2018) | | | X | |
| Ulmer and Thomas (2018) | | | X | |
| Ropero et al. (2019) | X | X | X | X |
| Kim and Moon (2019) | X | | X | |
| Bouman et al. (2018) | X | X | X | X |

1GV: one ground vehicle; 1D: one drone/UAV; C + D: nodes/clients are attended by carriers and drones; CDC: the drone can fly from or to the carrier.

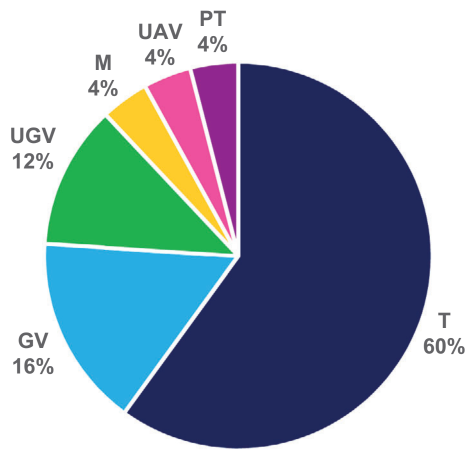


Fig. 12. Distribution of vehicles used in mixed approaches.

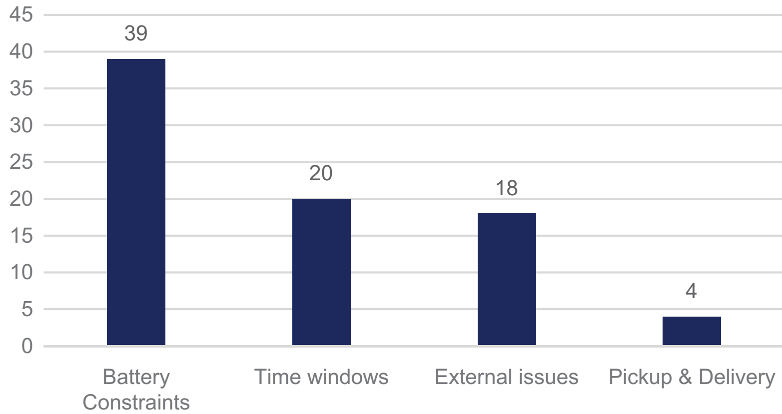


Fig. 13. Distribution of papers by type of constraint.

close distance. On the other hand, Yu et al. (2018), Tokekar et al. (2016), and Ropero et al. (2019) used UGVs as carriers for the UAVs, to provide them battery during the route and transport between locations. Additionally, Kim and Matson (2017) proposed to solve a problem that takes advantage of the existing PT to act as the carrier for drone delivery. Finally, Oruc and Kara (2018) designed a parallel scheduling problem using vehicles, motorcycles, and drones in a postdisaster scenario to provide a wider area of damage inspection; this means that in this case, the motorcycles do not act as the carriers of the UAVs.

### 3.5. Constraints

Figure 13 shows the distribution of papers according to the constraints considered in the problem in accordance with the typology previously presented. The most important constraint found was the battery restrictions of the UAVs, followed by time windows. Moreover, external issues were also a significant constraint considered, as they may include environmental concerns, climate changes, wind, obstacles, and threats to be avoided. These external factors may disturb the problem, affect the UAVs path, and cause damages in the aerial vehicles during travel. Finally, an interesting output of this review was that the delivery of parcels is most frequently addressed, while very few works considered the possibility of package pickup during the route. The classification of these findings is presented in Table 9.

From the literature, 39 publications addressed the battery constraints as well as the effects of the energy limitations of the UAVs. Chauhan et al. (2019) explicitly involve the energy consumption constraints within the integer linear programming formulation without considering the recharging of drone batteries, as the UAVs make several one-to-one trips (from the depot to the node and back) until the battery range is met. On the other hand, Luo et al. (2017), Kim and Matson (2017), Es Yurek and Ozmutlu (2018), among other authors, considered a ground vehicle to refresh the drone's battery for the next delivery. Furthermore, Dorling et al. (2016) demonstrate mathematically and experimentally that the payload and battery size or weight have significant variations on the drones'

Table 9
Relationship between authors and the implemented constraints

| Authors | Battery/energy/ fuel constraints | Time windows considerations | Pickup and delivery at the nodes/targets | External issues considerations |
|---|---|---|---|---|
| Murray and Chu (2015) | X | | | |
| Chang and Lee (2018) | | | | |
| Ha et al. (2017) | X | | | |
| Ham (2018) | | X | X | |
| Di Puglia et al. (2017) | X | X | | |
| Wang et al. (2016) | X | | | |
| Poikonen et al. (2017) | X | | | |
| Luo et al. (2018) | X | | | X |
| Dorling et al. (2016) | X | | | |
| Es Yurek and Ozmutlu (2018) | X | | | |
| Zhou et al. (2018) | | X | | |
| Luo et al. (2017) | X | | | |
| Furini et al. (2016) | | X | | |
| Mbiadou et al. (2018) | | | | |
| Schermer et al. (2018) | X | | | |
| Kim and Matson (2017) | X | | | |
| Natalizio et al. (2013) | | X | | |
| Agatz et al. (2016) | X | | X | |
| Freitas and VazPenna (2018) | X | | | |
| Modares et al. (2017) | X | | | X |
| Kim et al. (2017) | | | | |
| Ferrandez et al. (2016) | X | | | |
| Olivares et al. (2015) | X | | X | |
| Hu et al. (2018) | X | | | |
| Troudi et al. (2018) | X | X | | |
| Dai et al. (2018) | X | X | | X |
| Bouzid et al. (2017) | X | | | X |
| Cannioto et al. (2017) | X | | | X |
| Zillies et al. (2016) | | X | X | |
| Savuran and Karakaya (2015) | X | | | |
| Scott et al. (2016) | X | | | X |
| Avellar et al. (2015) | X | | | X |
| Guerriero et al. (2014) | | X | | |
| Guerrero and Bestaoui (2013) | | | | X |
| Xie et al. (2019) | | | | |
| Yu et al. (2018) | X | | | |
| Jang et al. (2017) | | | | |
| Olivieri and Endler (2017) | | X | | |
| Chen et al. (2017) | | | | |
| Greiff and Robertsson (2017) | X | | | X |
| Sonmez et al. (2015) | | | | X |
| Boone et al. (2015) | | | | |
| Ercan and Gencer (2018) | | X | | |
| Teo et al. (2015) | | X | | X |

*Continued*

Table 9
Continued

| Authors | Battery/energy/ fuel constraints | Time windows considerations | Pickup and delivery at the nodes/targets | External issues considerations |
|---|---|---|---|---|
| Phung et al. (2017) | X | | | X |
| Alemayehu and Kim (2017) | | | | |
| Tokekar et al. (2016) | X | | | |
| Sundar and Rathinam (2014) | X | | | |
| Sujit et al. (2012) | | | | |
| Gentilini et al. (2013) | | | | |
| Zhang et al. (2012) | X | | | X |
| Ny et al. (2012) | | | | |
| Shima et al. (2006) | X | | | X |
| Chauhan et al. (2019) | X | | | |
| Jeong et al. (2019) | X | | | X |
| Oruc and Kara (2018) | | | | |
| Chow (2016) | | X | | |
| Zhen et al. (2019) | | | | |
| Song et al. (2018) | X | X | | |
| Coutinho et al. (2018) | | | | X |
| Li et al. (2018) | X | X | | |
| Ramirez Atencia et al. (2019) | X | X | | |
| Ulmer and Thomas (2018) | | | | |
| Ropero et al. (2019) | X | | | |
| Yue and Jiang (2018) | X | | | |
| Perez-Carabaza et al. (2017) | | | | |
| Evers et al. (2014) | | X | | |
| Rosalie et al. (2018) | | | | |
| Jeauneau et al. (2018) | | | | X |
| Russell and Lamont (2005) | | | | |
| Lim et al. (2008) | | | | |
| Duan et al. (2009) | | X | | |
| Kahveci et al. (2007) | | X | | |
| Lim et al. (2010) | | | | |
| Kim and Moon (2019) | X | | | |
| Bouman et al. (2018) | | | | |
| Bo et al. (2014) | | | | X |
| Karaman and Frazzoli (2011) | | X | | |
| Manyam et al. (2016) | | | | |

energy consumption and flight time. Finally, Sundar and Rathinam (2014) proposed a UAV routing problem with a given set of targets and depots where the UAV can refuel at any depot to continue with the path plan while minimizing the total fuel required.

Regarding the external issues that may affect the UAVs routing planning, Luo et al. (2018) and Guerrero and Bestaoui (2013) designed their path planning problems under wind conditions and specifications, as it may affect the drones' speed and direction. On the other hand, Modares et al. (2017), Bouzid et al. (2017), Greiff and Robertsson (2017), Teo et al. (2015), and Phung et al.

(2017) proposed a problem by considering an area with obstacles to avoid during the route, such as buildings, towers, trees, or hills. Likewise, Jeong et al. (2019) and Bo et al. (2014) considered a context in which the UAVs must avoid specific zones named "nonflying zones" because of specific laws that prohibit to fly over airports, heliports, national parks, or stadiums. Similarly, Dai et al. (2018), Scott et al. (2016), and Sonmez et al. (2015) designed a coverage problem over an area of a complex environment by developing a 3D mapping of the terrain or urban area and constructing the problem based on it.

Instead, Ham (2018) proposed a delivery problem considering shipping priorities and time windows in which the UAVs can visit the same node several times in different periods, as well as a drop–pickup synchronization. On the other hand, Zhou et al. (2018) designed a UAV routing problem by considering weapon configuration and attacking time windows of the target. Guerriero et al. (2014) studied the concept of soft time windows for the temporal coverage of filming sports events.

## 4. Discussion of trends and future research

In this section, the trends of the UAVs' routing problems are presented, as well as some suggestions regarding future research focused on the applications and considerations unexplored by the reviewed literature. As this paper considered the contributions between 2005 and the first quarter of 2019, we also provide some remarks on recently published literature.

Regarding the objectives to be optimized, it was found that there is a trend to minimize time, distance, and costs. However, some of the optimization objectives were closely related. An example of this relationship between objectives was proposed by Sundar and Rathinam (2014), in which the main goal was to minimize the fuel required by the UAVs and it was represented as cost minimization. On the other hand, Zhou et al. (2018) designed a UAV routing problem, in which the main objective was to minimize the number of UAVs used, the costs, and the total flight time. However, they specified that the variables are related to each other and that while reducing the number of weapons used, the costs and flying distance will be potentially reduced. Likewise, Hu et al. (2018) proposed an algorithm for minimizing the time wasted for the vehicle and the UAV, and consequently decreasing the financial expenses. Besides, Shavarani et al. (2020) developed a biobjective mathematical model to account for the optimum number and spatial location of facilities among a set of candidate locations such that the total travel distance, costs, and lost demand are minimized simultaneously. Another possible relationship between objectives could be the reduction of energy consumption while minimizing the time or distance and *vice versa*.

### *4.1. Humanitarian approaches*

Humanitarian approaches are directed to solve a problem after a hypothetical disastrous event such as the proposed problems by Cannioto et al. (2017), Oruc and Kara (2018), and Zillies et al. (2016). Additionally, some authors just consider the possible application of their proposed model to these humanitarian scenarios, and adjust their proposed problem by not limiting their applicability in emergency response scenarios, but do not focus their research on this application, like the models designed by Dorling et al. (2016) and Chauhan et al. (2019). Moreover, it is suggested to extend the research of the mapping search to find missing people in a specific terrain, while maximizing the distance traveled and the coverage area, considering battery limitations. Also, there exists a research opportunity in-depth optimization research focused on humanitarian scenarios like the delivery routing problems between hospitals to reduce the delivery time of blood or medicines. Besides, efforts should be increased to investigate the application of drones in conflict zones, where they can detect antipersonnel mines or carry out cargo delivery for food and medicines.

### *4.2. Last-mile deliveries*

Last-mile deliveries have become fundamental to the industries due to the impact generated by E-commerce, for example, Amazon was reported to serve 310 million customers worldwide. Then, the idea of using UAVs or drones, for the last-mile delivery is gaining popularity (Aurambout et al., 2019). A recent work oriented to last-mile deliveries is from De Freitas and Penna (2020) who introduced the drone-assisted parcel delivery. The drone launches from the truck, proceeds to deliver parcels to a customer, and then is recovered by the truck at a third location. While the drone travels through a trip, the truck delivers parcels to other customers if the drone has enough battery to hover waiting for the truck. Likewise, Moshref-Javadi et al. (2020) presented a solution approach for the optimal planning of delivery routes in a multimodal system combining truck and UAV operations. In this system, truck and UAV operations are synchronized, that is, one or more UAVs travel on a truck, which serves as a mobile depot. In general, the reviewed literature and recent works consider synchronized truck–drone operation. However, there still room for contributions that handle the customer issues in last-mile deliveries, that is, speed, accuracy, security, and precision; and for handle business issues, that is, cost, efficiency, payload capacity theft, weather, safety, and durability.

### *4.3. Entertainment approach*

The entertainment approach is projected only to transmit sports events by the path plan of the UAVs with soft time windows. Natalizio et al. (2013) first proposed this kind of problem in a conference paper, and it was worked on later by Guerriero et al. (2014). This problem was also studied by Pugliese et al. (2017) in a conference paper. Therefore, these types of problems have been developed in publications with the participation of Natalizio and Guerriero, but there could be an unexplored research opportunity considering different types of drones, cameras, Wi-Fi range, or payload capacity. Additionally, some other entertainment events can be explored depending on the type of drone used. For example, a drone-racing event could be addressed through a routing problem by minimizing the time while considering drones driven by remote control, turning times, and environmental conditions. Another example is the usage of UAVs as the entertainment spectacle, by programming it for light shows at night, and it will be applicable for events like the Super Bowl halftime show, Coachella, Lollapalooza, or Disneyland shows.

### 4.4. Internal logistics

In terms of *internal logistics,* it is currently observed that this application has only been investigated through product assembly within a manufacturing plant by Olivares et al. (2015) to minimize the energy consumed. Therefore, there exists a research opportunity by including different usages of the drones within a company, like the inventory management, and the loading and unloading of parcels from trucks. Additionally, efforts should be increased to investigate the agricultural usage of drones besides the proposed problem by Tokekar et al. (2016) in which the unmanned vehicles just collect data and samples from the ground and air. However, it is essential to expand the studies on the possibility to spread seeds over a terrain with minimum time or operational costs.

### 4.5. Others

Regarding the *drone types*, it is proposed to further study the possibility to develop a routing problem by combining different unmanned vehicles. In the literature, a few works implemented a path planning problem with UAVs and UGVs (Tokekar et al., 2016; Yu et al., 2018; Ropero et al., 2019) who implemented a path planning problem with UAVs and UGVs. However, it is suggested more analysis of a mixed model with multiple unmanned vehicles from air, ground, and water, with different sizes and capabilities.

It is identified that the *constraints* taken into account while developing the proposed models are projected to consider battery constraints and time windows, while very few publications considered the possibility of the drones to pick up parcels, so it is suggested to explore more problem contexts that involve picking up issues at the nodes.

It is also observed that none of the UAV routing models were addressed for sustainable purposes other than reducing the energy consumed or the $CO_2$ by replacing traditional delivery methods with drones. Although including the UAVs in a routing plan is more ecological than the traditional methods, there is a research opportunity to use them for sustainable purposes, as the control and scanning of environmental conditions of a specific terrain or cleaning up litter from the environment.

## 5. Conclusions

This paper presents a literature review on the characterization of routing problems using drones, the research trends and the recent developments and improvements, in which 79 relevant publications were classified according to the objectives optimized, solution methods, applications, constraints and whether they use a complementary vehicle or not. Different solution methods were found to address these problems, which include the *exact methods, heuristic algorithms, metaheuristic* methods, and with little frequency, the *policies.* The main objectives to be optimized were the time, distance, and costs. It was identified as well that the logistics applications that stand out from the articles are the ones for parcels distribution/delivery and for collecting information and surveillance. Additionally, it was observed that a significant percentage of the publications considered mixing different vehicles within the same proposed problem for complementing the UAVs routing plan.

Among the constraints contemplated within the articles, the most representative restrictions were the battery/energy/fuel limitations and the time windows.

Future research may include water drones for ocean routing exploration and cleaning, as well as UGV path plan, considering that this literature review was limited to autonomous aerial vehicles. Likewise, future research should include other types of optimization problems besides routing ones, like task assignments.

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