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Drone-aided routing: A literature review

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ABSTRACT

The interest in using drones in various applications has grown significantly in recent years. The reasons are related to the continuous advances in technology, especially the advent of fast microprocessors, which support intelligent autonomous control of several systems. Photography, construction, and monitoring and surveillance are only some of the areas in which the use of drones is becoming common. Among these, last-mile delivery is one of the most promising areas. In this work we focus on routing problems with drones, mostly in the context of parcel delivery. We survey and classify the existing works and we provide perspectives for future research.

1. Introduction

The continuous technological advances over the past decade have lead to an increasing use of unmanned aerial vehicles (UAVs), commonly known as drones, in several areas, such as logistics, military operations, public security, traffic surveillance, and monitoring. In particular, the use of drones has recently gained popularity when several major online retailers, such as Amazon, Google, DHL, and Walmart announced the introduction of drones in their parcel delivery process (Yoo et al., 2018). In 2013 Amazon revealed “Amazon Prime Air”, the project of delivering packages to customers with drones up to five pounds in 30 min, and conducted the first pilot test in 2016 (www.amazon.com, 2016). Even if this project is still in development, the company succesfully introduced drones within a few months of the announcement and stated its ambitious goal of reaching 50% of zero-impact shipments by 2030. Alphabet Wing is the drone delivery service offered by Wing, a Google parent company. The company announced the starting of pilot tests for its unmanned aircraft in Christiansburg, Virginia (https://x.company, 2019) and of a trial service in Finland at the end of 2019 (www.bbc.com, 2019). “Parcelcopter” is the name of the DHL drone, which was used for the first time in 2013 in Bonn to deliver medicines to the Deutsche Post DHL Group employees from a pharmacy located on the other side of the Rhine. In 2014 the Trend Research Team of DHL Customer Solutions and Innovation published a report on the new trends in delivery processes and analysed the future role, the potential applications, and the limits of drones usage in this sector (www.dhl.com, 2014). During the 2013–2015 period, the parcelcopter capacity has been enhanced, and between January and March 2016, DHL successfully concluded a three-month test of its third parcelcopter generation in Bavaria through the winds and snow of the Alps (www.dpdhl.com, 2019). In July 2017, Walmart started testing drone services in Central New York and at Griffiss International Airport in Rome (www.newyorkupstate.com, 2017). In October 2019,

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it requested permission from the Federal Aviation Administration (FAA) to test its own delivery drones for commercial purposes (https://thewiredshopper.com, 2019).

Other companies have shown interest in using drones for their deliveries. In March 2015, Zookal, an Australian textbook distributor, tested delivery drones in Australia, Singapore, and Malaysia (www.cnn.com, 2013). In November 2015, Royal Mail announced its interest in using both drones and autonomous vehicles for mail delivering, the countryside areas are likely to be the first to experience the service (www.telegraph.co.uk, 2015).

In September 2016, UPS started testing drones for two main purposes: commercial deliveries to remote or difficult-to-access locations and internal transport between or within warehouses. The first test has successfully lead to delivery of urgent medicine from Beverly, Massachusetts to an island near Boston (https://pressroom.ups.com, 2016). In February 2017, UPS used an electric van equipped with a recharging station for battery-powered drones and launched the drone to drop off a package at a home in Florida (www.usatoday.com, 2017). In 2019, it was granted FAA approval for commercial drone deliveries (www.supplychaindive.com, 2019). The company announced that it is building its infrastructure, expanding its services for healthcare customers, and using drones for new purposes in the future.

In October 2016, Zipline International, an American start-up, launched a medical service in Rwanda, delivering medicines to remote parts of the country, with the aim of expanding its business in the U.S. (www.airmedandrescue.com, 2019). In 2019, it extended its UAV medical service in the south of Ghana, by opening four distribution centers and using 30 drones to distribute vaccines, blood, and life-saving medications to 2,000 health facilities, serving 12 million people across the country (www.airmedandrescue.com, 2019).

In 2017, the German auto manufacturer Mercedes-Benz, in collaboration with the drone manufacturer Matternet, started a pilot project for on-demand delivery of e-commerce goods (https://media.daimler.com, 2017). This project explores drone integration with Mercedes-Benz's commercial vehicles. Its "Vision Van" is a driverless vehicle that would be automatically loaded by robots at a warehouse. Autonomous drones would then be able to take the packages and depart from the van's roof to carry them to their final destination.

The use of drones for delivery applications is expected to grow significantly in the next few years. Indeed, due to the sharp increase in online shopping, customers are becoming more demanding in terms of speed of delivery service. Since the number of online stores is exponentially expanding, the time of delivery may affect the choice of customers' purchases. However, while fast delivery is a key factor of success for online retailers, it may prove very expensive. In addition, customers and companies are becoming increasingly aware of the ecological problems. The reduction of negative externalities (e.g., CO_2 emissions, noise, traffic) has become a worldwide goal. Therefore, introducing green solutions in transportation planning is becoming a crucial strategy. Finding an efficient, effective, and eco-friendly organization in last-mile delivery now poses an important challenge for retailers. In this context, drones could prove a good compromise between finding an innovative and faster solution for last-mile delivery and safeguarding the environment.

Contribution and organization of the paper. In this paper we present a structured literature review of the recent operations research contributions on drone-aided routing problems (RP-D). We focus on problems arising in parcel delivery and on the papers published between 2015 and May 2020. In the last few years, several reviews about the use of drones in logistics have been conducted (Barmpounakis et al., 2016; Otto et al., 2018; Khoufi et al., 2019; Coutinho et al., 2018; Rojas Viloria et al., 2020; Chung et al., 2020). Our survey is different from these works in several aspects.

The aim of the paper of Barmpounakis et al. (2016) is to review the research dedicated to the use of drones in transportation, with a specific emphasis on traffic monitoring, freight delivery, road construction and photogrammetry, and remote sensing. Hence, the focus of this paper is clearly different. Otto et al. (2018) give an extensive survey of the works addressing the use of drones in civil applications, with a broader scope than routing. The papers reviewed have been published between 2001 to 2017 and only a few related to routing problems in transportation are considered. Coutinho et al. (2018) review contributions in UAV trajectory optimisation, routing, and task assignment published between 2010 and 2017. In particular, they introduce a taxonomy and identify 20 attributes common to these classes of problems, for helping the readers to find the similarities among them. The number of reviewed papers which study routing problems is low and the focus of this paper is clearly different from ours. The contribution of Khoufi et al. (2019), shares some similarities with our work, since the authors give particular attention to the RP-D in transportation (i.e., extended variants of the traveling salesman problem and vehicle routing problem for drones). They describe in details the problems studied, their main features, and provide information on the proposed solution approaches. The survey of Khoufi et al. (2019) covers the period from 2015 to 2018 and only one paper on delivery routing problem, published in 2019, is analyzed. Hence, our work is complementary to the paper of Khoufi et al. (2019); indeed 46 additional papers (including 14 published in 2015–2018) are discussed in our review, but are not described in Khoufi et al. (2019). The recent work of Rojas Viloria et al. (2020) is aimed at reviewing papers addressing generic routing problem with drones. The authors classify the literature according to the objectives to be optimized, the constraints, the solution approaches, the applications area, and the fleet's characteristics (i.e., the possibility of using or not a complementary vehicle). Particular attention is devoted to applications. The papers are grouped in five classes: military, internal logistics, entertainment, surveillance and data collection, and parcel delivery. Our work has a different focus: we have selected the most recent papers, that consider RP-D in the context of parcel delivery (only 29 works on this topic are reviewed in Rojas Viloria et al. (2020)), and we have analyzed them mainly from an operations research point of view.

Another recent survey is that of Chung et al. (2020), which proposes a detailed review of optimization models and methods for drone-truck combined operations problems. The authors analyze papers dealing with routing, task assignment, area coverage, scheduling, communication, and facility location. They describe and discuss the main features of the problems, then the methodologies used to solve them. In conclusion, they identify possible research directions.

Our main purpose is to provide insights into current research trends in the application of operations research techniques to solve routing problems with drones and to outline possible future research directions. In particular, we review 63 articles that focus on routing problems for parcel delivery. We consider works published in scientific journals, conference proceedings, and book chapters. We searched in the following databases: Elsevier, Wiley, Springer, Scopus, Research Gate, and Google Scholar. We used several keywords such as “routing with drones”, “traveling salesman problem with drones”, “delivery with drones”, “vehicle routing with unmanned aerial vehicle”, “delivery with unmanned aerial vehicle”. We give a new and simple classification of the problems, then provide a detailed description of their main features, the similarities and differences among the works, and describe the approaches used to solve them. We also provide a summary of the main features of the problems in tables, which can help the researchers compare the works and explore new possible configurations.

The remainder of this paper is structured as follows. In Section 2 we provide a short description of the technological background and we analyse the most used classification of drones. We provide a classification and an accurate description of RP-D and the proposed solution approaches in Section 3. Final remarks are given in Section 4 along with potential future research directions.

2. Technological background

Several authors have proposed overviews and classifications of UAVs based on several parameters. In this section we provide a brief description of the main available classifications.

2.1. Application area

The application area is one of the characteristic used to classify drones. Indeed, drones are used in several fields such as monitoring, delivery, agriculture, wireless coverage, and military applications. Singhal et al. (2018) identify three main areas of application: civilian, environment, and defence, and then give a classification, reported in Fig. 1.

Civilian. Otto et al. (2018) review and classify the most promising emerging civil applications of drones: physical infrastructure including energy, roads, railways, oil and gas and construction, agriculture, transport, security, and entertainment and media. Barmpounakis et al. (2016) focus on drones in transportation and review works describing their use in traffic monitoring, logistics, road construction, photogrammetry, and remote sensing. The authors write that transportation is one of the most promising areas of drone applications, but future uses of drones have to take into account safe navigation above transportation infrastructures, efficiency in the use of energy, and mining of information based on predictive analytic.

The use of commercial drones in construction is becoming more common, especially for aerial photography, surveying, inspections, as well as safety and security monitoring activities on construction sites (Tantum and Liu, 2017). Li and Liu (2019) describe the phases of drone-based construction management, namely land surveying, logistics, onsite construction, maintenance and demolition. They discuss the advantages of using drones, as well as their main challenges. They recognize many advantages in using drones in the

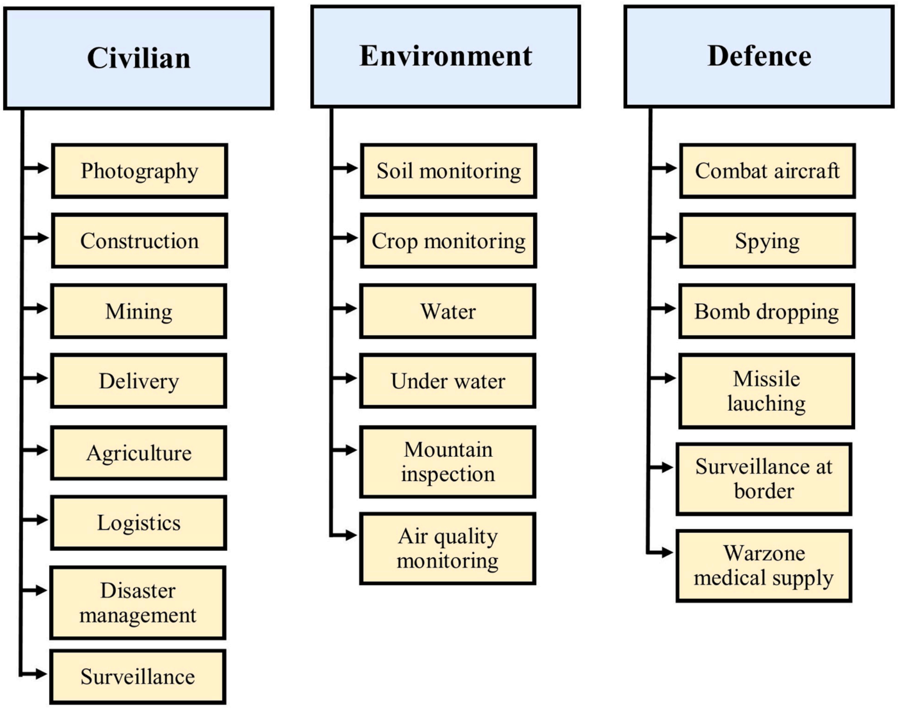

Fig. 1. Potential applications of drones (Singhal et al., 2018).

construction industry, such as avoiding dangerous operations to surveyors who usually work in a dangerous environment, speeding up the collection and automating the analysis of terrain data, having positive impacts on environment during some activities such as land mapping, aerial photography, and aerial surveying, that are usually performed by gasoline fuelled planes. They also point out that one of the main limitations in using drones in construction management is centered on the local regulations surrounding their usage, which may vary from one region to another. In addition, construction workers can be distracted by a flying drone during construction processes, professional operators are needed for guiding drone flights, and the use of drones may be limited by the weather conditions and their battery life.

Rao Mogili and Deepak (2018) propose a review of drone applications in precision agriculture for increasing crop productivity. Drones can be used for several purposes, in particular for spraying chemicals or water on crops, hence speeding up the process as well as the monitoring of the area. In the latter case, the monitoring system is composed of a multispectral camera mounted on a UAV. The UAV flies over the area, while the camera takes pictures and gives information about geographic coordinates. These pictures are then analysed by means of some indicators. Based on the results, it is easier to identify the infected areas where to spray the pesticides, which may reduce the waste of resources.

In the context of disaster management, drones can become very useful to save lives, for monitoring the area of disaster as well as for transporting essential goods for humanitarian logistics. Hence, this is a very promising area of application. Adams and Friedland (2011) provide a survey of UAV utilization for imagery collection for disaster monitoring and management. High-resolution images, collected by UAVs, can be analyzed and used to produce dense surface models, hazard maps, detailed building renderings and other disaster area characteristics. They analyze the benefits of using UAVs and describe how they have been employed in several real disaster events such as hurricanes Katrina, Wilma and Ike, Typhoon Morakot, and earthquakes in L'Aquila (2009), Haiti (2010), and Japan (2011). Erdelj et al. (2017) focus on the joint role that wireless sensor networks and multi-UAV systems can play in disaster management, by providing a detailed review of the relevant research activities and open issues on this topic. They identify six groups of applications and three unexplored areas of applications depicted in Fig. 2.

When a natural disaster occurs and roads are damaged, drones can be used as a mode of transportation for essential goods. In fact, since drones are not road constrained, they are not influenced by road conditions. Hence, on the one hand integrating drones into humanitarian logistics is convenient and efficient, on the other hand some critical technological factors have to be taken into account. In fact, drones have a limited payload and a limited flight time. Kim et al. (2019) develop a stochastic facility location model for integrating drones in humanitarian logistics, which takes into account the uncertainty on characteristics of drone operating conditions. In particular, they study the energy consumption and the uncertain factors affect the battery life. They also propose a fast algorithm to solve the problem. Recently, Glock and Meyer (2020) study and solve the problem of managing the mission planning after a disaster in order to coordinate emergency response teams, by using drones for fast mapping the area. Other interesting scientific contributions on the use of drones in disaster management are the papers by Restas (2015), Erdelj et al. (2015), Oubbati et al. (2019), Aiello et al. (2020), Akrama et al. (2020), Ejaz et al. (2020), and Park et al. (2020).

The use of drones for monitoring and surveillance activities in civilian application is very common. Vehicles or subjects tracking, traffic management or fire detection are only some of the possible applications. Surveillance activities can occur in indoors environments (Raja and Pang, 2016; Chakrabarty et al., 2016), in large outdoor environments such as air traffic monitoring (Kim and Sivits, 2015), maritime monitoring (Jeon et al., 2019; Suteris et al., 2018), ground-traffic monitoring (Roudet et al., 2016; Sutheerakul et al., 2017; Barmpounakis and Geroliminis, 2020) or, in general, for target tracking (Zorbas et al., 2013; Zorbas et al., 2016; Di Puglia Pugliese et al., 2016; Zhen et al., 2019).

Entertainment is another interesting civilian area in which drones can be used. Recently, some authors focused on the use of drones for filming sports events (see Natalizio et al. (2013), Di Puglia Pugliese et al. (2017), Natalizio et al. (2020)).

Environment. The use of drones in environmental actions, such as observing the effects of climate change, controlling air quality, managing national parks, and monitoring different ecosystems is becoming very common. Smith (2015) analyses the use of drones in environment management by using several international examples. Indeed, drones for monitoring destructive activities have been

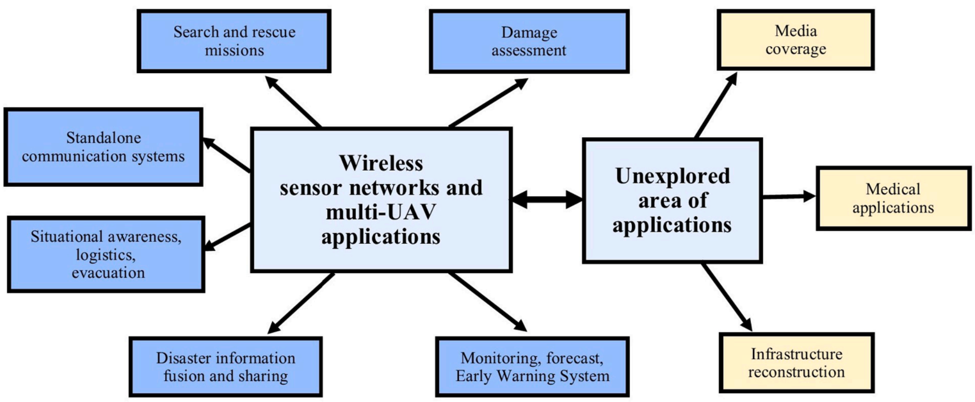

Fig. 2. Applications of wireless sensor networks and multi-UAVs in disaster management (Erdelj et al., 2017).

used by the World Wildlife Fund in Africa, as well as in Brazil by the environmental police to monitor deforestation in the Amazon.

Monitoring air quality using small sensors on-board a UAV is becoming very common as well as very complicated, for several reasons, such as power consumption and weight constraints, propeller effect and the choice of the sensors. Hence, several studies have focused on the development and evaluation of effective UAVs for monitoring air quality (see Juan et al. (2015) and Villa et al. (2016)). Other environmental research applications include soil and crop monitoring. Kavoosi et al. (2020) study the use of drones for monitoring soil residue cover, with a focus on crop residue management. Other applications for soil monitoring can be found in Capolupo et al. (2015) and Corbane et al. (2012). Capolupo et al. (2015) study the use of drones for the detection of soil contaminated by copper in the south of Italy, while Corbane et al. (2012) consider their use for the analysis of the soil surface characteristics in a Mediterranean area. Drones are also used in hydrology applications for measuring several parameters related to the water surface. Tauro et al. (2016) study the benefits of using drones in the context of hydrology, focusing on surface flow measurements. Indeed, drones have several application potentials for flow measurements in difficult-to-access water environments during adverse hydro-meteorological events. Instead, aquatic surface drones are used in marine environment monitoring for several purposes such as the monitoring of water quality, coral reefs, fish farms, and so on (Velez, 2015; Christensen et al., 2015). These drones operate on the surface of the water, but there exists another class of waterproof UAVs that operate underwater, the so-called underwater drones. These drones are divided into two main classes: remote operational vehicles, guided by remote human control, and autonomous underwater vehicles that operate in the water independently by direct human input. Both classes of underwater drones are used for studying sea animals. Some examples are the automatic fish recognition (see Meng et al. (2018)) or the monitoring and protecting of fishes species (see Dumiak (2017)), and also for investigating underwater regions as in Spears et al. (2014), where the authors present an application of underwater UAVs in under-ice conditions, to be used in polar regions.

Defence. Callam (2015) and Dunn (2013) focus on the use of UAVs in military applications. In particular, Callam (2015) traces the history of drone applications in the U.S. military since 1982, and then discusses the effect of armed UAVs on military capabilities, limitations, and costs. He concludes that even if drones improved military capability in terms of helping protect both soldiers and civilian people, they will never replace humans on the battlefield. Dunn (2013) discusses the use of drones in military operations, pointing out the scarce attention relative to the impacts of this technology on the traditional notions of safety and security.

2.2. Size

Drone sizes vary from vast fixed-wing UAV, with a wing span of 61 m and a weight of 15,000 kg, to smart dust (SD) which is composed of several micro-electro-mechanical systems, with a minimum size of one mm and a weight of 0.005 g (see Hassanalian and Abdelkefi (2017)). Between UAV and SD there are several types of drones, called micro-drones, such as the micro unmanned air vehicle (μUAV), the micro air vehicle (MAV), the nano air vehicle (NAV), and the pico air vehicle (PAV) (see Fig. 3).

Other classifications based on the weight are given by Arjomandi et al. (2006) and Weibel and Hansman (2006) who both identify five categories, whereas Singhal et al. (2018) divide drones into 10 classes.

2.3. Fuselage

Considering the shape of fuselage, we can identify three configurations widely used in the design of the UAVs, which are fixed-wing, rotary-wing, and flapping-wing. Shraim et al. (2018) compare the three types of drones showing their main features. We compile their classification in Table 1, characterized by eight rows; the first one (Maneuver) gives the measure of the maximum achievable time rate of change of the velocity vector at any point in the flight envelope (see Verbeke and De Schutter (2018)), the row Cost indicates the operational cost, construction and repairing effort is depicted in the third row. The fourth row indicates the energy consumption, that is the energy consumed to maintain the vehicle in the air, the fifth one reports the level of flight safety, which measures the loss of control's risk, while the sixth one gives the flight range, i.e. the distance an aircraft can fly between takeoff and landing. The last two rows indicate the potential drones' applications in civil and military sectors, respectively.

Fixed-wing. The main advantage of UAVs with fixed wings is their simpler structure, which requires less complicated maintenance and repairs. In addition, they are able to carry greater payloads for longer distances using less power. One of their main disadvantage is that fixed wings need a constant air movement during the flight, hence these drones cannot stay stationary. For this reason, they are not indicated for stationary operations such as monitoring.

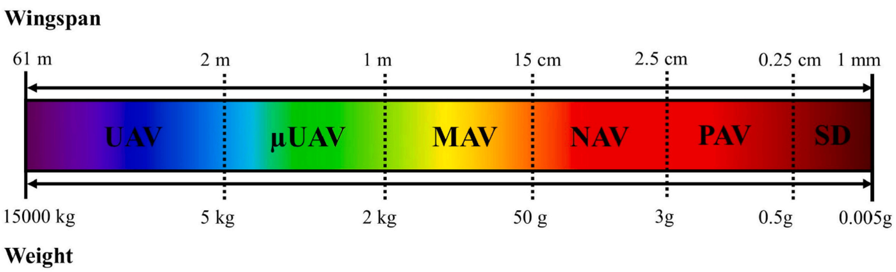

Fig. 3. Classification of drones based on size (Hassanalian and Abdelkefi, 2017).

Table 1
Comparison between rotary wings, fixed wings, and flapping wings, adapted from Shraim et al. (2018).

	Wings		
	Fixed	**Rotary**	**Flapping**
Maneuver	Low	High	Medium
Cost	Low	Medium	High
Construction and repairing	Low	Medium	High
Energy consumption	Low	High	Medium
Flight safety	High	Medium	Low
Range	High	Medium	Low
Civil applications	Low	High	High
Military applications	Medium	Medium	Medium

Rotary-wing. The most usual rotary winged UAV is the quadcopter (a UAV with four rotors). However, there are other common UAVs such as the helicopter (one rotor), the hexacopter (six rotors) and the octocopter (eight rotors) (see Shraim et al. (2018)). UAVs with 12 or 16 rotors have been developed but their use is not very common. Since the blades are in constant movement, the UAVs with rotary wings do not require air moving over their wings. The main advantage of these UAVs is that they can take off and land vertically, in a small place, thus they are more performing in terms of agility of manoeuvring. They are indicated for operations requiring a high level of precision maneuvering, such as monitoring. The electronic and mechanic structures of the rotary winged UAVs are more complex than those of the fixed wings, hence the main disadvantage of these drones is their higher maintenance cost.

Flapping-wing. Flapping wings mimic the birds flying, by using two identical mechanisms actuated by two motors (see Grand et al. (2008)). They usually belong to one of three classes, namely, MAV, NAV, and PAV (see Hassanalian and Abdelkefi (2017)). The design of MAVs wings is inspired from birds, PAV from insects, while NAV wings are inspired from very small birds and huge insects. The design and technology of flapping wings are more complex compared with those of fixed and rotary wings, due to their complex aerodynamics. Their operational costs are overall high and their flight time endurance is reduced because of the extreme power needed for the flapping technology. However, since flying with flapping wings yields unique maneuverability advantages when the size of UAVs is reduced, their interest among researchers is rapidly increasing.

Hybrid. Recently, some researchers have started to project hybrid UAVs which combine fixed-, rotary- and flapping-wing systems. The fixed or flapping-wing MAV is an example of a UAV that uses fixed wings for lift and flapping wings for propulsion (see Hassanalian and Abdelkefi (2017)).

2.4. Propulsion system

The propulsion systems may be classified into 10 categories, namely reciprocating piston engines, wankel rotary engines, propeller-based systems, gas turbine engines, rocket propulsion, electric motor-based systems, battery-based systems, proton exchange membrane fuel cell, photovoltaics, ultracapacitor (Griffis et al., 2009). Here, we focus on the most common and used types: the gas turbine, the electric motor-based and the battery-based propulsion systems.

Gas turbine. The gas turbine, commonly known as combustion turbine, is an internal combustion engine that generates chemical energy from fuel and converts it into mechanical energy. Gas turbine engines are widely used and their reliability is largely proven. However, this mechanism is very heavy. Recently, a new concept of microturbine engines has been developed. Thus, several small UAVs use a gas microturbine engine, especially in manufacturing. Among the advantages of gas microturbines, we note their high power density and thrust capability. However, they are expensive, loud and complex. Gas turbine are typically used in fixed and rotary wing drones (Hassanalian and Abdelkefi, 2017).

Electric motor. Electric motors use electricity to create rotational motion. For electric propulsion systems, electric motors are used

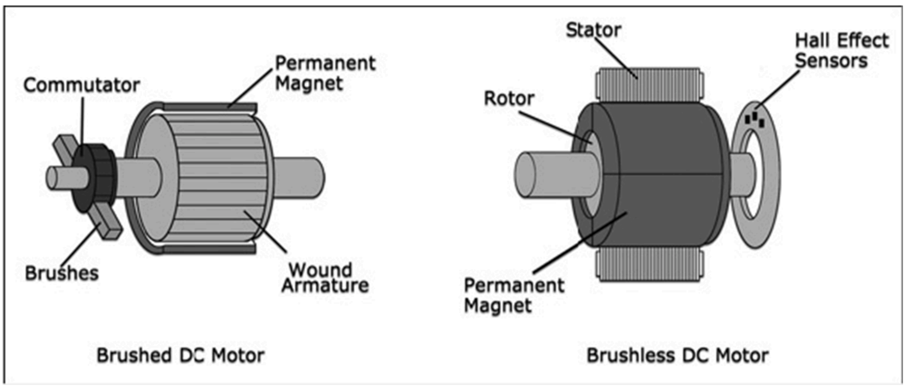

Fig. 4. Brushed direct current (DC) and brushless DC motors (www.e-jpc.com, 2018).

as a power plant to drive propeller blades for propulsion; all that is needed is a continuous source of electricity. On the one hand, electric motors which are conceptually very simple, have low costs due to economies of scale, require low maintenance, are robust and do not generate negative externalities. On the other hand, they may require large currents, they are sensitive to water or other conductive liquids and they can be affected by electromagnetic interferences. These types of motors usually constitute a good option for UAVs, and hence they are widely used. Nowadays, two types of electric motors are used in UAVs, namely brushed and brushless. Fig. 4 shows on the left side the brushed motor and on the right side the brushless one. In the brushed motor, there are permanent and stationary magnets on the outside, (i.e., the stator), and a spinning armature with electromagnets (wound wire coils) on the inside. The armature rotates, so it is called rotor. The stator, acting as a two-pole electromagnet, repels the rotor, which is attached to a shaft. The shaft houses a commutator, that is the device responsible for collecting current. As the magnetic field causes the rotor to spin, the commutator is being fed current by the brushes. The brushes, often made of carbon, lightly "brushed" against the commutator, giving a constant flow of electricity from the power source.

On the contrary, in the brushless motor, the permanent magnets are on the rotor and the electromagnets in the stator. The main difference between brushed and brushless motors is that the brushless one uses permanent magnets to generate power. Thus, brushless motors do not need a commutator and brushes, the electronic part of the motor is contained in the stator. It uses three phases of driving coils and a specialized sensor that tracks rotor position (http://toolsinaction.com, 2017; http://electronics.howstuffworks.com, 2006; www.e-jpc.com, 2018; Büchi, 2012).

The most appropriate are the brushless motors because they are smaller and lighter than the brushed ones. Generally, electric motors are used in flapping wings drones (Hassanalian and Abdelkefi, 2017).

Battery. Batteries are electrochemical energy storage devices consisting of one or more electrochemical cells, that convert stored chemical energy into electrical energy. Hence, they do not require fuel or oxygen. The most commonly used batteries are the rechargeable ones. In particular, due to their low weight, lithium batteries are the most used for micro-drones (Hassanalian and Abdelkefi, 2017). A rechargeable battery consists of one or more electrochemical cells in series. Electrical energy from an external electrical source is stored in the battery during charging; electricity can then be used to supply energy to an external load during discharging (Buckley et al., 2018). The advantages of battery-based systems are numerous: they are silent, lightweight, and self-contained (i.e., they do not require external reactants). In addition, because of the use of the electric motor as the prime mover, they are reliable, require low maintenance, have a high level of control and perform well in high-altitude operations. Among their main disadvantages we can cite the limited endurance and the limits of the recharge of batteries.

3. Drones in routing problems

We classified the problems into four categories: 1) the traveling salesman problem with drones (TSP-D) [3.1], 2) the vehicle routing problem with drones (VRP-D) [3.2], 3) the drone delivery problem (DDP) [3.3] and 4) the carrier vehicle problem with drones (CVP-D) [3.4]. We grouped these four categories into two macro-classes. The first two categories (i.e., TSP-D and VRP-D) belong to the macro-class of problems where deliveries may be performed by either the trucks or the drones. The third and fourth categories (i.e., DDP and CVP-D) belong to the macro-class of problems in which only drones perform the deliveries. Fig. 5 depicts our classification.

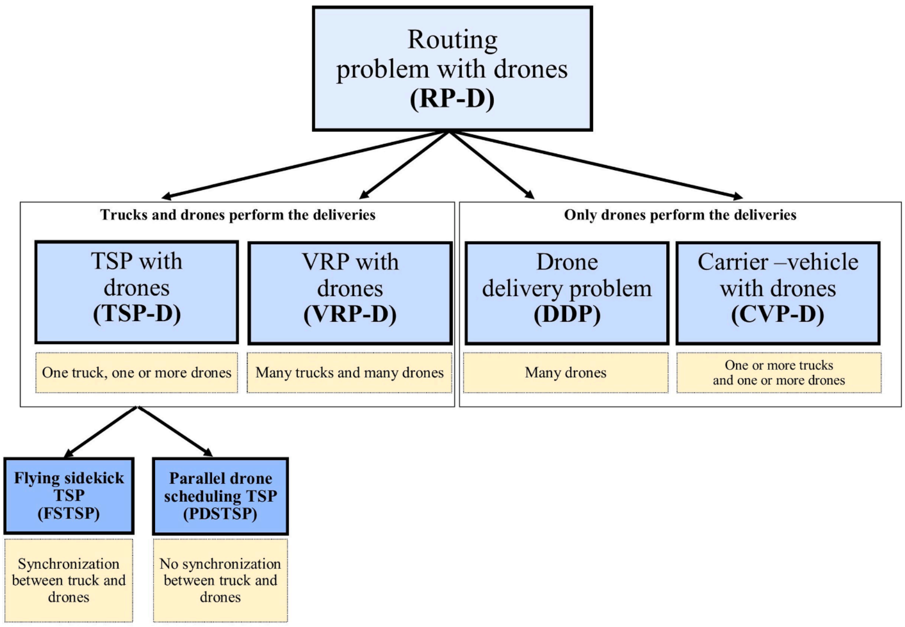

Fig. 5. Classification of routing problems with drones.

Fig. 6 shows the publication trend, during the period 2015–2020. It is worth noting that for 2020, we consider only the first five months of the year, hence, we highlighted this year in yellow. Looking at Fig. 6 and focusing on the period 2015–2019, an increasing trend is observed. The same tendency is also confirmed for the year 2020, since 15 papers have already been published in the first five months. Most papers focus on TSP-D variants; in fact, we have identified 28 papers on the TSP-D out of 63, that is about the 44% of the reviewed works. In addition, we surveyed 17 contributions on the VRP-D (26%), five on the DDP (about 8%), and 13 on the CVD-P (21%). The observed trend underlines an increasing interest in the other variants of the RP-D, in particular the VRP-D and CVD-P.

3.1. The TSP with drones (TSP-D)

Murray and Chu (2015) introduce the routing problem combining truck and drone. In this work the authors present two new variants of the traditional TSP called the flying sidekick traveling salesman problem (FSTSP) and the parallel drone scheduling TSP (PDSTSP), respectively.

The FSTSP considers the problem of serving a set of customers either with a single truck or a single drone. The objective is to minimize the completion time, that is the time required to service all customers and return both vehicles to the depot. Several constraints are related to the drone. In particular, a drone can visit only one customer, it has a restricted flight autonomy, and it cannot transport some heavy weight packages, which means that some customers can be served only by the truck. The vehicles must depart from, and return to a single depot exactly once, either in tandem (i.e., the truck transports the drone) or independently. In addition, they must visit any node at most once. Hence this also apply to the drone. The vehicles of a same type have the same speed. However, different travel times for the truck and the drone are taken into account. The authors present an integer linear programming model which is solved by Gurobi. Since solving instances with up to 10 customers requires several hours, they propose a heuristic which starts by finding a solution of the classic TSP, and then attempts to insert the drone and remove some customers from truck route by evaluating the achievable savings.

In the second model presented, i.e., the PDSTSP, the customers can be served by a single truck or by a fleet of one or more identical drones. The objective is to minimize the makespan, that is the time at which the truck returns to the depot. Since in this version of the problem drones and truck do not cooperate, there is no synchronization between them. The drones start and end their routes at the depot, can serve one customer at a time and can perform multi-trips leaving the depot more than once. To solve this model, the authors propose a heuristic based on constructing an initial solution in which the drones serve all the eligible customers (e.g., those requiring parcels that not exceed the drone capacity) and then applying local search heuristics to improve this solution.

Agatz et al. (2018) propose two route-first, cluster-second heuristics based on local search and dynamic programming to solve a TSP-D very similar to the FSTSP presented by Murray and Chu (2015). In contrast to the FSTSP, a drone can join the truck at the node where it was released, and the drone is faster than the truck. Thus, different speeds for the two types of vehicles are taken into account. In particular, these authors confirm the findings of Ferrandez et al. (2016), namely the net speed of drones must be twice higher than that of the vehicles.

Several authors have proposed algorithms to solve the problems introduced by Murray and Chu (2015) and Agatz et al. (2018). In addition, these two works serve as a basis for several TSP-D extensions and variants. Yurek and Ozmutlu (2018), Ponza (2016), Freitas and Penna (2020), Mbiadou Saleu et al. (2018), Bouman et al. (2018), propose several algorithms for these problems.

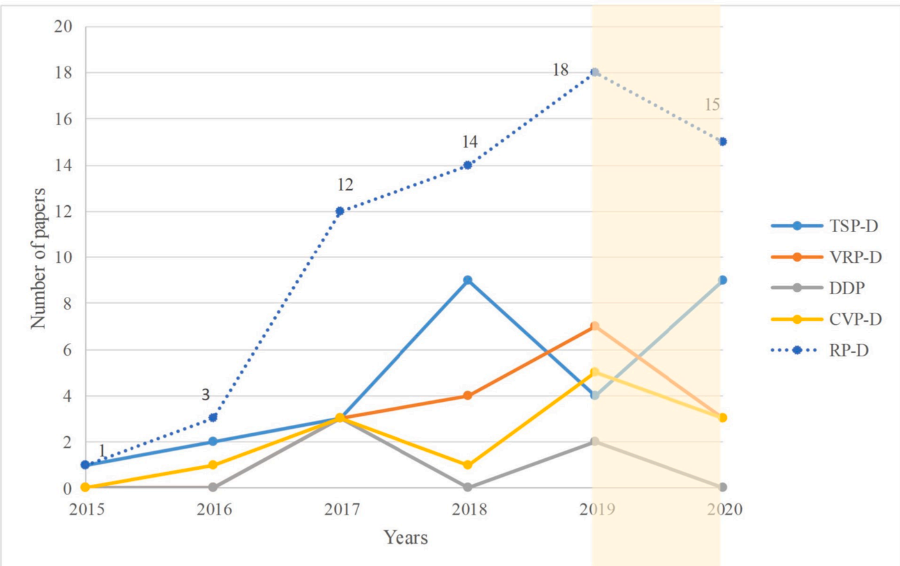

Fig. 6. Trend representation of reviewed publications during the period 2015–2020.

3.1.1. The FSTSP and its variants

Ferrandez et al. (2016) study a truck-drone in tandem delivery system. They propose a *K*-means clustering approach to determine the vehicle stops (the places from which to launch the drone) and a genetic algorithm to construct a tour for the truck (i.e., they solve a TSP). They analyse the system in terms of time and energy. In particular, they estimate energy consumption as a linear function of the flight time and assume a constant speed for both the drone and the truck. Their studies confirm that the use of drones is significant in terms of reducing times, only when their speed is at least twice that of the truck.

Carlsson and Song (2017) analyse the benefit of using a delivery system with a single truck and a single drone, and describe how much improvement can be realized by introducing drones to deliver packages. In their model, the drones may be launched from several points not restricted to customer locations. Ponza (2016) proposes a simulated annealing heuristic for the FSTSP, by adding constraints to avoid two infeasible situations. The first one happens when a drone is launched before it comes back to the truck, the second one when a drone has both a launch and a rendezvous preceded by a launch. He tested his methodology on a new set of instances with up to 200 customers.

Since the formulations of Murray and Chu (2015) and Agatz et al. (2018) require huge computational times to be solved, Yurek and Ozmutlu (2018) propose an iterative algorithm by decomposing the problems into two stages and solving a mixed integer linear programming (MILP) model in the second stage. They describe an optimization-based heuristic. They introduce a new set of instances for the problem and evaluate the performance of their exact algorithm on small size instances with 10, 11 and 12 customers. They then evaluate the heuristic performance on 20-customer instances.

Freitas and Penna (2020) propose a metaheuristic to solve both the FSTSP and the TSP-D variants. They start by solving a TSP using a MILP solver, then apply a variable neighbourhood search metaheuristic to enhance the solution and insert the drone deliveries. They tested their heuristic on two benchmark sets (Ponza (2016) and Agatz et al. (2018)) as well as on a new set of instances derived from well-known TSP instances with up to 200 customers. Overall, the proposed heuristic outperforms the existing methods.

Bouman et al. (2018) present an exact dynamic programming algorithm to solve the TSP-D variant of Agatz et al. (2018). Their computational study demonstrates that their algorithm outperforms solving a MILP directly. In addition, they show that restrictions on the number of locations the truck can visit while the drone is away can reduce the solution times without worsening the overall solution quality.

In addition, Poikonen et al. (2019) propose four heuristic approaches based on branch-and-bound for the TSP-D variant of Agatz et al. (2018). The only difference between the two works is that they modified the partitioning procedure of Agatz et al. (2018) such that the truck may remain stationary while the drone makes a delivery. In their computational study, they compare their four heuristic approaches in terms of effectiveness and efficiency, analysing the trade-off between objective value and computation time. In addition, they analyze the effect of drone battery duration and speed on the TSP-D solutions, concluding that a single drone with a battery life of 20 min and double the speed of the truck produces very significant savings.

Starting from the work of Murray and Chu (2015), Ha et al. (2018a) propose two heuristics for the FSTSP, considering a different objective function which aims at minimizing operational costs (i.e., the transportation cost and the cost related to wasted time for synchronizing drone and truck) instead of the completion time. The first heuristic is based on the approach presented by Murray and Chu (2015), while the second algorithm is a GRASP. They tested their algorithms on a new set of instances with up to 100 customers.

Phan et al. (2018) extend the work of Ha et al. (2018a) by considering an adapted version of their GRASP to solve a variant of the TSP-D, called the TSP with multiple drones. They propose an adaptive large neighbourhood search (ALNS) for the TSP with multiple drones. Their results show that the ALNS is more effective than the extended GRASP.

Ha et al. (2018b) and Salama and Srinivas (2020) propose a multi-objective variant of the FSTSP. In particular, Ha et al. (2018b) extend their previous work (see Ha et al. (2018a)), by considering two objective functions for the FSTSP: the first one minimizes the total operational cost, while the second one minimizes the completion time. The authors propose a hybrid genetic algorithm, which combines genetic search and local search, to solve the problem under both the objective functions. They test their heuristic on the benchmark sets of Murray and Chu (2015) and Ha et al. (2018a) concluding that on average, it performs better than the GRASP proposed by Ha et al. (2018a) both in terms of effectiveness and efficiency.

Salama and Srinivas (2020) present mathematical programming models to jointly optimize customer clustering and truck and drones routing. As in Phan et al. (2018), the fleet is composed of one truck and multiple drones. In particular, a single truck carries several drones to some focal points in each cluster, from which to launch the drones. The drones then dispatch the packages to customers, performing one delivery per trip and one for each cluster. Customers can be served either by a drone or by a truck, in which case the customer location becomes a launching point for a drone. The authors consider two objective functions: the first one minimizes the total delivery costs, while the second one minimizes the completion time. Since these objective may be conflicting, the authors consider them separately as well as together to generate a set of best trade-off solutions. They propose a machine learning warm-start procedure to accelerate the MILP solution. The heuristic contains three main steps: the first one iteratively uses the *K*-means clustering to find the focal point, the second phase aims at moving each cluster focal point to the nearest delivery location that is served only by a truck. Finally, the third phase aims at finding an optimal truck route using a standard TSP model. In order to investigate how much the location of truck stops impacts the solution quality, the authors compare two policies: in the first one drones can be launched from a truck at a customer location only, while in the second strategy drones can be launched from anywhere in the delivery area, i.e., at a customer location or at a non-customer location. After an extensive computational study, the authors conclude that allowing the focal points to be anywhere in the delivery area, instead of restricting them to customer locations, yields substantial savings with respect to cost and completion time.

Multiple drones are also considered by Moshref-Javadi et al. (2020a), Moshref-Javadi et al. (2020b), Chang and Lee (2018) and Murray and Raj (2020). In particular, Moshref-Javadi et al. (2020a) and Moshref-Javadi et al. (2020b) propose a new formulation for the FSTSP by modelling it as a special case of the traveling repairman problem. In the variant of Moshref-Javadi et al. (2020a) multiple drones can be launched from the same place, but the truck does not wait for them to return. The objective is to minimize the overall customer waiting time. In contrast, in the variant of Moshref-Javadi et al. (2020b) drones have to be retrieved at the place where they were launched. Hence, the truck has to wait for the return of all the drones launched before continuing its route. In addition, drones can be launched more than once from the same truck stop location to serve multiple customers consecutively. Moshref-Javadi et al. (2020a) develop an efficient algorithm to solve real-world-size instances, based on the well-known ALNS metaheuristic. They test their model and their metaheuristic on several benchmark small-size instances, on which the metaheuristic finds near-optimal solutions within short computing times. They also solve instances generated considering a real-world case study of e-commerce deliveries in São Paulo, Brazil. They compare their model with the classical traveling repairman problem, showing the effectiveness of using a multi-modal system delivery with the respect of a single truck system. Moshref-Javadi et al. (2020b) propose a hybrid tabu search-simulated annealing algorithm for solving their variant on real-world-size problem instances. They conduct several bound analysis to demonstrate the reduction in customer waiting times obtained with the truck-drones system delivery compared with a truck-only system. They conclude that the most influential parameters on the performance of the system are the number of drones per truck, the speed ratio of the drones to truck, and the service times of the truck and drones.

Chang and Lee (2018) develop an integer non-linear programming model to compute a delivery route for a truck carrying drones, minimizing total delivery time. As Ferrandez et al. (2016), they propose a heuristic based on *K*-means clustering and TSP modeling. In particular, their problem solving approach consists of three steps: 1) clustering delivery locations, 2) routing centers of clusters, 3) finding shift-weights. The authors consider different speeds for the truck and the drone, and the objective is to minimize the total delivery time (i.e., the traveling time of truck and drones, and the service time).

In the FSTSP variant of Murray and Raj (2020) drones may have different travel speeds, payload capacities, service times and flight endurances. To take flight endurance into account, the authors consider an equal power consumption across all flight phases and calculate the minimum energy required by a drone to complete a visit. The energy used by a drone is evaluated as a linear function of parcel weight, speed and operation time (see Dorling et al. (2017)). To accurately determine the operation time, hence to estimate the time of endurance, the authors divide the drone flight into eight phases. They consider two variants of the problem. In the first one drone may leave or enter to the depot only if the truck is present at the depot; in the second one the drone is independent. The problem is solved by a three-phase heuristic, considering realistic size tests with up to 100 customers.

Practical limitations of drones are also considered in the TSP-D variant introduced by Jeong et al. (2019). In particular, they propose an energy-payload consumption model and a two-phase heuristic to account for the limited battery capacity and "no-fly zones", which are areas where flying is forbidden. Drones may serve one customer at a time and the objective is to minimize the completion time.

Starting from the model proposed by Agatz et al. (2018), Marinelli et al. (2017) extend the TSP-D assuming, for the first time, that the drone can be launched and connect to a truck either at a node or along a route arc. They add several constraints to the original model in order to include the possibility of stopping the truck at any point along an arc. This allows a better exploitation of the battery of the drone, by reducing the travelled distance and consequently overall travelling costs. They present a GRASP for the problem. They then evaluate the effectiveness of their algorithm on a set of instances proposed by Bouman et al. (2018).

As Agatz et al. (2018), González-R et al. (2020) propose an FSTSP that allows the truck to wait for the drone at the same location, in addition, the drone may perform multiple visits. However, they note that this holds even if they do not impose explicitly that a truck cannot wait for a drone at the same place where it was launched. The authors model constraints taking into account drone energy consumption but for simplicity, as in Ferrandez et al. (2016), they suppose that it is linear to the distance flown. The battery of the drone is swapped at certain a priori rendezvous points hence, when a drone route starts after the swapping, its battery is fully charged. They propose an iterative greedy search heuristic combined with simulated annealing. They study the performance of their approach on benchmark instances.

In the variant of the TSP-D proposed by Agárdi et al. (2020), the drone must be launched and retrieved at the same node. Hence, the truck may wait for the drone. Multiple visits for the drones are allowed and the objective is to minimize the total distance travelled and flown. The authors propose four heuristics: a nearest neighborhood algorithm, an arbitrary insertion algorithm, a genetic algorithm, and a hill climbing algorithm. Their computational study shows that the genetic algorithm exhibits the best performance.

Luo et al. (2017) propose a variant of the classic two-echelon TSP, where the truck carries a drone available for deliveries. In particular, the drone visits a predetermined set of customers unreachable by the truck. In the network, there are several rendez-vous points where the truck can stop and the drone can take off or land. The drone can serve more than one customer before landing. The objective is to minimize the total routing time for the drone. The authors formulate the model and provide two constructive heuristics and an exact depth-first search algorithm to solve small-size instances.

3.1.2. The PDTSP and its variants

Mbiadou Saleu et al. (2018) focus on the PDTSP proposed by Murray and Chu (2015). They propose an iterative two-step heuristic considering the PDTSP as a bilevel problem in which the first level partitions the customers between the trucks and the drones, and the second one optimizes the routing. In their computational study, they first evaluate the efficiency of their heuristic on the Murray and Chu benchmark instances (Murray and Chu, 2015), concluding that it is very fast. They then propose a new set composed of six larger size instances, with up to 229 customers, and analyse the benefits of using drones in a delivery system. Dell'Amico et al. (2020) propose a simplified MILP model and several matheuristics for the PDTSP, all based on the classical Lin-Kernighan algorithm for the TSP combined with local search procedures and the resolution of the MILP. The authors test their algorithms on the benchmark instances introduced by Mbiadou Saleu et al. (2018) and Murray and Chu (2015). Their computational study confirms that the proposed

Table 2
Summary of the main features of TSP-D contributions in the scientific literature.

Reference	#Drones	#Depots	Objective function	Time windows	Drop-pickup	Drone Multiple visits	Drone energy	Drone recharge	Drone release	Drone capacity	Synchronization	Dyamic/ Stochastic
Murray and Chu (2015)	1	1	completion time*	no	no	no	no	no	node	no	yes	no
Murray and Chu (2015)	n	1	makespan**	no	no	no	no	no	node	no	no	no
Ferrandez et al. (2016)	$1/n$	1	delivery time	no	no	no	estimation	no	node	no	yes	no
Ponza (2016)	1	1	completion time	no	no	no	no	no	node	no	yes	no
Luo et al. (2017)	1	1	drone routing time	no	no	no	no	no	node	no	yes	no
Marinelli et al. (2017)	1	1	operations costs	no	no	no	no	no	node/arc	no	yes	no
Carlsson and Song (2017)	1	1	completion time	no	no	no	no	no	node	no	yes	no
Agatz et al. (2018)	1	1	operations costs	no	no	no	no	no	node	no	yes	no
Mbiadou Saleu et al. (2018)	n	1	completion time	no	no	no	no	no	node	no	no	no
Bouman et al. (2018)	1	1	completion time	no	no	no	no	no	node	no	yes	no
Yurek and Ozmutlu (2018)	1	1	completion time	no	no	no	no	no	node	no	yes	no
Phan et al. (2018)	n	1	routing cost***	no	no	no	no	no	node	no	yes	no
Chang and Lee (2018)	n	1	delivery time	no	no	no	no	no	node	no	yes	no
Ha et al. (2018a)	1	1	operational costs	no	no	no	no	no	node	yes	yes	no
Ha et al. (2018b)	1	1	routing cost & drone waiting cost	no	no	no	no	no	node	yes	yes	no
Li et al. (2018)	1	n	operations costs	no	no	no	no	no	node	no	no	no
Poikonen et al. (2019)	1	1	operations costs	no	no	no	no	no	node	no	yes	no
Kim and Moon (2019)	n	2	delivery time	no	no	no	no	no	node	yes	yes	no
Jeong et al. (2019)	n	1	completion time	no	no	no	model	no	node	no	yes	no
Freitas and Penna (2020)	1	1	completion time	no	no	no	no	no	node	no	yes	no
Murray and Raj (2020)	n	1	completion time	no	no	no	model	no	node	yes	yes	no
Schermer et al. (2020)	n	n	makespan	no	no	no	no	no	node	no	no	no
Dell'Amico et al. (2020)	n	1	completion time	no	no	no	no	no	node	no	no	no
Salama and Srinivas (2020)	n	1	completion time & routing cost	no	no	no	no	no	node	no	yes	no
Dayarian et al. (2020)	1	1	maximize the orders	no	no	no	no	no	node	yes	yes	dynamic
Moshref-Javadi et al. (2020a)	n	1	customers waiting time	no	no	no	no	no	node	no	yes	no
Moshref-Javadi et al. (2020b)	n	1	customers waiting time	no	no	no	no	no	node	no	yes	no
González-R et al. (2020)	1	1	completion time	no	no	yes	estimation	no	node	no	yes	no
Agárdi et al. (2020)	1	1	distance	no	no	yes	no	no	node	yes	yes	no

* completion time = time required to service all customers and return both vehicles to the depot.
** makespan = latest return time to the depot.
*** routing cost = cost of the tour.

algorithms yield competitive results with the respect to the state-of-the-art methods, especially on small- and medium-size instances, in terms of both efficiency and effectiveness.

Dayarian et al. (2020), Li et al. (2018), Kim and Moon (2019) and Schermer et al. (2020) propose several variants of the PDTSP. In particular, Dayarian et al. (2020) introduce an innovative dynamic variant in which the role of drones is not the conventional one, i.e., the drones do not deliver packages. In fact, they study a delivery system in which trucks make deliveries and are regularly resupplied by a drone. Resupply can take place anywhere as long as the delivery truck is stopped. This system is particularly efficient for dynamic deliveries, because it can speed up the process at low costs. The authors formally introduce the problem as a VRP-D, describing the main features and the constraints; however, they focus on the single-drone, single-truck variant. For this reason, we have classified this work as a particular case of the TSP-D. The authors develop different algorithms and compare their performance. In addition, they quantify the potential benefits of drone resupply, both in terms of increasing in the number of orders served and reducing service time.

Li et al. (2018) describe continuous approximation methods for a particular variant of the PDSTSP in which the delivery system is organized in a three-tier structure with one main distribution center and multiple depots. They partition the region, in which the customers are uniformly distributed, into hexagonal sub-regions, considering the limited delivery range of the drones. The truck starts its route from the distribution center, leaves some packages at each depot which will be delivered by drones, and then continues its route to deliver the remaining packages to the customers. Even if the designed distribution system would require a synchronization between truck and drones, the authors consider the two fleets to be independent. Their objective is to minimize the total delivery cost of the delivery service. They use continuous approximation to study the impact of several key factors on delivery costs, such as the number of hexagons and customer density. Hence, they conclude that the use of a joint delivery system with truck and drones is more effective than that one with only trucks, particularly when customer density increases.

Kim and Moon (2019) solve an extension of the PDSTSP introduced by Murray and Chu (2015). To overcome the limitations of flight range of the drones, they develop a TSP with a drone station. The drone station is a facility that stores drones and charging devices. The authors assume that the station can supply a sufficiently large number of drones and is positioned near customers areas, away from the depot. Thus, the main difference is that the drones are stored in, and launched from, a drone station. Even if the drones can be charged at the station, the time needed to recharge a drone is not considered. The authors propose an approach very similar to that of Murray and Chu (2015), based on a decomposition of the problem. However, their decomposition guarantees an optimal solution. For their computational study they generate instances with up to 80 customers; however, the TSP with a drone station is solved only for instances with at most 11 customers.

Similarly to Kim and Moon (2019), Schermer et al. (2020) consider drone stations as well. In their variant, there are several stations with no fixed cost whose locations are decision variables. In particular, they assume that some stations may be opened for drone deliveries. Several drones are located in each station and each drone may serve one customer at a time. The primary objective function is to minimize the makespan. The authors also introduce an alternative objective which minimizes the overall costs. In this case, a fixed cost for using a station is considered. The authors model their problem and solve it with a commercial solver, considering the

Table 3
Mathematical model, algorithm and instances proposed for the TSP-D.

Reference	Problem class	Mathematical model	Approach	Instances
Murray and Chu (2015)	FSTSP	yes	heuristic	new: up to 10 customers
Murray and Chu (2015)	PDSTSP	yes	heuristic	new: up to 10 customers
Ferrandez et al. (2016)	FSTSP	no	heuristic	new: 100 customers
Ponza (2016)	FSTSP	yes	heuristic	new: up to 200 customers
Luo et al. (2017)	FSTSP	yes	heuristic/exact	new: up to 20 customers
Marinelli et al. (2017)	FSTSP	yes	heuristic	Bouman et al. (2018)
Carlsson and Song (2017)	FSTSP	no	heuristic	new: up to 500 customers
Agatz et al. (2018)	FSTSP	yes	heuristic	new: up to 100 customers
Mbiadou Saleu et al. (2018)	PDSTSP	yes	heuristic	new: up to 229 customers & Murray and Chu (2015)
Bouman et al. (2018)	FSTSP	no	exact	new: up to 20 customers
Yurek and Ozmutlu (2018)	FSTSP	yes	heuristic/exact	new: up to 20 customers
Phan et al. (2018)	FSTSP	yes	heuristic	Ha et al. (2018a)
Chang and Lee (2018)	FSTSP	no	heuristic/exact	new: 30 customers
Ha et al. (2018a)	FSTSP	yes	heuristic	new: up to 100 customers
Ha et al. (2018b)	FSTSP	yes	heuristic	Murray and Chu (2015) & Ha et al. (2018) Ha et al. (2018a)
Li et al. (2018)	PDSTSP	yes	heuristic	new: up to 20 customers
Poikonen et al. (2019)	FSTSP	no	heuristic	new: up to 200 customers
Kim and Moon (2019)	PDSTSP	yes	heuristic	new: up to 80 customers
Jeong et al. (2019)	FSTSP	yes	heuristic	new: 10 customers
Freitas and Penna (2020)	FSTSP	no	heuristic	Ponza Ponza (2016) & Agatz et al. (2018)
Murray and Raj (2020)	FSTSP	yes	heuristic	new: up to 100 customers
Schermer et al. (2020)	PDSTSP	yes		new: up to 50 customers
Dell'Amico et al. (2020)	PDSTSP	yes	heuristic	Mbiadou Saleu et al. (2018) & Murray and Chu (2015)
Salama and Srinivas (2020)	FSTSP	yes	heuristic	new: up to 35 customers
Dayarian et al. (2020)	FSTSP	no	heuristic	new: up to 60 customers
Moshref-Javadi et al. (2020a)	FSTSP	yes	heuristic	new: up to 101 customers
Moshref-Javadi et al. (2020b)	FSTSP	yes	heuristic	new: up to 159 customers
González-R et al. (2020)	FSTSP	yes	heuristic	new: up to 250 customers
Agárdi et al. (2020)	FSTSP	yes	heuristic	

minimization of the makespan. They generated instances with up to 50 customers and three drone stations. Their results highlight the benefits of using drone stations in terms of reducing the delivery time.

3.1.3. Sum-up on the TSP-D

Table 2 summarizes the main characteristics of the surveyed TSP-D. For each contribution indicated in the first column “Reference”, 13 additional columns correspond to the following parameters: #DR and #DP represent the number of drones and depots, respectively, the objective function, “TW” refers to the presence of time windows while “Drop-pickup” indicate the presence of drop and pickup operations. Then, there are five parameters describing drones: 1) whether drone can perform multiple visits, 2) whether energy consumption is evaluated, 3) whether recharge before a new drone sortie, calculated by using an energy model, is considered, 4) drone departure occur on a node or along an arc, 5) whether capacity is considered. Table 2 also gives information about truck capacity constraints, synchronization between truck and drones, and whether the problem contains stochastic or dynamic information.

Looking at Table 2 it is clear that no contribution considers customer time windows and drop and pickup operations. In addition, all authors suppose that the capacity of trucks is unlimited. Except for two, all studies considered state that a drone may perform a single delivery and a large part of them do not consider drone capacity but suppose that all customers may be served by drones. In addition, most papers do not use an energy consumption model or make an accurate evaluation of the energy spent, but impose a limit on the maximum distance or the maximum flight time of drone. Only one work considers a dynamic framework. Most contributions work with deterministic information, hence dynamic or stochastic situations have not been widely studied.

Table 3 summarizes the practical contributions given by the TSP-D surveyed. In particular, for each contribution, it shows whether a mathematical model is formulated, and specifies the proposed mathematical approaches and the instances used for testing them. It is worth noting that the majority of the works develop heuristics to solve the variant of TSP-D, and only four out of 19 propose an exact algorithm. Since it is very difficult to find an optimal solution of the TSP-D, the largest instance size is 30 customers (see Chang and Lee (2018)).

3.2. The VRP with drones (VRP-D)

The VRP-D is a generalization of the TSP-D in which the fleet is composed of several trucks and of one or more drones.

Wang et al. (2017) introduce the VRP-D, considering a fleet of trucks equipped with drones delivering parcels to customers. Drones can be dispatched from and picked up by the trucks at the depot or at any of the customer locations. The authors conduct an analysis of several worst-case scenarios, from which they propose bounds on the best possible time savings achievable when using drones and trucks instead of trucks alone. The authors ignore cost, as well as the limited battery life of a drone, and assume that the trucks and the drones follow the same distance metrics.

Schermer et al. (2018) propose two heuristics for the VRP-D introduced by Wang et al. (2017), considering the minimization of makespan. The heuristics are composed of two main phases: initialization and improvement. The initialization phase is a route-first cluster-second heuristic. It is used in both heuristics to compute an initial solution for a TSP using trucks only. The improving phase is composed of several local search moves. The main difference between the two heuristics is that the first one is a two-stage approach which initially ignores the presence of drones and inserts them during the improvement phase. Instead, in the second approach, which is a single-phase heuristic, drones are inserted before starting the improving phase. In the computational phase, the authors consider uncapacitated trucks and limit drone deliveries to one package. They conclude that the two-stage heuristic is the best option.

Starting from the work of Wang et al. (2017), several authors have extended the VRP-D model by adding new constraints or considering several variants. Poikonen et al. (2017) extend the study of the worst-case results performed by Wang et al. (2017), by considering limited battery life for a drone, using different metrics for trucks and drones and focusing on a different objective function that also takes economic savings into account. The minimization of completion time is the primary objective, but the authors also consider a cost function.

Ulmer and Thomas (2018) present a dynamic variant of the VRP-D in which trucks and drones working separately may serve a set of customers within a delivery deadline. Drones and trucks differ with respect to their capacity (drones may deliver at most one package, trucks are uncapacitated), their charging requirement (drones require charging their battery), their speed (as in Agatz et al. (2018) drones are faster than trucks), and the network (trucks are limited to the links of the network). The objective is to maximize the expected number of customers served during a working day, and hence the total reward. The proposed model allows subsequent adaption of decisions, due to the presence of stochastic requests. The authors present a Markov decision process model for the dynamic VRP.

Di Puglia Pugliese and Guerriero (2017) extend the VRP-D by introducing time windows for customers and a time limit for the vehicles. The objective of the VRP-D with time windows is to minimize the total travel cost. The authors carry out a numerical study comparing the VRP with time windows and the VRP-D with time windows. They then discuss the advantages and drawbacks of using drones in last-mile delivery. Drones allow a reduction of the completion time but the activation of the drones is highly influenced by the transportation cost. Considering the same transportation cost for the trucks and the drones, the latter are no longer profitable. The higher the truck transportation cost, the higher the number of deliveries performed by the drones.

Time windows are also considered by Ham (2018), which extends the PDSTSP of Murray and Chu (2015) by considering a fleet of several trucks and two different types of drone tasks: drop and pickup. After a drone completes a drop, it can fly directly to another customer for pickup, or it can fly back to the depot and start a new tour. In addition, a customer can order multiple products with different time windows. Drones and trucks work separately and have to start and end their tours at the depot. The objective is to minimize the makespan. In addition, the author proposes also a multi-depot variant, where the objective is to minimize the completion time. The problem is solved by means of a constraint programming procedure, improved by using variable ordering heuristics.

In the VRP-D variant of Daknama and Kraus (2018), drones may deliver one package at time and have to return to a truck to recharge their battery after each delivery. As in Poikonen et al. (2017) drones and trucks use different metrics, in particular, the drones move according to the Euclidean metric while the trucks move according to the Manhattan metric (see Murray and Chu (2015)). The main difference with the model presented by Poikonen et al. (2017) is that a drone can change the truck from which it was launched after visiting a customer. The objective is to minimize the total delivery time. The authors propose a local search heuristic for the problem, which firstly solves a multi-TSP ignoring drones and then applies local search moves to explore neighbourhoods and add the drones.

Wang and Sheu (2019) extend the work of Wang et al. (2017) by introducing multiple visits for drones, with the goal of minimizing the logistics cost. They propose an arc-based model formulation, then reformulate it as a path-based model and apply branch-and-price to solve it. They carry out a computational study for testing the behaviour of their approach, as well as a sensitivity analysis by varying the maximum flying duration of drones. They conclude that using drones with a higher flying duration can reduce the total logistics cost by about 10%.

Schermer et al. (2019a) assume that drones may also be launched and collected at some discrete locations on each arc. They call this problem the VRP-D with en route operations. The authors assume that drones may not be retrieved at the same location from which they were launched, and that the battery of each drone is recharged instantaneously after each delivery operation. They model the VRP-D with en route operations as a MILP and use it to solve to optimality small-size instances through a commercial solver. They then propose a heuristic that combines the variable neighborhood search and tabu search. Their numerical study highlights how the introduction of en route operations can lead to more efficient solutions, due to the potential reduction of the makespan. Schermer et al. (2019b) formulate a MILP model for a new variant of the VRP-D that allows the execution of cyclic operations for drones, i.e., operations that start and end at the same vertex. Since the problem is high complex, the authors introduce several additional valid inequalities and discuss the benefits of using the new MILP formulation when it is solved through a commercial solver. They then propose a matheuristic that decomposes the problem into an allocation component and a sequencing component, solved heuristically through a classical savings heuristic and local search procedures for the VRP, and drone assignment and scheduling, determined through the modelling and resolution of a MILP. In their computational study, they show the benefits of using drones to minimize the makespan and conclude that their heuristic is both effective and efficient.

Chiang et al. (2019) focus on the environmental impact of using drones in tandem with vehicles. In particular, they present a VRP-D that incorporates the evaluation of CO_2 emissions. In their configuration, each vehicle carries one drone that can make a single delivery before returning to the vehicle. A vehicle may perform deliveries while the drone is flying, and hence the drone returns to the vehicle at a point different from its point of departure. The authors estimate the carbon emissions as a function of weight and distance travelled. In particular, they consider the curb weight of the vehicle, the weight of the drone when it is on the vehicle, the weight of the parcels, and the distance travelled. In addition, they propose two objective functions: the first one minimizes CO_2 emissions, the second one total cost, including fuel cost. The authors solve their problem with a genetic algorithm. They analyse the effects of using drones in the delivery process on both total cost and emissions. Their study highlights that the use of drones leads to solutions that are cost effective as well as environmentally friendly.

Recently, Di Puglia Pugliese et al. (2020) also focus on the environmental impact of using drones in parcel delivery, by evaluating polluting emissions produced of both trucks and drones. In particular, they evaluated the CO_2 emissions of trucks as a function of the distance travelled and the weight carried by the truck. Since drones are characterized by zero emissions, the authors consider the CO_2 produced by the facilities which are involved in the process of power generation. Starting from the work of Di Puglia Pugliese and Guerriero (2017), Di Puglia Pugliese et al. (2020) model several configurations of the problem: a classical VRP with only trucks, a DDP with only drones and a VRP-D with trucks and drones. They then solved the models and compared the results. The numerical results collected on an extensive computational study, suggest that the VRP-D configuration has the best trade-off between efficiency and reduction of negative externalities. Kitjacharoenchai et al. (2019) and Sacramento et al. (2019) define two VRP-D variants starting from the FSTSP model proposed by Murray and Chu (2015). In particular, Kitjacharoenchai et al. (2019) extend the FSTSP model to the case of multiple drones and trucks. They call this problem the Multiple Traveling Salesman Problem with Drones. The objective is to minimize the delivery time. The authors suppose that each truck has an unlimited capacity to carry either drones and packages, hence limitations on truck capacity and on customer demand are not considered. A truck may launch or retrieve only one drone at the same customer location, each drone may transport one package at a time and can complete its delivery and return to the truck before complete discharging of the battery. The proposed heuristic contains two phases. The first phase constructs an initial solution for the multi-TSP, while the second phase uses several remove and insert operators to find a solution for the multi-TSP with drones. Since the initial solution strongly influences the effectiveness of the second phase, the authors develop three heuristics: a genetic algorithm, a combined *K*-means and nearest neighbour algorithm, and a random cluster and tour approach. The model presented by Kitjacharoenchai et al. (2019) has been extended by Kitjacharoenchai and Lee (2019), through the introduction of capacity constraints for both trucks and drones. Kitjacharoenchai and Lee (2019) tested their model on a real-world scenario setting, based on the map of Lafayette and West Lafayette.

Sacramento et al. (2019) take into account the time at which a truck or a drone visits a customer. The drones and the trucks are synchronized during the tour, but at the end of the deliveries they may return to the depot in tandem or separately. The objective is to reduce the operational cost. The authors propose an ALNS metaheuristic to solve their problem and use several real-life values of parameters to test it on instances with up to 200 customers. They perform a detailed sensitivity analysis on several drone features, i.e., the battery cost, the endurance, the drone speed and the payload capacity, and they study the effects on the planning of the transport

Table 4
Summary of the VRP-D contributions in the scientific literature.

Reference	#Depots	Objective function	Time windows	Drop-pickup	Drone Multiple visits	Drone energy	Drone recharge	Drone release	Drone capacity	Trucks capacity	Synchronization	Dyamic/ Stochastic
Wang et al. (2017)	1	completion time	no	no	no	no	no	node	no	yes	yes	no
Poikonen et al. (2017)	1	completion time & routing cost	no	no	no	no	no	node	no	yes	yes	no
Di Puglia Pugliese and Guerriero (2017)	1	travel costs	yes	no	no	no	no	node	no	yes	yes	no
Daknama and Kraus (2018)	1	delivery time	no	no	no	no	no	node	no	no	yes	no
Schermer et al. (2018)	1	completion time	no	no	no	no	no	node	no	no	yes	no
Ulmer and Thomas (2018)	1	expected number of customers served	no	no	no	no	no	node	no	no	yes	stochastic requests
Ham (2018)	2	makespan	yes	yes	no	no	no	node	no	no	no	no
Wang and Sheu (2019)	1	logistics costs	no	no	yes	no	no	node	yes	yes	yes	no
Kitjacharoenchai et al. (2019)	1	delivery time	no	no	no	no	no	node	no	no	yes	no
Kitjacharoenchai and Lee (2019)	1	delivery time	no	no	no	no	no	node	yes	yes	yes	no
Sacramento et al. (2019)	1	operational costs	no	no	no	no	no	node	yes	yes	yes	no
Schermer et al. (2019a)	1	makespan	no	no	no	no	no	node/arc	no	yes	yes	no
Schermer et al. (2019b)	1	makespan	no	no	no	no	no	node	no	no	yes	no
Chiang et al. (2019)	1	costs & CO_2 emissions	no	no	no	no	no	node	yes	yes	yes	no
Kitjacharoenchai et al. (2020)	1	completion time	no	no	yes	no	no	node	yes	yes	yes	no
Liu et al. (2020)	1	operational costs	no	no	yes	model	no	node	yes	yes	yes	no
Di Puglia Pugliese et al. (2020)	1	travel costs	yes	no	no	no	no	node	yes	yes	yes	no

operations. They conclude that the drone endurance has a clear impact on solutions as well as on the payload capacity. In contrast, the speed of the drone does not affect the cost.

Kitjacharoenchai et al. (2020) and Liu et al. (2020) describe the delivery process which involves trucks and drones as a two-level delivery system. The first level is the routing of the trucks from the main depot to customers, the second one the routing of drones from truck to customers. Hence, both the works propose the two-echelon VRP-D. In particular, Kitjacharoenchai et al. (2020) consider a limited capacity for both trucks and drones, as well as a limited battery capacity for drones, defined as the maximum amount of flight time. The drone has to be launched and retrieved only once by the same truck and can perform more than one delivery. The objective is to minimize the completion time. The authors propose a MIP model and two heuristics to solve their problem, the first one based on a construction algorithm and the second one on large neighbourhood search. They test their algorithms on instances derived from benchmark instances of the capacitated VRP. Their computational study highlights that the heuristic based on the large neighbourhood search is more performing than the constructive one, and is also efficient for solving the classical capacitated VRP. They also study the impact of using one or multiple drones in the delivery configuration, concluding that the multiple drone configuration is more suitable. Liu et al. (2020) consider truck and drone capacity and the effect of varying payload on energy consumption for drone battery. In particular, they use a consumption model that considers the payload, the efficiency of the motor, the distance travelled and the constant flying speed. The authors propose a hybrid heuristic based on nearest neighbourhoods and savings strategies. They then conduct several experiments on random test instances with different scales to assess the efficiency of the proposed algorithm. In addition, they carry out a sensitivity analysis based on a practical case in China, with three factors: the ratio of light parcels, the maximum payload of drone, and the drones' battery power. They conclude that the use of the drones could save more costs when there are more light parcels and a higher drone capacity, payload and battery power.

3.2.1. *Sum-up on the VRP-D*

Table 4 summarizes the main features of the surveyed VRP-D. Time windows are considered in three out of 17 contributions, only one considers pickup operations as well as multiple visits for the drones. It is worth noting that energy consumption and recharge are considered only in two contributions; in particular, Liu et al. (2020) propose an energy consumption model, while in Ulmer and Thomas (2018) a fixed amount of energy is supposed to be recharged. As in the TSP-D, most of the works consider a maximum distance or a maximum flight time endurance for drones and suppose that the time needed to charge the battery or swap it is fixed. Only seven works consider drone capacity, but the majority of the papers take truck capacity into account. Stochastic requests are considered in only one contribution.

Table 5 provides information on the presence of the mathematical formulation for the proposed VRP-D variant, the algorithm and the test instances. With the exception of one work, all the surveyed contributions that propose a solution approach use a heuristic. Instances size varies from 13 to 1,000 customers.

3.3. *The drones delivery problem (DDP)*

The DDP is a variant of the VRP in which the fleet is composed of drones only. Usually, this problem takes into account several particular aspects related to drones such as energy consumption, battery capacity, and limited flying range.

Dorling et al. (2017) solved a DDP in which drones may perform multi-trips and serve more than one customer per route. They model energy consumption as a function of a battery and payload weight, considering a constant speed value. The authors present a MILP formulation and develop a simulated annealing heuristic.

Yadav and Narasimhamurthy (2017) develop a heuristic to optimize delivery schedule of drones. Drones may serve one or several customers, depending on the capacity constraints, but they do not take into account battery life limits.

Table 5
Mathematical model, algorithm and instances proposed for the VRP-D.

Reference	Mathematical model	Algorithm	Instances
Wang et al. (2017)	no		
Poikonen et al. (2017)	no		
Di Puglia Pugliese and Guerriero (2017)	yes		new: up to 100 customers
Daknama and Kraus (2018)	no	heuristic	new: up to 200 customers
Schermer et al. (2018)	no	heuristic	new: up to 1000 customers
Ulmer and Thomas (2018)	yes	heuristic	new: up to 800 customers
Ham (2018)	no	heuristic	new: up to 100 customers
Wang and Sheu (2019)	yes	exact	new: up to 13 customers
Kitjacharoenchai et al. (2019)	yes	heuristic	new: up to 50 customers
Kitjacharoenchai and Lee (2019)	yes		
Sacramento et al. (2019)	yes	heuristic	new: up to 200 customers
Schermer et al. (2019a)	yes	heuristic	Agatz et al. (2018)
Schermer et al. (2019b)	yes	heuristic	Agatz et al. (2018) & Murray and Chu (2015)
Chiang et al. (2019)	yes	heuristic	new: up to 500 customers
Kitjacharoenchai et al. (2020)	yes	heuristic	Augerat (1995)
Liu et al. (2020)	yes	heuristic	new: up to 100 customers
Di Puglia Pugliese et al. (2020)	yes		Di Puglia Pugliese and Guerriero (2017)

Coelho et al. (2017) propose a multi-objective DDP and, to overcome difficulties related to limited driving range, they introduce charging stations. In order to evaluate energy consumption, the authors use a consumption rate only related to the speed of the drone, which is a decision variable, and evaluate the amount of energy needed to recharge at the charging stations. They propose a mathematical formulation and a metaheuristic. In the variant of Troudi et al. (2019), drones may perform multiple visits and multiple missions per day. To calculate the energy consumption during a mission, they propose an approximation model similar to that of Dorling et al. (2017). Their objective consists of minimizing simultaneously the total distance flown, the total number of drones in the solution, and the total number of batteries used.

Liu (2019) focuses on an on-demand meal delivery process and proposes a dynamic drones delivery model to optimize this process. He formulates both a static model and a dynamic model, which take into account several constraints and assumptions related to food delivery. In particular, a drone may transport a single food carton, which can hold several orders of a standard size. However, different types of food (hot meals and cold drinks) cannot be carried in the same carton. Hence a single order may have to be split among several drones. The model is designed for real-life situations, hence it considers several practical issues such as the uncertainty of the orders locations and size, battery consumption and swapping. The objective function contains three components: ensuring safety, minimizing lateness, and maximizing efficiency. The author proposes an optimization-drive, progressive algorithm for online dispatch operations, suitable for online use as well as for offline simulation studies, and adopts a first-come first-serve principle.

3.3.1. Sum-up on the DDP

Looking at Table 6, which depicts the main features used in the DDPs surveyed, it is clear that a major degree of attention has been devoted to drone characteristics. Indeed, all the works consider capacitated drones and multiple visits. In addition, three contributions propose a model to describe energy consumption. In particular, Dorling et al. (2017) and Troudi et al. (2019) use a factor to evaluate energy consumption which does not consider speed and flight time. Coelho et al. (2017) use a simple function that depends on the drone speed to evaluate energy consumption, and they allow the recharging of drones at some stations. No paper considers time windows and only one allows pickup operations. Two works consider a real-time scenario, in which orders may arrive during throughout the day. Table 7 summarizes the information related to the presence of mathematical formulation, the type of algorithm and the instances used for the computational study in each work.

3.4. The carrier-vehicle problem with drones (CVP-D)

The carrier-vehicle problem is a combination of TSP-D, VRP-D and DDP, where a team of cooperating vehicles with complementary capabilities performing autonomous deliveries. In this delivery system, large and slow carriers (e.g., ships or large ground vehicles) transport small-size and high-speed vehicles (e.g., drones) with a limited operational range. The main idea is to allow fast vehicles to visit a set of customers within a short time, using the slow carrier as a base for multiple trips.

In their variant, Mathew et al. (2017) study a system in which a drone carried by a slow and large truck has to perform parcel deliveries. In particular, the role of the truck is to carry all the packages to be delivered as well as the drone. The role of the drone is to perform single deliveries from the truck to the specific delivery point. Thus, the drone flies for the final length of each delivery. The authors also propose a special case of this problem, where the drone can visit customers and some fixed depots.

In the work of Savuran and Karakaya (2020) the route of the carrier is fixed a priori. Thus, a big aircraft is used as mobile depot for a single drone that must visit a set of fixed targets. Unlike Mathew et al. (2017), multiple visits for the drone are allowed, while respecting its given flight range. The goal is to visit as many targets as possible. The authors propose a genetic algorithm for their problem.

The problem presented by Bin Othman et al. (2017) is strongly related to that of Mathew et al. (2017). In fact, the authors use the same configurations, but assume that the truck route is predetermined, as in Savuran and Karakaya (2020). The authors study four

Table 6
Summary of the DDP contributions in the scientific literature.

Reference	#Depots	Objective function	Time windows	Drop-pickup	Multiple visits	Drone energy	Drone recharge	Drone capacity	Dyamic/ Stochastic
Yadav and Narasimhamurthy (2017)	1	completion time	no	no	yes	max distance	no	yes	no
Dorling et al. (2017)	1	delivery time	no	no	yes	yes	no	yes	no
Coelho et al. (2017)	1	multi objective*	no	yes	yes	yes	yes	yes	dynamic
Liu (2019)	*n*	multi objective**	no	no	yes	no	no	number	dynamic
Troudi et al. (2019)	1	distance, number of drones & batteries	no	no	yes	yes	no	yes	no

* total traveled distance; drone maximum speed; number of used drones; makespan; average time spent with each package; maximize batteries load at the end of the schedule.

** minimize lateness, ensure safety, maximize efficiency.

Table 7
Mathematical model, algorithm and instances proposed for the DDP.

Reference	Mathematical model	Algorithm	Instances
Yadav and Narasimhamurthy (2017)	yes	heuristic	new: up to 45 customers
Dorling et al. (2017)	yes	heuristic	new: up to 500 customers
Coelho et al. (2017)	yes	heuristic	new: up to 10 customers
Liu (2019)	yes	heuristic	new: up to 353 customers
Troudi et al. (2019)	yes		new: up to 10 customers

different cases of the problem, combining the following features: the drone can immediately take off from the truck after getting the parcel or can "hitch a ride" on the truck before proceeding, the truck is allowed or not to wait for the drone at the same place before proceeding. They propose a polynomial-time approximation algorithm for the graph problem.

Boysen et al. (2018) also consider a CVP-D in which the route of the truck servicing a set of customers is already given. They model the problem as a particular case of the FSTSP. Since the route of the truck is known a priori, the authors focus on the optimization of the drone schedule launched and collected from the truck during its fixed route at some fixed points, hence the truck can be viewed as a carrier. The authors consider both the cases where there is one or several drones on the truck, and differentiate on the degree of freedom with respect to where a drone returns to the truck, i.e., whether the take-off and landing stops are the same or not. In particular, they examine three policies. In the first one the start and landing points coincide, in the second one the drone may be collected no later than the next stop after the start, in the third one no restriction are considered. Hence, combining all scenarios, they obtain six variants and investigate their computational complexity. They conclude that a configuration with two drones, that can be collected no later than the next stop after the start, is the most beneficial in terms of reducing the makespan. In addition, they integrate their drone subproblem into a metaheuristic framework, considering the first two policies and a single drone configuration, which are solvable in polynomial time.

Poikonen and Golden (2019) extend the work of Savuran and Karakaya (2020) considering that the route of the carrier is not already fixed a priori. They take into account two possible scenario: in the first one, a drone can carry one package at time, while in the second one multiple deliveries are allowed. The authors propose a branch-and-bound algorithm capable of solving small-size instances. They also describe heuristics based on greedy approaches and local search strategies for larger instances.

The main goal of the work presented by Gambella et al. (2017) is to solve to optimality the generic carrier-vehicle problem which minimizes the completion time. The authors present a mixed-integer, second-order conic programming model and propose a ranking-based exact enumeration procedure.

Karak and Abdelghany (2019) and Wikarek et al. (2019) propose two pickup and delivery variants of the CVP-D. In particular, in the configuration proposed by Karak and Abdelghany (2019) drones are mounted on a single vehicle and may visit one or more customers to pick up or deliver their packages. In addition, the drones can be dispatched and collected several times from the same station, but each station may be visited only once. Hence the truck waits at the station until all the drones that are planned to return to that station have been collected. Drones batteries are replaced with fully charged batteries whenever they are collected by the vehicle. The authors model the problem and propose a hybrid savings heuristic (Clarke and Wright, 1964) along with the vehicle-driven and drone-driven heuristics.

In the Wikarek et al. (2019) variant, drones may be launched or retrieved from the truck only at specific predefined mobile distribution centers. The launch and landing locations can be different. The authors focus on the optimization of the routing of drones as well as on the location of the mobile distribution centers, but they do not consider truck routes.

Bai et al. (2019) introduce precedence constraints on the ordering of the customers to be served for a CVP-D with one truck equipped with one drone. They propose several task assignment algorithms for their problem and carry out a computational study, comparing their approach with a state-of-the-art genetic algorithm. The numerical experiments have shown the efficiency of the proposed algorithms.

Dukkanci et al. (2019), Poikonen and Golden (2020) and Han et al. (2020) propose three variants of the CVP-D that explicitly consider the drone energy consumption, expressed as a function of several parameters. Dukkanci et al. (2019) study a delivery system that may be viewed as a combination of systems used in FSTSP proposed by Murray and Chu (2015) and the DDP studied by Dorling et al. (2017). Even if they consider the possibility of using trucks to transport drones, only drones serve the customers by starting or ending their routes from or at the depot or the trucks. The speed of the drone is a decision variable and the energy consumption is modelled explicitly. They formulate a non-linear model for the problem that minimizes operational costs, and then reformulate it as a second-order cone-programming problem. Their results on realistic problem tests demonstrate the impacts of making deliveries with drones. In the Poikonen and Golden (2020) variant, the drones carried by a truck may perform multiple visits and carry multiple heterogeneous packages. An energy dissipation rate is used to account for the limited capacity of the drone battery. The authors consider two values for the drone speed: 10 m per second and 15 m per second, but they suppose that the energy consumption is not affected by the speed choice. They propose a heuristic called "route, transform, shortest path" to solve the problem.

Han et al. (2020) propose an artificial bee colony heuristic for a CVP-D with time windows. In their variant, trucks carry both goods and drones to customers locations, while drones deliver vertically the packages to the customers. Each truck is equipped with a single drone. The objective aims at minimizing the weighted sum of three terms: the total energy consumption of trucks, the energy consumption of drones, and the number of trucks employed. The energy consumption is evaluated with a coefficient that depends on distance and speed. The CVP-D variant proposed by Moeini and Salewski (2020) is different from the previously introduced works,

Table 8
Summary of the CVP-D contributions in the scientific literature.

Reference	#Trucks	#Drones	Objective function	Time windows	Drop-pickup	Multiple visits	Drone energy	Drone recharge	Drone capacity	Dyamic/ Stochastic
Savuran and Karakaya (2020)	1	1	targets number	no	no	yes	no	no	no	no
Mathew et al. (2017)	1	1	total distance & total time	no	no	no	no	no	no	no
Bin Othman et al. (2017)	1	1	total distance	no	no	no	no	no	no	no
Gambella et al. (2017)	1	1	completion time	no	no	no	no	no	no	no
Boysen et al. (2018)	1	$1/n$	makespan	no	no	no	no	no	no	no
Dukkanci et al. (2019)	m	n	operational costs & energy	yes	no	no	yes	no	no	no
Karak and Abdelghany (2019)	1	n	operational costs	no	yes	yes	no	no	yes	no
Wikarek et al. (2019)	m	n	total distance	no	yes	yes	no	no	yes	no
Bai et al. (2019)	1	1	completion time	no	no	no	no	no	no	no
Poikonen and Golden (2019)	1	1	completion time	no	no	no	no	no	no	no
Poikonen and Golden (2020)	1	n	completion time	no	no	yes	yes	no	yes	no
Moeini and Salewski (2020)	1	n	total distance	no	no	no	no	no	yes	no
Han et al. (2020)	m	n	trucks number & energy consumption	yes	no	no	no	no	no	no

because the carrier is equipped with a mixed fleet of drones and autonomous transport vehicles (ATVs). The vehicle visits a set of designated points only once to dispatch and collect drones and ATVs. Each drone as well as each ATV may perform one delivery at a time. The authors develop a genetic algorithm to solve their problem and show the advantages of using a combination of drones and ATVs.

3.4.1. Sum-up on the CVP-D

Table 8 presents the main features of CVP-D surveyed. In the majority of the works the fleet is composed of one truck and one or several drones. Only two contributions out of eight consider more than one truck carrying several drones, only two papers deal with time windows, and two allow for picking operations. Two contributions propose an energy consumption model, but recharges are not allowed. Focusing on energy consumption model, Dukkanci et al. (2019) propose an explicit calculation of the energy consumption as a function of the drone speed, which is a variable, while in Poikonen and Golden (2020) the energy function takes into account the package weights. All papers are restricted to deterministic scenarios. Table 9 gives information about the presence of a mathematical model, the algorithm type and instances used for the computational tests.

3.5. Technological features of drones in routing problems

Since the majority of contributions provide theoretical insights on routing problems with drones, they often do not provide specific information about real technological setting of drones and measurement values in benchmark instances. Several contributions on TSP-D and VRP-D, carry out a sensitivity analysis by varying the value of drone speed, with the respect to the truck speed. In particular, the authors choose speed values for drones that range from 1 to 5 times the speed of the trucks (see, Agatz et al., 2018; Mbiadou Saleu et al., 2018; Bouman et al., 2018; Phan et al., 2018; Poikonen et al., 2019; Kim and Moon, 2019; Schermer et al., 2020; Moshref-Javadi et al., 2020a; Moshref-Javadi et al., 2020b; González-R et al., 2020; Schermer et al., 2018; Schermer et al., 2019b; Kim and Moon, 2019) and range from 5 km/h to 90 km/h. Considering also the DDP and the CVP-D, in the majority of the works, the speed value is fixed to around 30 km/h, on average. Payload capacity ranges from 1.2 kg (see Troudi et al. (2019)) to 20 kg (see Poikonen and Golden (2020)).

Flight endurance is measured either in minutes or kilometers. The values proposed for this parameter are widely different and range from 10 min to 30 min and from one km to about 24 km. Even if the majority of the works consider flight endurance as a fixed parameter, actually it depends on the loaded cargo (Murray and Raj (2020)).

Only four studies consider realistic features for drones. We summarize the main characteristics in Table 10. Looking at Table 10, it is evident that all the works consider a rotary-wing configuration of the fuselage. Indeed, as introduced in Section 2, the main advantage of this type of drone is the agility of manoeuvring. In addition, it has a medium flight range and can take off and land vertically in small places, like balconies or private dedicated areas. Hence, rotary-wing drone seems the most suitable for delivery applications, especially in the last-mile context. The number of rotors varies from four to eight and the payload capacity from 1.2 kg to 20 kg. Jeong et al. (2019), Dorling et al. (2017) and Troudi et al. (2019) also provide information about the type of the battery used, that is a lithium polymer battery (LiPo), and the motor, an electric brushless type, that is the most commonly used. Focusing on the number of rotors, Poikonen and Golden (2020) conduct a comparative analysis of two types of drones: quadcopter and octocopter. Their results highlight that with larger octocopters, which have a larger effective range, an average improvement in terms of objective function values of about 8% is obtained.

4. Conclusions and research perspectives

We have reviewed the main contributions related to transportation systems in which deliveries are performed by trucks and drones. Our literature review confirms the interest of the scientific community in delivery processes aided by drones. We have identified four main problem classes: 1) the traveling salesman problem with drone, TSP-D; 2) the vehicle routing problem with drones, VRP-D; 3) the drones delivery problem, DDP, and 4) the carrier-vehicle problem with drones, CVP-D.

Table 9
Mathematical model, algorithm, and instances proposed for the CVP-D.

Reference	Mathematical model	Algorithm	Instances
Savuran and Karakaya (2020)	yes	heuristic	new: up to 1100 customers
Mathew et al. (2017)	yes	heuristic	new: up to 12 customers
Bin Othman et al. (2017)	yes		
Gambella et al. (2017)	yes	exact	new: up to 15 customers
Boysen et al. (2018)	yes	heuristic	new: up to 100 customers
Dukkanci et al. (2019)	yes		new: up to 30 customers
Karak and Abdelghany (2019)	yes	heuristic	new: up to 100 customers
Wikarek et al. (2019)	yes	heuristic	new: up to 20 customers
Bai et al. (2019)	yes	heuristic	new: up to 120 customers
Poikonen and Golden (2019)	no	exact	new: up to 200 customers
Poikonen and Golden (2020)	yes	heuristic	new: up to 50 customers
Moeini and Salewski (2020)	no	heuristic	new: up to 75 customers
Han et al. (2020)	yes	heuristic	new: up to 100 customers

Table 10
Realistic drone features.

	Type of drone	Rotors	Flight endurance	Speed	Payload capacity	Landing time	Drone cost/ energy cost	Battery	Motors
Jeong et al. (2019)	Octocopter (MK8-3500)	8	4 km/40 min		2/3.5 kg			4500mAh, 6S, LiPo	brushless
Dorling et al. (2017)	Hexacopter (3DR ArduCopter Hexa-B)	6		6 m/s	3 kg	60 s	$500/ 0.1 $/kJ		brushless
Troudi et al. (2019)	Quadcopter (MD4-1000)	4	1 km/ 56 min	13 m/s	1.2 kg			22.2 V, 6S2P 13 Ah, LiPo	brushless
Mathew et al. (2017)	Quadcopter	4	0.15 km	8.3 m/s		30 s			
Poikonen and Golden (2020)	Quadcopter	4		10 m/s	3 kg		0.0556 $/kJ.		
	Octocopter	8		15 m/s	20 kg		0.0556 $/kJ.		

For each class, we have analysed the contributions based on the operational assumptions, features, and methodologies. We have also summarized, for each class of problem, the main characteristics of each work in several sum-up tables, which are useful for quickly comparing the main features of the different problems and detecting the unexplored variants, characteristics, and combinations.

Several authors focus on the optimization of the completion time. This is a common objective since the major advantage of using the drones is that they are not influenced by traffic conditions, hence they are faster than trucks. This implies a better quality of service and helps achieve on-time deliveries. Some contributions focus on the minimization of the transportation cost and a fraction of them take into account time window restrictions to guarantee quality of service. Clearly, the issue of energy consumption and CO_2 emissions has not been sufficiently studied.

There is also a lack of contributions regarding uncertain data. Few papers on the VRP-D and the DDP consider stochastic or dynamic requests. Other parameters subject to uncertainty, such as travel times, and energy consumption, have not been taken into account.

Given the above general considerations, we propose possible directions for future research in what follows.

Environmental impacts. The integration of drones in last-mile deliveries has a less negative impact on environment than that observed for the classical engine-fuelled vehicles. In particular, drones do not produce CO_2 emissions, they are less noisy and they can help in reducing traffic congestion in city centers. Thus, studying the use of drones under a "green" perspective would be very interesting. Among the reviewed papers, only two have focused on negative externalities. In particular Chiang et al. (2019) calculate the polluting emissions of classical vehicles. They then study the benefits of using drones in terms of minimizing CO_2 emissions with the respect of the truck-only configuration. Di Puglia Pugliese et al. (2020) calculate the polluting emissions of classical vehicles as well as the CO_2 emissions produced by the facilities which are involved in the process of power generation for drones. They also analyze the effect of using drones in deliveries, by considering several system configurations (i.e. only trucks, trucks and drones, only drones). Both these papers conclude that the use of drones leads to more suitable solutions in terms of reduction of negative externalities. Several features related to CO_2 emissions could be taken into account. In fact, the production of polluting emissions is strongly related to the load of the classical trucks. Investigating how the use of drones in tandem with trucks with the respect of a non-synchronized fleet could be studied. In this perspective, the use of transshipment depots, as parking bases for drones could be investigated. In addition, these studies could be extended by considering the use of alternative fuel vehicles, such as electrical vehicles.

Energy evaluation. Energy management is crucial for implementing an efficient and safe delivery process. Specifically for drones, energy disruptions could cause severe damage in urban areas. Several aspects related to energy consumption and recharging strategies are worth investigating. The majority of the reviewed papers consider energy consumption as an approximate maximum time or distance on the flight of drones. Also, battery recharging time is considered to be instantaneous. These contributions are mainly related to the DDP and CVP-D where recharging aspects are also considered. To the best of our knowledge, no papers on TSP-D and VRP-D have been published with a focus on energy consumption and on related recharging issues. More accurate energy consumption models can be incorporated in the definition and in the resolution process of the problems. Intermediate service or recharging points can be considered in order to prevent energy disruptions.

Realistic drone parameter. Using realistic technological features of drones, for testing the models and the methods, could be very relevant for practitioners. In fact, among the reviewed papers, a few uses realistic settings and only four of them give information about the types of drones used, the real models and their main characteristics. Drones with a rotary-wings fuselage seems to be the most suitable type. However, comparing the performance of this model with other technologies, such as hybrid drones, can lead to more effective and efficient solutions. Even if the use of drones could improve the efficiency of the service, it is very important to evaluate the real costs of using them in delivery operations. On the one hand, drones with wings-rotary fuselage are the most agile, on the other hand, they have a high energy consumption, hence a higher routing cost. Future research could focus on finding a good trade-off between maximizing performance and minimizing cost, considering more realistic scenarios.

Dynamic systems. Last-mile delivery is becoming a crucial part of logistic processes, especially for on-line retailers. In fact, on-line customers are becoming more and more responsive to quality of service. Hence, providing a fast service to a lower price is a key issue for the retailers. Drones can help speed up the deliveries at lower cost. Only two of the surveyed works address this topic. Dayarian et al. (2020) proposed a delivery system for dynamic customer requests, in which a drone resupplies one truck dynamically during its tour, while Liu (2019) focuses on an on-demand meal delivery process. Optimizing the dynamic deliveries is a new and interesting challenge. Future research should study the impacts of using drones in dynamic system, considering all the real technological constraints related to drones, and should also propose efficient algorithms to solve this problem.

Uncertainty. The behaviour of transportation systems with drones under uncertainty is worth studying. Beside uncertain travel times and requests, it should be interesting to consider others parameters connected to the drone operations, which can be affected by uncertainty. We mention, for example, energy consumption, which depends on weather conditions, and the amount of available energy, which is influenced by the atmospheric temperature.

Safety. Policies and regulations for drone flights vary between regions. However, safety constraints have to be taken into account when a drone-based delivery system is studied. For example, the maximum allowable flight altitude and the maximum transportable load. Other constrains are time restrictions, in fact, usually drones cannot fly after dark. There are also some forbidden areas, where drones cannot fly. Among the analyzed papers, only Jeong et al. (2019) introduce the concept of no-fly zones. Hence, the design of drone routes under no-fly zones restrictions is certainly an important topic worthy of scientific investigation.

Relaxing some assumptions. Other operational assumptions related to drones can be considered. For example it could be worth investigating a multi-delivery setting along with the possibility for the drones to take off and land on different trucks. Technological advances now allow drones to land on a moving truck. This assumption can improve the overall delivery service, but synchronization issues need to be properly addressed. The majority of the contributions assume a single delivery per trip for the drones. However, new drones are equipped with a multi-package payload compartment which allows the possibility of carrying more than one item (see, e.g., www.unmannedsystemstechnology.com (2020, 2019, 2018)), meaning that multiple deliveries can be performed in the same trip. This operational assumption is certainly worth investigating. It is also important to analyze the behaviour of both the trucks and the drones under time restrictions. Several variants can be addressed by exploiting the versatility of the drones.

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