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Optimization approaches for civil applications of unmanned aerial vehicles (UAVs) or aerial drones: A survey

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Abstract

Unmanned aerial vehicles (UAVs), or aerial drones, are an emerging technology with significant market potential. UAVs may lead to substantial cost savings in, for instance, monitoring of difficult-to-access infrastructure, spraying fields and performing surveillance in precision agriculture, as well as in deliveries of packages. In some applications, like disaster management, transport of medical supplies, or environmental monitoring, aerial drones may even help save lives. In this article, we provide a literature survey on optimization approaches to civil applications of UAVs. Our goal is to provide a fast point of entry into the topic for interested researchers and operations planning specialists. We describe the most promising aerial drone applications and outline characteristics of aerial drones relevant to operations planning. In this review of more than 200 articles, we provide insights into widespread and emerging modeling approaches. We conclude by suggesting promising directions for future research.

KEYWORDS

drones, operations planning, optimization, survey article, UAVs, unmanned aerial vehicles

1 | INTRODUCTION

Aerial drones or unmanned aerial vehicles (*UAVs*) are pilotless aircraft that are used, or can potentially be used, in a wide range of civil (nonmilitary) applications. UAV technology is rapidly evolving and may significantly change the business landscape in the coming years. The steam-powered flying pigeon of Archytas the Tarantine in ancient Greece, which may have been the first aerial drone, was allegedly able to fly only about 200 m [59, 102]. However, modern parcel delivery drones can fly up to 15 km with about a 3 kg (6.5 pound) payload [143, 224] and fixed-wing drones for medical supply delivery fly up to 150 km [250]. We call aerial drones simply as drones throughout this article.

Drones come in a variety of designs, such as a fixed-wing drone, which looks like a plane, or a rotorcraft drone, which looks similar to a helicopter, though often with multiple rotors (usually up to eight). The latter has vertical takeoff and landing capabilities and it can hover, which makes this design particularly attractive in close quarters, such as crowded urban areas. Tilt-wing drones combine features of fixed-wing and rotorcraft drones using wings that can be swiveled. Drones may use different types of propulsive power, including internal combustion engines, electric batteries, and solar and hydrogen fuel cells [38]. Some drones must be closely remote controlled by a human pilot, while fully autonomous drones are able to decide how to accomplish complex tasks in an uncertain environment [60].

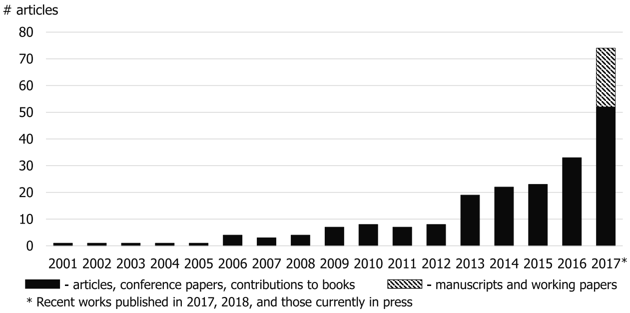

FIGURE 1 Interest in optimization of civil operations of drones is growing

In the US, current regulations significantly restrict operations of drones in order to safeguard the congested airspace and people and property on the ground by, for example, requiring operations to remain within the visual line of sight of a human operator. However, other countries have very different regulations, and, even in the US and the EU, regulations have changed substantially since 2013, when the roadmaps for airspace integration of civil drones were introduced [79, 230]. As stakeholders gain experience in drone technology and as collision avoidance systems mature, it is expected that regulations will be relaxed significantly, thus opening a range of new, attractive applications for drones. Therefore, market forecasts predict a rapid development of the commercial drone market. For example, the Teal Group Corporation, commissioned by the Federal Aviation Administration (FAA), predicts that the operational fleet of small commercial drones in the US will reach about 500,000, or \$3.3 billion in purchase value, by 2020 [80]. Drones already perform regular commercial operations (eg, [224, 250]), and ideas for many new potential applications regularly appear in the media.

As drones play a growing role in business operations, questions of planning and optimization increase in practical and academic importance. The aim of this survey is to review *optimization problems arising in the operations planning of drones in civil applications*.

This survey seeks to summarize the knowledge generated in 217 articles and provides insights based on many additional articles as supporting literature. Time series statistics on the surveyed literature indicate the growing academic interest in the topic (see Figure 1). For *researchers*, our survey provides a fast entry point into the topic, as well as directions for future research and further reading. For *practitioners*, we provide guidance on the existing literature and point to sources on operational enhancement, cost and profit optimization, and how to estimate the business payoffs of emerging drone technologies.

Because of its breadth, the topic of our literature survey intersects with a number of other related topics that are beyond the scope of this article:

- We do not include articles on military and security applications of drones, including patrolling applications. However, note that there is no sharp boundary between military and civil applications, since some models and methods can be used in both contexts.
- We include only those papers that explicitly address drones in their title, abstract, or keywords using any relevant term or description. For instance, our search included, but was not limited to, such terms as "unmanned aerial vehicle," "UAV," "drone," "unmanned aircraft," "unmanned aerial system," "UAS," "remotely piloted aircraft," and "remotely piloted vehicle." Note that operations planning of drones are closely related to more general topics, such as operations planning of mobile robots (including ground-based drones) and mobile sensors as well as vehicle routing and machine scheduling, which are not part of this survey.
- We consider complex drone operations that usually involve several tasks. Thus, we do not include articles on obstacle-avoiding path planning from a given starting point to a given end point [12, 63, 108, 153, 194, 203, 220, 227, 245, 306] or on planning trajectories of drones flying in formation [220]. We refer the interested reader to the work of Goerzen et al. [92], Khaksar et al. [129] and Yang et al. [307] on path planning problems.
- We survey articles that formulate an optimization problem, describing objective functions, decision variables, and the set of feasible solutions. Note that optimization may be part of control approaches, such as motion control or communication control.

- We survey papers written in English and published in peer-reviewed journals as well as in some peer-reviewed conference proceedings that are indexed in the databases of Web of Science. To ensure our survey is current, we have also included the latest manuscripts from open-source archives, which we highlight in Figure 1. Due to the large number of publications, only the most recent manuscripts from open-source archives and only select conference papers are included in this survey. While we are unable to include all the publications, we believe that the reviewed articles provide a comprehensive overview of the topic.

The existing literature surveys on drones mostly focus on specific fields of application, such as glaciology [30], coastal surveying [279], or precision agriculture [317]. A number of literature surveys investigate topics other than planning of drone operations or optimization; these are, for example, Chen et al. [44] and Sujit et al. [261] on path following and control, Gupta et al. [105] on communication protocols, Nex and Remondino [190] on drone platforms for 3D mapping, and Jawhar et al. [116] on communication aspects of drones. Other articles elaborate on adaptations of specific optimization problems to robotic applications in general, such as Galceran and Carreras [87] on coverage path planning and Robin and Lacroix [228] on target tracking. General reference works on drones include LeMieux [145], Murphy [185], Valavanis and Vachtsevanos [282], and Siciliano and Khatib [249]. The history of drones as well as a summary of present innovations and research developments can be found in Nonami [196] and van Blyenburgh [284]. Only one survey, by Coutinho and Fliege [56], relates to optimization aspects of drone operations. However, these authors study publications related to a particular optimization problem—the vehicle routing and trajectory optimization problem. For this reason, to the best of our knowledge, this article is the first to provide a comprehensive general overview of optimization problems arising in operations planning of civil drone applications.

We proceed as follows. We provide an overview of popular civil applications of drones in Section 2. In Section 3, we summarize some important characteristics of drones for consideration in operations planning. Based on our extensive survey of the literature, we then describe planning problems for drone operations in Section 4 and planning problems for combined operations of drones and other robots or vehicles in Section 5. Section 6 is devoted to strategic, tactical, and operational issues linked to drone operations. Section 7 discusses the extent to which drone operations pose new optimization problems as opposed to new instances of well-studied ones. Section 8 outlines directions for future research and concludes our article.

2 | CIVIL APPLICATIONS OF DRONES

Many industries can potentially benefit from pilotless technology because it can reduce labor cost. Drones can operate in dangerous environments that would be inaccessible to humans. Furthermore, pilotless technology lowers the weight of the aircraft, and thus its energy consumption, by making the cockpit and environmental systems, which provide air supply, thermal control, and cabin pressurization, unnecessary. Drones do not require roads and can, thus, access locations that are difficult to reach by roads. Figures 2–5 illustrate several models of drones.

The increasing utility of drones is driving a corresponding increase in their financial impact. PricewaterhouseCoopers [170] predicts the potential market value of business services that may benefit from drone technology to reach several billion dollars in a number of industries (see Figure 6). In this section, we will discuss the most promising emerging drone applications according to their potential market value.

- Physical *infrastructure* includes such industries as energy, roads, railways, oil and gas, and construction. Drones have already been used to examine terrain at future construction sites, to track progress at existing construction sites, to inventory the assets, and to regularly inspect facilities as part of maintenance (see the octocopter in Figure 2). Drones not only provide high resolution 3D aerial recordings at low cost, but also offer safety benefits by replacing humans for risky inspections. For example, the first pilot project of Lufthansa and its partner DJI was to use drones to inspect rotor blades of wind turbines, a costly and dangerous task traditionally performed by industrial climbers [157].
- *Agriculture* is another promising application of drone technology: Drones may map soil properties, assess crop health, spray targeted fertilizer and other treatments, and monitor livestock. Japanese farmers have been using drones since the early 1990s, and as early as the mid-2000s, drones sprayed about 10% of all sprayed paddy fields in Japan [196]. Several market analysts predict agriculture to be the largest application for drones in the US in the coming years [42]. Figure 4 illustrates a popular agricultural drone, Yamaha RMAX (1 m in height, 2.75 m in length), which can carry a payload of about 28 kg and can spend about 1.5 hours in flight. Figure 5 depicts a fixed-wing drone owned by AeroTerrascan and used for remote sensing.

FIGURE 2 Introspect's drone *B 3.1* is used for taking aerial images. A photograph by Molnár Zsolt distributed under a CC0 1.0 license. Source: https://commons.wikimedia.org/wiki/File:Interspect_UAV_B_3.1.png [Color figure can be viewed at wileyonlinelibrary.com]

FIGURE 3 DHL's drone *Paketcopter* used in package delivery. A photograph by Frankhöffner distributed under a CC BY-SA 3.0 Source: https://commons.wikimedia.org/wiki/File:Package_copter_microdrones_dhl.jpg [Color figure can be viewed at wileyonlinelibrary.com]

FIGURE 4 Yamaha's drone *RMAX*, powered by gasoline, is popular in agricultural applications. A photograph by Gtuav distributed under a CC BY-SA 3.0 license. Source: https://commons.wikimedia.org/wiki/File:YamahaRMax.jpg [Color figure can be viewed at wileyonlinelibrary.com]

FIGURE 5 AeroTerrascan's drone *Ai450* mapping a field in Indonesia. A photograph by GIII distributed under a CC BY-SA 4.0 license. Source: https://kids.kiddle.co/Image:Agriculture_UAV.jpg [Color figure can be viewed at wileyonlinelibrary.com]

- *Transport*, or delivery applications, have recently received considerable media attention, mainly because of the prospect of door-to-door express deliveries at low cost. Delivery applications include package deliveries to remote rural regions and first- and last-mile deliveries in urban and suburban areas as well as express deliveries of, for example, defibrillators to treat out-of-hospital cardiac arrests [51] or customized parts to assembly lines. Delivery of medical supplies, especially of vaccines and blood, may significantly improve the quality of medical service in developing countries, where road infrastructure is poor and some parts of the route may become impassable during certain seasons. Unsurprisingly, the first production-level use of a delivery drone to move beyond a pilot test or demonstration project was blood delivery in Rwanda by Zipline's fixed-wing drone [250]. According to expert estimates, the cost savings of the drone vaccine transport compared to the vaccine transportation by common trucks surpass the required fixed cost for establishing drone infrastructure [107].

  Perhaps the most critical stage in the drone delivery process is package release, because the transported goods may be damaged. Numerous technical solutions have been developed to fit various applications, including drone landing at specified locations (eg, platforms or "delivery rugs") and the use of a parachute or tether to lower the item [236, 250].

  Overall, although the total distance traveled in a drone-only delivery system will likely be longer than in a truck-only delivery system due to the drone's limited payload, drones may be faster than trucks, have a lower cost per mile to operate, and emit less CO_2. Thus, they represent a greener alternative to conventional delivery modes [95]. However, regulations will potentially restrict development of the delivery segment more than other fields of application [83]. Operations of drones in urban areas will be especially regulated due to safety and privacy issues.

Further applications of drones include *security*, where drones perform observations, and *entertainment and media*, where drones are used for filming, taking pictures, and for special effects. The category *other* encompasses examination of disaster and accident sites for risk assessment and risk monitoring by insurance companies, mapping and surveying of open-cast and underground mining sites, as well as applications of drones in telecommunications [170]. In the latter, several technological solutions have been proposed to extend internet and mobile access. Google's project *Loon* and Facebook's drone *Aquila* are

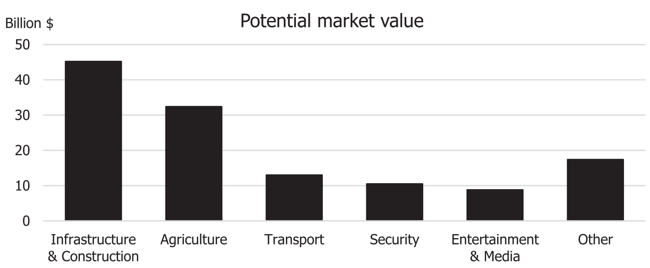

FIGURE 6 Potential market value of commercial drone applications estimated by Mazur et al. [170]

examples of so-called high-altitude platforms that would be deployed in the stratosphere [251, 252]. These platforms serve as a gateway and establish communication links for computing devices. By comparison, low-altitude platforms, such as fixed-wing drones, rotorcrafts or kite-balloons, provide advantages of rapid deployment and low cost and are most suited for temporary events [43]. Such temporary events may be, for instance, festivals, sporting events, and disaster management operations in regions with damaged communication infrastructure [315]. Recently, Nokia has tested drones equipped with mobile base stations to improve coverage in a rural region in Scotland [231]. Drones may also serve as cloudlets and relieve energy consumption of mobile devices by taking over computations, which are energy consuming; they may also perform data storage and provide video on demand services at camping sites [119, 120]. In *internal transport*, drones like Fraunhofer Institute's flying and rolling robot *Bin:Go* serve warehouses by lifting payloads of up to 1 kg from shelves [64]. Drones are also actively used in *disaster management and in environmental monitoring*, such as monitoring of bush fires and icebergs or post-storm coastal erosion assessment, as well as in collecting data from sensors [6, 148, 279]. Besides that, drones may assist the blind and escort individuals as they walk alone through dangerous areas at night [155]. In sum, drones might be advantageously used in a number of industries to perform a wide range of operations.

To realize the potential market value in any of the discussed applications, firms should be able to deploy drones in civil airspace safely and at low cost. Drones may be part of an integrated airspace, which will be shared with piloted aircraft, or alternatively, certain airspace zones may be reserved exclusively for drones. For example, Amazon proposed two classes of drone-only airspace: a low-speed zone below 200 feet (61 m) and a high-speed zone between 200 and 400 feet (61–122 m). The company also recommends a no-fly zone between 400 and 500 feet (122–152 m) to serve as a buffer zone between drones and piloted traffic [124]. Other experts, including those at NASA, recommend reserving specialized drone corridors, also called air highways, for groups of drones traveling in the same direction [134].

Note that, contrary to a widespread perception that drone technology has merely entered the testing phase, drones are already in production use in a number of applications, as discussed in this section, such as blood transport in Rwanda and postal service provided by delivery company DPD in a rural region of Southern France [224, 250].

3 | CHARACTERISTICS OF DRONES RELEVANT TO OPERATIONAL PLANNING

Drones have peculiarities that must be considered in modeling. In this section, we briefly summarize common parameters and restrictions used in existing modeling approaches for drone operations (see Figure 7) and introduce some abbreviations we will use to describe the contributions of the articles in this survey.

- *Specifics of motion*. Drones are able to move in 3D space. Autopilots of drones are usually able to maintain flight stability, hold the required altitude, and autonomously land and take off. Nevertheless, certain aspects of drone motion may need to be taken into account in planning of drone operations. One of them is the minimum turning radius restriction while changing directions in flight [17, 242, 265], which is especially important for fixed-wing drones. For example, this restriction should be considered while spraying farmland in order to avoid blank spots. Although rotorcraft drones, such as quadcopters, may easily reverse their flight direction by making sharp turns,

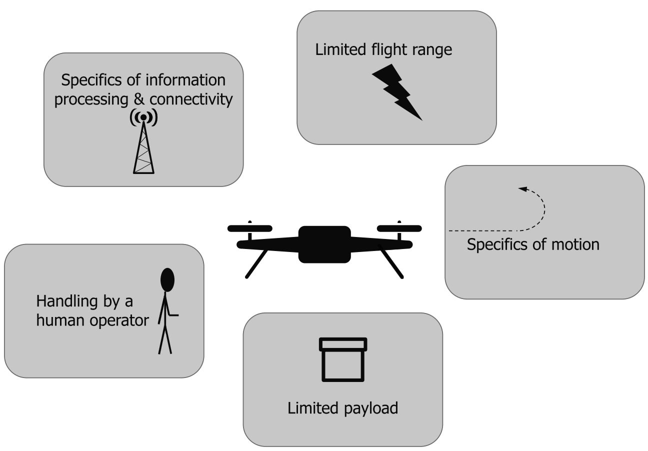

FIGURE 7 Characteristics of drones relevant to operational planning

each reversal requires additional time and energy, as the drones must come to a halt before moving in a different direction [208, 276]. Therefore, researchers look for smooth, constant-speed trajectories respecting the minimum turning radius also for rotorcraft drones [127, 152, 208]. Small and micro drones are highly susceptible to weather conditions, such as wind, which may be modeled as uncertain travel times [202]. Requirements for minimum and maximum flight angles of fixed-wing drones should be taken into account during landings and takeoffs [86, 209]. Some optimization problems introduce constant setup-time parameters for each landing and takeoff [274]. In photography applications, certain terrain types, such as mountains or trees, may require a specific angle of flight in order to optimally position the camera [36].

- *Limited payload*. Payloads for package delivery drones do not usually exceed 3 kg (6.5 pounds), and a drone usually carries just one package per sortie [3]. Limitations on the payload are closely related to the capacity of the drone's energy storage unit and the size and configuration (and cost) of the drone. For example, to maintain a stable flight, the propeller of a rotorcraft drone should generate enough thrust to counter the force of gravity. Therefore, a heavier drone needs more energy than a lighter drone to fly the same distance [68].
- *Limited flight range*. Most drones, with the exception of tethered drones receiving energy via a power cord, carry an energy unit of a limited capacity. Energy consumption of a drone depends on a multitude of factors, such as type of drone (fixed wing vs. rotorcraft), flying altitude (eg, propellers of rotorcrafts have to rotate faster at higher altitudes because of lower air density), flight conditions (such as hovering vs. forward flight), climbing speed, payload, and weather conditions, such as wind. The trade-off between energy consumption and flying altitude is especially important in surveillance applications: a higher flying altitude enables observation of a larger area at the cost of higher energy consumption [216]. The limited capacity of the energy unit is usually modeled as maximal operation time [274, 292], maximal flying distance [104, 244], or the limited number of addresses a drone can visit during one flight [75, 237]. Emerging technologies, such as thin film photovoltaic panels, enable so-called energy harvesting: Small drones may recharge their batteries during flight in the sunlight [162]. Battery swaps and refueling usually require assistance of a human operator [292]; however, there exist fully automated platforms able to exchange or to recharge the battery of a drone in just a couple of minutes [53, 268, 269, 275].
- *Specifics of information processing and connectivity*. Drones have to maintain communication links with the ground control station to receive instructions and transfer the collected information. Since line-of-sight communications are typically required, the signal gets weaker in the shadow of buildings in urban areas, indoors, or under the crowns of trees. Additionally, transmission lines and telecommunication towers may cause signal interference. Therefore, path planning methodologies may avoid or penalize visitation of certain regions [75]. Whenever mobile devices, for example, cell phones, cannot establish a direct connection to the macrocell base station, drones may also serve as intermediaries, acting as flying base stations [5, 91, 178]. Drones may use different wireless access methods to provide communication services, which may require assignment of particular time slots and/or frequencies to the users. Another consideration is that the power density of the signal reduces as it passes through a communication channel. Moreover, the signal can vary (fade), for example, due to shadowing from obstacles or due to multipath propagation. Fading may be modeled, for example, as Rayleigh fading (more appropriate for heavily built-up urban environments), Rician fading (if line-of-sight communication dominates), or Nakagami-*m* fading [46, 98, 123, 147]. Therefore, drone positioning as a flying base station depends on signal fading along the communication path, path loss, interferences, and noise. Other connectivity challenges emerge when several drones perform tasks cooperatively, since they may need to exchange information by establishing communication links that are subject to noise and dependent on transmission distance [100, 290]. Drone-to-drone communication also enables drones to attend a GPS-denied area while maintaining a communication link with another drone able to receive the GPS signal [164]. The limited memory capacity of the drone should be respected in gathering data from sensors, such as RFIDs attached to wild animals or sensors for pipeline monitoring [117, 148, 159, 260].
- *Handling by a human operator*. In a number of countries, drone regulations require human operators [185, 305]. Generally, a human operator performs a number of setup operations before the drone's takeoff and, after its landing [186], he or she may have to control the drone and to examine information collected by the drone in real time.

In the overview tables in Sections 4–6, we provide some keywords on modeling parameters of drones for each surveyed article. In these tables, articles may appear several times, for example, when the authors have provided several models describing different types of operations. Observe that some articles simply model drones as vehicles moving at a constant speed as an approximation [222, 239]. In such cases, we left the column "Drone characteristic(s)" in Tables 2–7, 9, and 10 empty.

In the following sections, we review articles on drone operations (Section 4), on combined operations of drones and other vehicles, such as trucks or ships (Section 5), and on strategic and operational aspects of preparation for drone operations (Section 6).

4 | PLANNING DRONE OPERATIONS

Possible civil drone applications are manifold and, therefore, so are the possible related planning problems. Observe that similar optimization problems may emerge in different applications. Consider a drone that has to visit several locations, which can be modeled as the traveling salesman problem (TSP). This problem emerges in the infrastructure industry, where a drone has to inspect points of interest of a building; in agriculture, where a drone collects information on sample points in a field; in delivery applications, where a drone delivers blood to several hospitals; and in entertainment, where a drone takes pictures of tourist sites. Therefore, we align our classification to the problem specifics instead of areas of application. We arrange our literature review by different *types of drone operations* (see Figure 8), such as

- Area coverage (Section 4.1), where drones should cover a certain area with a sensor of a limited footprint,
- Search operations (Section 4.2), where drones have to find a stationary or moving object,
- Routing for a set of locations (Section 4.3), where drones have to visit a discrete set of addresses,
- Data gathering and recharging in a wireless sensor network (WSN) (Section 4.4), where drones have to gather information from a discrete set of locations while considering communication scheduling and memory capacity constraints,
- Allocating communication links and computing power to mobile devices (Section 4.5), where drones are positioned (or routed) to provide communication links to mobile devices of sufficient quality, and
- Operational aspects of a self-organizing network of drones (Section 4.6).

See Sections 4.1–4.6 for more detailed definitions of the operation types.

Figure 9 shows that most of the surveyed articles consider routing for a set of locations. Drones in these operations perform surveillance and delivery tasks mostly in the context of infrastructure, agriculture, transport, and entertainment and media applications.

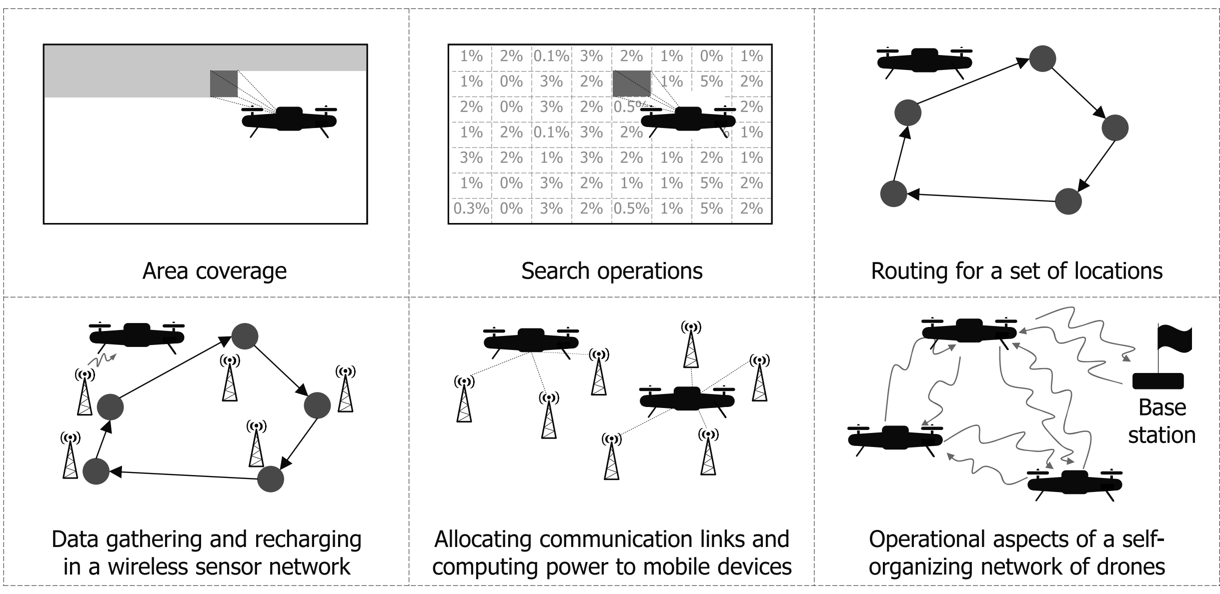

FIGURE 8 Classification of drone operations

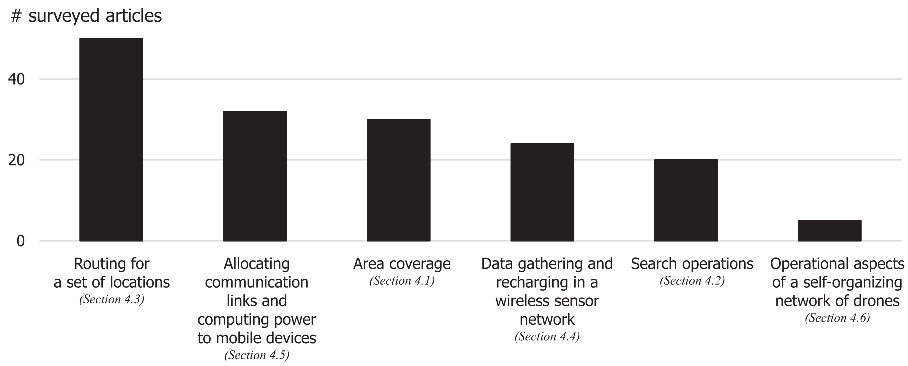

FIGURE 9 Distribution of the surveyed articles according to types of drone operations

We have selected the following approach for the literature review in Sections 4.1–4.6 that reflects the broadness of the selected topic and heterogeneity of the articles coming from different disciplines: operations research, engineering, and informatics. In Tables 2–7, arranged by the operation type, we summarize a number of characteristics for each publication: information on methodological contribution to planning drone operations, characteristics of the drones that have been taken into account in modeling, application that motivated the publication, and whether one or several drones have been considered. The notation used in Tables 2–7 is explained in Table 1. In the accompanying text in Sections 4.1–4.6, we provide a general overview for each operation type. We illustrate typical applications, outline what is specific about drone operations, discuss some emerging optimization problems, and typical objective functions. Note that because of the broadness of the topic, we cannot provide details on decision variables, constraints, and objective functions for each surveyed publication in the limited space of a journal article.

Overall, the articles surveyed in Sections 4–6 propose various solution approaches to optimize operations of drones. In addition to presenting centralized optimization methods, some articles design agent-based, or decentralized, algorithms [22, 142, 321]. Such algorithms are scalable to new drones entering the system, are robust, since drones may not be connected to the control station at all times, and naturally enable parallelized computation with each drone optimizing its own local sub-problem. For complex operations with heterogeneous drones belonging to different providers, such as disaster management, coordinated planning frameworks with a clear assignment of roles and efficient communication procedures have been proposed to ensure efficient coordination in achieving common goals [212, 296]. Game-theoretic approaches depict drones as strategic rational or adversarial players as in situations when drones belonging to different organizational entities compete for clients [137] or for the most energy-efficient position in a flying formation [225].

4.1 | Planning of area coverage

In coverage problems, one or more drones equipped with sensors of a limited footprint have to monitor (cover) some area P, which can take different shapes. This problem arises in disaster management, such as post-earthquake assessment, in agriculture, such as in observation of vegetation indexes, and in creating digital terrain maps. The *coverage path planning problem*, which is to find paths of drones equipped with sensors of a limited footprint to cover *all* points of area P at the lowest possible cost, is discussed in Section 4.1.1. Section 4.1.2 examines the dual planning problem of maximizing information collected from the *partially* covered area, given some budget constraints. Section 4.1.3 reports on *stationary* positioning of drones so that their sensors cover all points of P.

Although coverage problems with drones are closely related to general coverage problems, some peculiarities may arise. First of all, since drones perform observations from the air, there is a trade-off between taking pictures from a higher altitude with a larger camera footprint, but lower resolution and higher energy consumption, and taking pictures from a lower altitude with a smaller camera footprint, but higher resolution and lower energy consumption. Secondly, cameras and sensors may be attached to a drone at different orientations (eg, side-aimed cameras vs. directly-downward facing cameras) [66], so that different shapes and positions of the camera footprint relative to the drone are possible. Moreover, more sophisticated sensors can change their orientation during flight. Lastly, because drones, especially fixed-wing drones, may traverse long distances quickly, coverage problems involving nonconvex or disconnected areas gain importance. Table 2 provides an overview of the surveyed articles.

TABLE 1 Glossary of abbreviations

M	Mathematical model ready for input into an off-the-shelf solver (eg, Gurobi, IBM ILOG Cplex)
P	Theoretical studies on problem properties, such as non-trivial complexity analysis of the problem, worst- or best-case analysis, approximation guarantees for algorithms, polynomial exact algorithms, proofs for stability and adaptivity of online algorithms, proofs for asymptotic optimality of the proposed algorithms, studies on convergence
E	Closed-form solution for a non-linear problem, exact solution with methods of convex optimization
Control	Control algorithms, such as flight altitude control or nonlinear drone trajectory control, that update "on the fly" based on new information as well as frameworks for cooperative control
Control P	Theoretical studies on properties of the formulated control algorithms, such as convergence
Game P	Theoretical studies on properties of the formulated games, such as existence of Nash equilibrium, stability, optimality, convergence, price-of-anarchy analysis
Game H	Adaptive algorithms for individual strategic players (rational or adversary) that maximize the player's utility and potentially converge to a Nash equilibrium
BnB, BnC, BnP, DP, CP, CG, LR	Branch-and-bound, branch-and-cut, branch-and-price, dynamic programming, cutting plane, column generation, or Lagrangian relaxation algorithms, respectively
Bnd	Customized bounds other than LR that are not part of BnB or BnC approaches
(Decentral) MH	One or several (decentralized) metaheuristic algorithms. Metaheuristic algorithms may describe online decision making in the receding, or rolling, horizon. Articles may provide memory and computational complexity analysis of the proposed algorithms
(Decentral) H	One or several customized heuristic algorithms, apart from metaheuristic algorithms. Heuristic algorithms may describe online decision making in the receding, or rolling, horizon. Articles may provide memory and computational complexity analysis of the proposed algorithms
EmpCS	Empirical results and case studies. Empirical results derive parameters and/or constraints or provide detailed explanations of how to derive model parameters from empirical data, they may suggest elements of control other than motion control that are relevant for real-world operations (eg, computer vision-based feedback control). Case studies test suggested operations planning concepts on real drones
Exp	Computational experiments on artificial or real-world data

4.1.1 | Coverage path planning for full coverage

Coverage path planning with drones refers to finding paths of drones such that all points of some area P are covered at least once (see general surveys by Choset [49] and Galceran and Carreras [87] on coverage path planning for robotics). Preferred paths of drones have to avoid unproductive movements, such as repeated surveillance of the same points in P or "idle" flights to the next zone of operation. Common objective functions aim to minimize some distance-related cost function [66, 199, 276, 300], completion time (in case of several drones or setup times between drone flights) [17, 22, 176, 188], or energy consumption (because the drone's energy consumption depends on the altitude of flight and the direction of acceleration) [146]. Furthermore, since each turn of the drone requires additional time and energy (see Section 3), a cost-minimizing path will generally contain fewer turns. Therefore, cost functions are sometimes approximated as the required number of turns [149, 283].

Especially if area P contains obstacles or is non-convex, coverage path planning is a highly nontrivial task. Therefore, some articles assume paths of specific patterns (see Figure 10a,b). For example, a drone may move in a lawn mowing pattern along parallel lines that are perpendicular to a ray denoting the sweep direction. Note that for some convex area P, the number of turns is minimized if the largest difference in ℓ-coordinates between a pair of points belonging to P, when measured along the chosen sweep direction $\vec{\ell}$, is at its minimum [115, 168]. Another common pattern involves spiral trajectories [176]. Note that if terrain elevations are present, an energy-efficient coverage path may differ greatly from conventional path patterns, such as lawn mowing paths [146]. Overall, as Li et al. [146] discuss, neglecting terrain elevation in coverage path planning may lead to a severalfold increase in coverage-path length and energy consumption.

One possible solution approach to the coverage path planning problem is to partition area P with a fine raster into a collection of possibly irregular cells [188, 207, 283, 300]. Afterwards, we can capture information on the connectivity of cells and distances between them in a graph (see Figure 10c). In this way, if we code the cells as nodes of the graph [218], the coverage path planning problem can be transformed into a traveling salesman or a vehicle routing problem (VRP). If we code the cells as edges of the graph, a Chinese postman problem arises [2]. Desired path properties may be enforced with additional constraints, such as

TABLE 2 Overview of the surveyed articles: Area coverage

Publication	Contribution	Subjects of planning	Drone characteristic(s)	Application
Coverage path planning for full coverage *(Section 4.1.1)*				
[17]	M, EmpCS, Exp	several drones	limited flight time, sensor with a limited footprint	agriculture
[20]	H, Exp	several drones	sensor with a limited footprint, drones have heterogeneous area coverage (sensing) capability per unit of time	other (environmental protection and disaster management)
[22]	Decentral H, Control, EmpCS, Exp	several drones	limited flight time, equations of motion, sensor with a limited footprint	agriculture
[66]	H, Exp	drone	minimum turning radius, side-facing camera, sensor with a limited footprint	general
[146]	MH, EmpCS, Exp	drone	energy consumption depends on the altitude and speed of flight, sensor with a limited footprint	general
[149]	H, EmpCS, Exp	drone	sensor with a limited footprint (depends on the drone altitude), function of energy consumption (higher consumption for the turning motion compared to flat flying)	general
[168]	H, Exp	several drones	limited flight distance, sensor with a limited footprint	other (environmental protection and disaster management)
[176]	H, EmpCS	drone	equations of motion (eg, no sharp turning angles allowed), sensor with a limited footprint	agriculture
[188]	M, Exp	several drones	limited flight time, sensor with a limited footprint	other (environmental protection and disaster management)
[199]	M, Decentral H, EmpCS, Exp	several drones	limited flight time, minimum turning radius, minimum separation distance between each two flying drones, sensor with a limited footprint	general
[200]	M, Decentral H, H, Exp	several drones	minimum turning radius, limited flight time, sensor with a limited footprint	general
[207]	H, Exp	several drones	limited flight distance	general
[217]	EmpCS	several drones	flying in formation, sensor with a limited footprint	other (environmental protection and disaster management)
[276]	H, Exp	drone	sensor with a limited footprint	general
[283]	MH, EmpCS	several drones	energy consumption function (depends on the amplitude of the turn), sensor with a limited footprint	agriculture
[300]	P, H, EmpCS, Exp	drone	sensor with a limited footprint, discussed: influence of wind, restrictions on the turning radius	other (rescue)
Coverage path planning for partial coverage: Maximum information collection *(Section 4.1.2)*				
[36]	MH, EmpCS, Exp	several drones	equations of motion, sensor with a limited footprint, information collection with the sensor declines with the distance to the target	general

(*Continued*)

TABLE 2 (Continued)

Publication	Contribution	Subjects of planning	Drone characteristic(s)	Application
[74]	MH, Exp	drone	limited flight time, information collection is lower at a larger distance from the camera to the target, equations of motion, sensor with a limited footprint	general
[75]	MH, Exp	several drones	limited flight distance, information collection is lower at a larger distance from the camera to the target, equations of motion, sensor with a limited footprint	general
[76]	M, H, Exp	drone	limited flight time, uncertain flight times	general
[97]	Control, Exp	drone	limited energy, minimum turning radius, energy consumption equations (eg, depends on the turn rate), sensor with a limited footprint	general
[101]	P, H, Exp	drone, several drones	limited flight time, limited buffer size, communication constraints (eg, signal fades with the distance), sensor with a limited footprint	general
[161]	P, H, Exp	drone	equations of motion, sensor with a limited footprint	agriculture
[184]	M, H, CG, Exp	several drones	limited flight time, minimum payload (limited number of sensors), travel time depends on the number of sensors due to increased payload	general
[208]	MH, EmpCS, Exp	drone	minimum turning radius, limited flight distance	general
[272]	M, BnB, H, Exp	several drones	drone-to-target assignment constraints	general
[274]	P, H, EmpCS, Exp	drone	limited flight time, sensor with a limited footprint	agriculture
Coverage from stationary positions: Continuous observation ***(Section 4.1.3)***				
[216]	M, H, Exp	several drones	energy consumption depends on the altitude of flight, limited energy pro flight, sensor with a limited footprint	other (environmental protection and disaster management)
[235]	P, H, EmpCS, Exp	several drones	minimum and maximum camera angles, sensor with a limited footprint	general
[321]	M, H, Decentral H, Exp	several drones	energy consumption depends on the altitude of flight, limited energy pro flight, sensor with a limited footprint	general

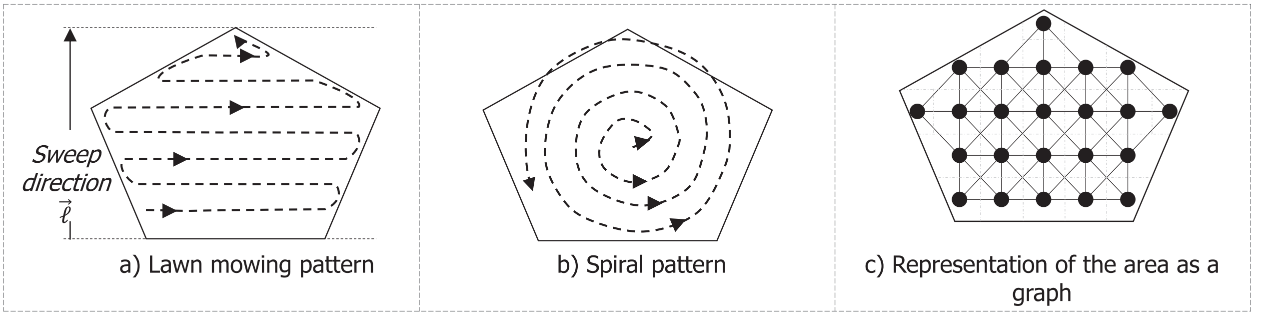

FIGURE 10 Selected path patterns and area representations in area coverage

requiring that the drone enters and leaves certain cells from opposing sides [188]. Notice, however, that we may miss optimal solutions by discretizing area *P*, because we force the drone to visit centers of the cells.

Several articles consider one drone covering some possibly non-convex area *P* [149, 176, 276, 300]. Other articles take the limited energy capacity of drones into account, so that area coverage may require several drones, each possibly starting from different depots [17, 188, 217]. Balampanis et al. [20] partition a nonconvex polygonal area into coverage assignments for a heterogeneous fleet of drones. In Avellar et al. [17], drones must be launched or relaunched by a human operator, so they have to wait their turn if the operator is busy, delaying task completion. Independent strategic drones may negotiate a solution for partitioning *P* into individual areas of responsibility according to some specified auction protocol [22, 283]. Coverage of a road network is examined in Dille and Singh [66], Oh et al. [199], and Oh et al. [200].

4.1.2 | Coverage path planning for partial coverage: Maximum information collection

Budget constraints, such as limited energy or time, may prohibit drones from covering the whole area *P*, giving rise to the problem of maximizing information collection. For example, Çakici et al. [36], Ergezer and Leblebicioğlu [74, 75], and Gramajo and Shankar [97] maximize the covered area while possibly avoiding forbidden regions. Gu et al. [101] minimize information delay between the point of information collection (such as a taken photo) and its arrival at the processing unit. Objective functions may incorporate penalties for long traveled distances [36, 184], energy expenditures [36, 75], and entering forbidden regions [36, 75].

Overall, in some applications, such as maintenance inspection and precision agriculture, information on some regions of area *P* may be more valuable than on other regions. Therefore, another common objective function is to maximize the value of the collected information [76, 161, 195, 208, 272, 274]. For instance, Tokekar et al. [274] and Ma and Karaman [161] examine soil analysis, that is, classification of soils according to the nitrogen levels, with the assistance of aerial images. In the problem setting of Ma and Karaman [161], a drone may detect in flight some anomalies with associated rewards, or importance scores, and may then decide to take an aerial image of some of these anomalies. The authors investigate the maximum achievable average reward in discrete and continuous problem formulations for different motion equations of the drone and for different detection ranges of the drone's sensors.

As discussed in Section 4.1.1, area *P* can be discretized and represented as a graph with information value (or rewards) assigned to each node [274]. In this case, the problem of maximum information collection becomes equivalent to the *orienteering problem*. In the orienteering problem, a drone cannot visit all the points of interest during its sortie. Therefore, we have to find a tour over some (possibly not all) nodes in a way that maximizes the total collected reward (see Vansteenwegen et al. [285] for a general survey on the orienteering problem). Pěnicka et al. [208] formulate the Dubins orienteering problem to take into account restrictions on the minimum turning radius of the drone.

In Mufalli et al. [184] and Thi et al. [272], each node of the graph may be surveyed with several drones or several sensors with different information gathering abilities. In Mufalli et al. [184], a set of drones must be equipped with sensors, where each sensor brings additional (additive) benefit in surveying a node, and tours of drones starting and ending at their depots should be selected so that the potential benefit is maximized and travel distance is minimized (the objective function incorporates both factors as a weighted sum). Evers et al. [76] examine an orienteering problem relevant for police and media applications. A drone has to film several episodes during a sporting event for a certain duration within the predefined time windows. The filming locations are positioned in the nodes of a graph. However, some urgent, unforeseen incident, such as a riot, may occur with a certain probability in the neighborhood of the nodes of the graph and would require the immediate attendance of the drone. In this scenario, the rewards of the node visits depend on the number of potential incidence locations in the neighborhood and on the probabilities of events occurring.

In Niu et al. [195], a drone collects information on transport flows in road segments, with some segments being more important (eg, with frequent traffic jams) than others. Due to regulations, the drone can only fly over the highways in the network and cannot take any shortcuts by flying over the terrain between designated roadways. The authors formulate a multiobjective problem that evaluates trade-offs between the value of the collected information and the flying time.

4.1.3 | Coverage from stationary positions: Continuous observation

Environmental monitoring, monitoring of transportation networks or emergency response activities may require allocation of several heterogeneous drones to stationary observational positions, that is, monitoring positions where drones hover or loiter for a long time. Pugliese et al. [216] and Zorbas et al. [321] set up optimization models in which a given set of objects should be covered by the sensor range of at least one drone. Each object should be monitored for a certain amount of time, so that if the drone's energy is insufficient to cover the required time span, a new drone jumps into the surveillance position and the drone with depleted energy returns to the depot. The higher the altitude of the drone, the larger its sensor range is; however, its energy consumption also increases. The authors consider minimizing the number of drones to cover the target and the total energy consumption of the drones. In Saeed et al. [235], drones must take frontal pictures of objects. The authors look for positions and orientation to provide the minimum number of drones that will cover all the objects, which are modeled as sets of oriented line segments.

4.2 | Planning of search operations

In the search problem with drones, which is readily observed in wildlife monitoring and search and rescue applications, a search path for one or several drones must be determined to find an object with an unknown location. Search problems have a long and rich history in the operations research *(OR)* literature, and we refer the interested reader to Koopman [135, 136], Stone [255], and Alpern and Gal [11] for essentials of search theory and to Benkoski et al. [26], Hu et al. [114], and Robin and Lacroix [228] for general surveys of the literature on the search problem. Obviously, search problems with drones closely resemble search problems with piloted aircraft. Innovations in modeling and methodology in articles on drones are mainly motivated by applications that are now profitable due to the low cost of drone technology when compared to piloted aircraft. Such applications include monitoring of livestock and environmental monitoring (eg, icebergs). See Table 3 for an overview of the surveyed articles.

In the search problem, a map of the search area P is given and is usually partitioned into a collection of cells (eg, with a grid) each labeled with the probability of finding a targeted object in this cell. Due to possible obstacles in the line of sight, such as trees or buildings, Lin and Goodrich [151] and Yao et al. [309] recommend modeling detection probabilities specific for each cell. Most publications assume a stationary object, even if the target is a person or an animal, because the speed of the object is usually much slower than that of the drone. In the case of a moving object, the probability map evolves over time [218, 219, 291]. Due to imperfect sensors, a drone detects an object with some probability $\pi < 1$ if it visits the cell where the object is located [142], so it may make sense to visit some cells several times. The probability of detecting the object may be higher in the center of the sensor's footprint and decline at the footprint's edge [121, 142, 191, 273]. Given the information collected by a drone and the initial base rate, we can perform a Bayesian update of the cell label [33].

A common objective is to maximize the cumulative probability of finding the object within the given time span or, alternatively, to minimize the time to achieve the desired cumulative probability of finding the object. Note that because a drone collects information in all the cells visited along its path, an optimal path does not necessarily contain a grid cell with the highest probability of finding the object. Some articles propose alternative approaches to evaluating the search map. Thus, Sujit and Ghose [256, 257] label cells with general information uncertainty indices, which decrease by a constant factor after each drone visit. The objective function in this case aims at maximum total uncertainty reduction [308].

Due to limited flight duration, drones may require refueling at the depot or, for gliding drones, using thermals (rising bubbles of hot air) [191]. As a result, cells near the depot may get searched more intensively than remote cells [256, 257]. If information exchange between the drones via a ground control station is restricted, drones may have to exchange some information between each other while taking possible limitations of the communication channels into account [121, 257, 308]. Drones that belong to different organizational entities may also interact strategically as selfish, cooperative, or adversarial players [257].

In some articles, drones not only have to locate the object, but also estimate its motion [6, 109, 110, 303]. For example, Haugen and Imsland [109, 110] and Albert et al. [6] set up a control framework to estimate parameters of motion of several objects with drones equipped with imperfect sensors. The application is motivated by detection of icebergs and assessment of their direction of movement, position, and velocity, as well as estimation of ice concentration in the sea. For instance, Albert et al. [6] use a graph-theoretical approach to assign objects (icebergs) to drones and to determine tours of the drones over these objects, so that the objects with the highest observational uncertainty are visited first. In Darbari et al. [61], the drone must discover obstacles and predict their motion in order to cover a maximum area within the limited flight time while avoiding collisions. Several articles investigate the cyclic-routing drone problem, in which drones fly back and forth to update information on the objects' positions [112, 270].

4.3 | Routing for a set of locations

In a number of surveillance and delivery applications, drones have to perform a tour over some set of locations which starts and ends at a depot. The resulting planning problems can be modeled as generalized versions of one of the basic routing problems, such as the TSP [214, 239], the multiple TSP [8, 19, 25, 163, 222, 266, 286, 288], or the VRP [96, 125, 133, 154, 213].

TABLE 3 Overview of the surveyed articles: Planning of search operations

Publication	Contribution	Subjects of planning	Drone characteristic(s)	Application
[6]	M, EmpCS, Exp	several drones	equations of motion (minimum turning radius), sensor with a limited footprint	other (environmental protection and disaster management)
[33]	Control, Exp	drone	equations of motion, sensor with a limited footprint	other (rescue)
[61]	Control, Exp	drone	minimum turning radius, limited flight time, minimum speed, limited climb-rate, sensor with a limited footprint	general
[109]	M, EmpCS, Exp	several drones	equations of motion, sensor with a limited footprint	other (environmental protection and disaster management)
[110]	M, EmpCS, Exp	several drones	equations of motion, sensor with a limited footprint	other (environmental protection and disaster management)
[112]	P	several drones		general
[121]	Control P, Decentral H, Control, Exp		minimum turning radius, sensor with a limited footprint, target detection probability of the sensor declines with the distance to the target, limited communication range	general
[142]	Decentral H, Exp	several drones	sensor with a limited footprint, target detection probability of the sensor declines with the distance to the target	general
[151]	H, Exp	drone	sensor with a limited footprint	other (rescue)
[191]	H, EmpCS, Exp	drone	equations of motion (gliding), equations for energy gains by visiting thermals (eg, depends on the wind strength and the time spent in the thermal), target detection probability of the sensor declines with the distance to the target	general
[218]	M, Exp	drone	equations of motion, sensor with a limited footprint, target detection probability of the sensor declines with the distance to the target	other (rescue)
[219]	M, H, Exp	drone	equations of motion, sensor with a limited footprint	other (rescue)
[256]	H, Decentral H, Exp	drone, several drones	limited flight time, sensor with a limited footprint	general
[257]	Decentral H, Game H, H, Exp	several drones	limited flight time, sensor with a limited footprint	general
[270]	H, Decentral H, Exp	several drones	minimum turning radius, sensor with a limited footprint	general
[273]	H, EmpCS, Exp	drone, several drones	equations of motion, sensor with a limited footprint, target detection probability of the sensor declines with the distance to the target	general
[291]	H, Exp	drone	equations of motion, sensor with a limited footprint	other (rescue, environmental protection)
[303]	Decentral H, Exp	several drones	limited communication range, sensor with a limited footprint	general
[308]	Decentral H, Exp	several drones	minimum turning radius, sensor with a limited footprint, statistical learning unit at each drone	general
[309]	Decentral H, Exp	several drones	minimum turning radius, sensor with a limited footprint	general

We provide an overview of the articles surveyed in this section in Table 4. Note that routing for a set of locations intersects with area coverage problems examined in (Section 4.1). Indeed, as an approximation, we could discretize area P and represent it as a graph, so that the coverage path planning becomes a routing problem. Recall, however, that such discretization only represents one of the possible heuristic solution approaches to area coverage, and exact solution approaches rely, for instance, on the tools of analytic geometry.

Drones face a problem that some vehicles (eg, long-distance trucks and electric vehicles) also face, as drones have to periodically refuel or recharge their batteries at depots to overcome their limited travel range [103, 131, 132, 172, 253, 254, 265, 278, 312]. In contrast to trucks, however, drones may select a battery of the most suitable size for the tour, taking into account that energy consumption depends heavily on the weight of the drone [68]. Drones also fly in 3D space without a road network and may have to make a detour to avoid obstacles or dangerous zones (eg, bad weather regions) [86, 173, 175, 209].

Another influence on route planning is that drones have a minimum turning radius if they travel at a constant speed [18, 55, 103, 163, 223, 242, 299]. Drones travel a path with a curvature radius that cannot fall below some minimum level, which (if it is twice differentiable almost everywhere) is referred to as a *Dubins path*. Studies have proven that the shortest Dubins path between two points in space, given the starting and the final heading of the vehicle (ie, the direction in which a drone is pointing), consists either of a straight-line trajectory and/or of turning left or right at the minimum turning radius [69] (see Figure 11a).

Several articles consider the TSP or the VRP with a restriction on the minimum turning radius, called the Dubins TSP and the Dubins VRP, respectively [55, 197, 223, 242, 299, 304, 320]. The Dubins TSP is NP-hard in the strong sense and an optimal solution of the Euclidean TSP corresponding to the Dubins TSP can be *arbitrarily* worse than an optimal solution to the original problem, if the problem instance is sufficiently large [197]. Rathinam et al. [223] and Savla et al. [242] propose decomposition heuristics with performance guarantees where tour planning is performed by solving a conventional Euclidean TSP or VRP and only afterward, as a downstream planning problem, is the drone's path adjusted to respect the minimum turning radius condition. Savla et al. [242] also provide some analysis of the expected results in stochastic and dynamic versions of the problem. Ny et al. [197] show that a performance guarantee can also be provided for a very simple heuristic: random assignment of heading angles to each node, computing shortest Dubins path for each pair of nodes, and solving the resulting problem as an asymmetric TSP. Manyam et al. [163] propose several lower bounds for the Dubins multiple TSP. Woods et al. [295] study the k-neighbor TSP, which is an alternative modeling approach to find a flight tour of the minimum travel distance. Whereas in the classic TSP, the length of the tour is equal to the sum of edge lengths, in the k-neighbor TSP, the length also depends on the sequence of edges in this tour (see [295] for a more precise definition).

Some drone operations, especially those that involve collecting samples in maintenance inspection and precision agriculture, are modeled as routing problems with neighborhoods [21, 139, 299] (see Figure 11b). For example, since nearby points in an agricultural field are correlated [139], collecting information about just one spot/point may be sufficiently representative of the status of the surrounding area of interest [21]. In another setting, a drone is able to collect the required data from a range of different positions, which would depend on the footprint of the drone's sensor [198]. Given a collection of regions, referred to as neighborhoods, in some m-dimensional space and a distance function between points in this space, the *routing problem with neighborhoods* requires finding a minimum cost route for one or several drones so that each neighborhood is visited at least once. For instance, Gentilini et al. [90] propose a branch-and-cut algorithm for a TSP with ellipsoid or polyhedral neighborhoods. If we interpret neighborhoods as a set of distinct nodes of a graph, so that exactly one node of the graph in each neighborhood must be visited and each neighborhood must be visited by exactly one drone, then a one-in-a-set problem arises [241]. We refer the interested reader to Arkin and Hassin [16], de Berg et al. [62], and Elbassioni et al. [71] for approximation results on some variants of the TSP with neighborhoods.

To address the problem of unreliable data, Niendorf et al. [193] compute stability regions for problem parameters, that is, parameter intervals, for which the computed solution will remain optimal. Motivated by surveillance for maintenance of bridges and other infrastructure subject to wind gusts between pylons, Guerrero and Bestaoui [103] elaborate on the shortest path calculation in a windy environment based on Zermelo's navigation equations. In Alighanbari and How [9], a set of tasks is known, but their profits are uncertain and data uncertainty (ie, the standard deviation of possible profits) varies between tasks. The authors propose a robust online planning algorithm that penalizes reassignment of tasks.

In disaster management, such as oil spills, forest fires, earthquakes, or in on-call services, such as surveillance of traffic incidents, surveillance requests appear dynamically and have to be assigned to available drones (see Figure 11c). Because service times of such surveillance requests are often uncertain, a variant of the m-vehicle dynamic traveling repairman problem often arises [28, 29]; see Bullo et al. [35] and Ritzinger et al. [226] for surveys. Enright et al. [72, 73], Pavone [204], Pavone

TABLE 4 Overview of the surveyed articles: Routing for a set of locations

Publication	Contribution	Subjects of planning	Drone characteristic(s)	Application
[8]	M, Exp	several drones	drones with heterogeneous capabilities	general
[9]	M, H, Exp	several drones	sensor measurements are prone to errors	general
[15]	P, Decentral H, Exp	several drones	a general framework: no specific drone characteristics are formulated	general
[18]	H, Exp	drone	minimum turning radius	general
[19]	M, P, H, Exp	several drones	travel cost are specific for each drone (eg, because drones have different minimum turning radii)	general
[21]	H, Exp	drone	limited flight distance, sensor with a limited footprint, resolution depends on the altitude of flight	agriculture
[25]	M, H, Exp	several drones	limited flight time, maximum number of possible targets per drone	general
[40]	M, P, Decentral H, Exp	several drones	speed of work differs among drones	infrastructure & construction
[48]	M, Decentral H, Exp	several drones	minimum turning radius	general
[54]	M, Exp	several drones	limited payload, maximum speed, limited energy capacity, energy consumption depends on speed, given speed of battery recharge	transport
[55]	M, P, H, Exp	drone	minimum turning radius	general
[68]	M, MH, EmpCS, Exp	several drones	limited carrying capacity, energy consumption depends on the drone's weight	transport
[72]	P, H, Decentral H	drone, several drones	minimum turning radius, sensors of limited range	general
[73]	P, H, Exp	several drones	minimum turning radius	general
[86]	M, H, BnC, CP, Exp	drone	maximum rate of climb, maximum rate of descent	other (air traffic management)
[90]	M, H, BnC, Exp	drone	sensor with a limited footprint	general
[96]	M, H, Exp	several drones	minimum turning radius	general
[103]	MH, H, Control, Exp	drone	limited flight time, minimum turning radius, influence of wind	infrastructure & construction
[104]	M, Exp	several drones	limited flight distance	entertainment & media
[125]	M, MH, Exp	several drones	limited payload	transport
[128]	M, Decentral BnP, Exp	several drones	a general framework: no specific drone characteristics are formulated	general
[130]	M, H, MH, Exp	several drones	limited energy, given duration of recharging	other (manufacturing)
[131]	M, BnB, H, Exp	several drones	limited flight time	general
[132]	M, MH, Exp	several drones	limited flight time	general
[133]	LR, H, Exp	several drones	limited flight time, limited payload	transport
[144]	DP, H, Exp	several drones	energy consumption equations, equations of motion	transport
[154]	M, MH, Exp	several drones	limited flight distance	other (traffic surveillance on roads)
[163]	M, LR, Bnd, Exp	several drones	minimum turning radius	general

(*Continued*)

TABLE 4 (Continued)

Publication	Contribution	Subjects of planning	Drone characteristic(s)	Application
[172]	MH, H, Exp	several drones	limited flight time	other (environmental protection and disaster management)
[173]	Decentral MH, Exp	several drones	limited flight distance	other (rescue)
[174]	Decentral H, EmpCS, Exp	several drones	a general framework: no specific drone characteristics are formulated	general
[175]	Decentral H, Control, EmpCS, Exp	several drones	equations of motion	general
[192]	Decentral MH, Exp	several drones	heterogeneous drones (eg, different equipment)	general
[193]	M, H, Exp	drone		general
[195]	M, Exp	drone	limited flight time	other (traffic surveillance on roads)
[197]	P, H, Exp	drone	minimum turning radius	general
[198]	P, H, Exp	drone	minimum turning radius	general
[204]	M, P, H, Decentral H, Exp	several drones	minimum turning radius	general
[205]	P, H, Exp	several drones		general
[206]	Survey on selected results of the dynamic traveling repairman problem with several drones			
[209]	MH, Exp	drone	equations of motion	other (air traffic management)
[213]	MH, Exp	several drones	limited payload	transport
[214]	M, MH, Exp	drone	limited camera footprint	infrastructure & construction
[222]	M, P, H, Bnd	several drones		general
[223]	P	drone, several drones	minimum turning radius	general
[233]	Game H, Exp	several drones	communication constraints (probability of successful transmission depends on distance and message size, limited speed of data collection)	telecommunications
[234]	Game P, Game H, Exp	several drones	communication constraints (probability of successful transmission depends on distance and message size, limited speed of data collection)	telecommunications
[239]	MH, Exp	drone		general
[240]	M, Game P, Exp	drone		transport
[241]	MH, Exp	several drones	sensor with a limited footprint	general
[242]	P, H	drone	minimum turning radius	general
[253]	M, EmpCS, Exp	several drones	limited flight time	general
[254]	M, H, Exp	several drones	limited fuel/energy capacity, time for refueling/recharging the battery depends on the required amount of fuel/energy	general
[258]	H, Exp	drone	equations of motions (eg, minimum turning radius)	other (geology)

(*Continued*)

TABLE 4 (Continued)

Publication	Contribution	Subjects of planning	Drone characteristic(s)	Application
[264]	M, LR, H, Exp	several drones	minimum turning radius (given heading angles at each target)	general
[265]	M, P, H, Exp	drone	limited flight distance	general
[266]	M, BnC, Exp	several drones	minimum turning radius	general
[278]	M, P, H, EmpCS, Exp	drone	limited energy, energy consumption function	general
[280]	M, P, Decentral H, EmpCS, Exp	several drones	limited communication range, equations of motion, safety distances	general
[286]	M, P, H, Bnd, Exp	several drones	limited energy	general
[288]	H, Exp	several drones	communication within the visual line of sight, limited communication range	general
[294]	M, MH, Exp	several drones	limited carrying capacity	transport
[295]	P, E	drone	the authors study the k-neighbor-TSP that may describe heading-angle-dependent distance metrics	general
[299]	MH, Exp	drone	minimum turning radius	general
[304]	M, H, DP, LR, Exp	several drones	minimum turning radius	general
[312]	P, EmpCS, Exp	drone	limited energy	transport
[320]	P, H, MH, Exp	drone	equations of motion (minimum turning radius, motion in the wind)	general
[319]	M, LR, H, Exp	several drones	limited flight time	other (traffic surveillance on roads)

et al. [205] and Pavone et al. [206] provide several algorithms that result in a bounded expected waiting time for request completion (ie, time from the request arrival to the request completion). Moreover, some algorithms guarantee system stability and have suitable properties both under light-load conditions, that is, when only a few requests per drone of low required service time arise, and under heavy-load conditions. For example, Enright et al. [73] show the following policy, known as the median circling policy, to be efficient under light-load conditions: Each drone loiters around the median of its Voronoi region and serves requests arriving in its region in a first-come-first-served order. Overall, in a number of problem settings, policies based on the first-come-first-served rule are mostly suitable for light-load conditions, whereas in heavy-load conditions, several requests should be accumulated or batched before planning an order of service [35]. Turpin et al. [280] investigate allocation of several accumulated requests to drones and design noncollision trajectories of drones. Agent-based and game-theoretic modeling is another methodology to deal with uncertain and dynamic environments [15, 48, 128, 174, 233, 234]. In the receding-horizon

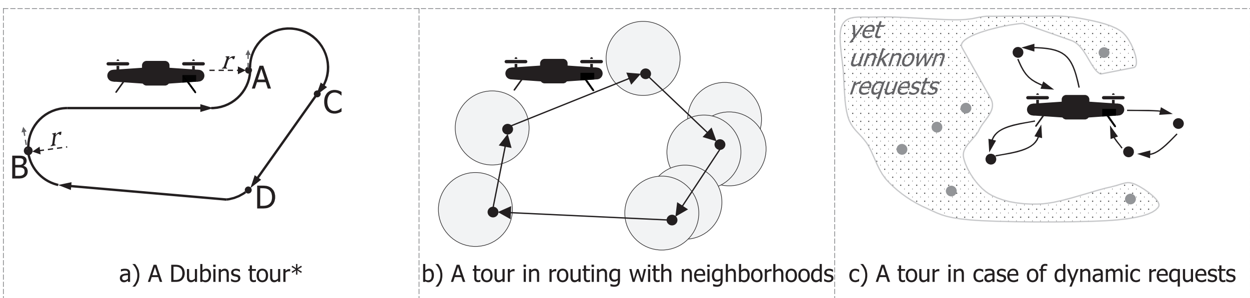

FIGURE 11 Illustration of some possible drone tours. * Each path between a pair of nodes in a tour is a Dubins path. For example, path BA consists of a right turn, a straight segment and a left turn, where turns are performed at the minimum turning radius r

setting, drones (or agents) bid for tasks that they should perform next and each task is allocated to the lowest-cost bidder. In Sanjab et al. [240], a delivery drone has to find a path from the depot to a customer while taking into account a possibility of the malicious attack that will damage the drone with some probability of success so that a new delivery drone will have to be sent to the customer. The authors formulate a zero-sum game on a graph where node labels depict success probabilities of the attack and edge labels denote travel times of the drone.

In some surveillance applications, such as filming sporting events, traffic monitoring and control, and monitoring traffic incidents or disaster regions, drones have to visit locations within specified time windows [104, 130, 253, 254, 319]. Moreover, soft time windows may indicate time intervals, such as overtime in a football game, when filming is most valuable for the customers [254]. Photos may have to be taken at certain angles and at a desired height to optimize resolution [258]. Moreover, some locations may be visited only by a subset of drones equipped with a suitable set of sensors [264].

Several publications consider routing issues in the context of delivery applications, where a drone may deliver several customer orders per tour before returning to the depot [68, 294]. Wen et al. [294] consider express deliveries of blood. In order to guarantee optimal environmental conditions for the transported blood, the authors decide on temperature and volume of the additional payload—which is water or ice serving as cooling and heating agents. Suzuki [213] formulates a pickup and delivery problem motivated by drones delivering goods to human packers in a warehouse. In Lee [144], drones are assembled from the most suitable variants of given modules (rotors, carriers, and batteries) to achieve low energy utilization and fast delivery for each particular customer request.

Coelho et al. [54] examine routing of drones given the possible traffic infrastructure of cities in the future. For instance, airspace may be separated into two layers: one for heavy and fast drones and a lower one for smaller and slower drones. The city would have a set of stationary recharging stations for drones, as well as some vertical displacement points for drones from different airspace layers to exchange packages.

A special case arises when task processing times are much longer than the travel times. In this case, routing for a set of locations can be approximated as a scheduling problem. For instance, in Caraballo et al. [40], drones equipped with robotic arms perform assembly operations, such as assembly of a bridge. The authors look for a task allocation among drones that minimizes the maximum completion time. Niccolini et al. [192] consider allocation of delivery or surveillance tasks to drones as the task assignment problem.

Overall, the most common objectives in routing for a set of locations include minimizing operational cost [68, 103, 130, 173, 242, 286], minimizing fixed costs (mostly the number of required drones [104, 154, 213, 294]), and minimizing makespan [40, 173, 241, 312]. Several articles consider objectives related to customer service and customer satisfaction, such as expected waiting time of customers for service [73, 204], share of successfully served customer orders [213], total customer satisfaction [104], and resolution of photographed images [21].

4.4 | Planning of data gathering and recharging in a wireless sensor network

A wireless sensor network (WSN) describes a collection of spatially distributed wireless sensors that gather information about the environment and transmit it to the base station. Drones serve as an additional layer between a network of stationary sensors and the base station: spatially distributed sensors gather information about the environment, and drones gather data from stationary sensors and transmit it or carry it back to the base station.

In a number of relevant applications, data gathering from stationary sensors without drones would be slow, cost-prohibitive or even impossible. Therefore, new problems involving routing of drones arise in the modeling of WSNs. For example, underwater gas pipelines, some of which extend for more than 1000 km, are monitored by periodically placed stationary sensors that are difficult to access. Another example is the monitoring of wild animal habitats [301]. Regions impacted by disaster and extreme natural phenomena, such as volcanic activities and bushfires, can be monitored by sensors scattered from an airplane [57]. One promising application is the location of earthquake survivors by a network of sensors able to locate weak signals of mobile phones [67]. In the latter case, data gathering and information transmission to the base station should occur with the shortest possible delay.

In contrast to the routing operations of drones examined in Section 4.3, data gathering operations of drones in WSNs have to respect communication, memory, and data recency constraints. For instance, the communication range is limited and reliability of data transmission depends on the communication distance. Direct information transmission from one node (sensor or drone) of the WSN to another node or the base station is called a hop. Because of the limited communication range, nodes may have to perform a multihop transmission (see Figure 12). The limited memory capacity of drones and sensors is another constraint.

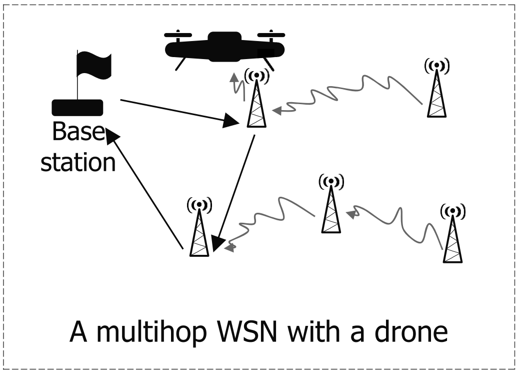

FIGURE 12 Illustration of wireless sensor networks. Straight arrows depict a drone tour, wavy arrows depict communication links

Drones may perform different roles in a network of stationary sensors. For example, they may recharge sensors inductively by generating an electromagnetic field [23]. Existing models of drones can transfer about 5–15 Watts during flight. In simulations of Basha et al. [23], a lifetime increase of 100% to 300% was achieved for medium-sized networks that were recharged in this way. The expected gain depends heavily on the applied recharging policy, and the gain declines with the size of the WSN. Xu et al. [302] derive an optimal trajectory for a drone to recharge two energy receivers.

Another promising application is the use of drones as ferrying nodes, which collect information from stationary sensor nodes and carry it to the base station. This may increase the range of communication and increase the throughput rate because the drone can position itself directly over the sensor to receive data. Ferrying nodes also reduce energy consumption in the WSNs and, thus, prolong the WSN's lifetime because they reduce the number of costly multihop transmissions. Indeed, in conventional multihop transmissions in WSNs, *sink nodes* that are adjacent to the base station run out of power quickly and the WSN becomes disconnected.

Existing models investigate various WSN architectures. Some articles examine *two-hop WSNs* (see Figure 12), in which stationary sensors transmit the collected information directly to drones and the drones (serving as ferrying nodes) carry it to the base station [1, 7, 57, 169, 189, 237, 267, 293]. Sahingoz [237] and Mazayev et al. [169] design tours for drones. Abdulla et al. [1] consider drones performing cyclic moves along some given trajectory; in this setting, stationary sensors have to schedule time slots for data transmission to drones. Other articles consider *WSNs with hierarchical data transmission*, where information may have to travel many (more than two) hops via sensors and/or drones before reaching the base station (see Figure 12) [52, 67, 111, 221, 259, 260, 301]. Here, drones collect data only from a subset of sensors (so-called sink nodes or cluster heads), which in turn aggregate data from their neighboring sensors. Most articles propose a hierarchical planning approach: Stationary sensors are clustered first and a node in each cluster is nominated to be the sink node of this cluster, then drone routes over the sink nodes are planned [39, 259]. Liang et al. [150] propose a WSN architecture with a mobile sink node. In each time period, a drone visits some stationary sensor. This sensor assumes the role of a sink node: It aggregates information from all the other stationary sensors in the network and transmits it to the drone. In this way, the role of the sink node gets periodically reassigned. A common problem of WSNs with multihop data transmission is rapid energy depletion of sensors located close to the sink node. By selecting sensors with the highest energy level to be the sink nodes, the drone distributes the energy consumption evenly over sensors and, thus, prolongs the WSN lifetime. Jawhar et al. [117] examine *linear WSNs*, in which stationary sensor nodes are arranged along a straight line. Such WSNs are especially relevant for monitoring of pipeline infrastructure. In Mozaffari et al. [181], drones have to collect information from sensors that are active only within some (potentially unknown) time windows.

Other studies consider WSNs with incomplete information on sensors [67, 117]. The base station may not possess information on the current energy level of stationary nodes, on the number of stationary nodes, or on the amount of the information collected by each stationary node. Stationary nodes may have only some limited information and only on their neighbor nodes, as well. In such a setting, trade-offs between costs, such as additional energy expenditure to collect more information on the state of the WSN, and information delays may arise.

Overall, because data collection and transmission consume the limited energy of sensors and drones, a widely used objective function is to maximize the WSN lifetime, that is, the time interval before the first sensor failure due to energy expiration [23, 150], or maximal energy consumption among sensors to transmit the collected information [318]. Some articles minimize makespan [100], total travel distance of the drone [111] and the energy required for the drone's operations [39, 148].

We refer the interested reader to Akyildiz et al. [4], Yick et al. [310], Younis and Akkaya [311], and Wang and Liu [289] on the issues of node placement and data collection in general WSNs. Table 5 provides an overview of the surveyed articles.

4.5 | Planning allocation of communication links and computing power to mobile devices

To establish connectivity with a drone, a mobile device should be located within its communication range. Therefore, the ensuing planning problems involve decisions about area coverage. However, in contrast to the planning problems examined in Section 4.1, these decisions involve probability theory and nonlinear equations describing communication constraints. For instance, drones have to allocate communication links (and communication time slots) to mobile devices and select such locations that minimize interference and ensure acceptable levels of signal-to-noise ratio. We refer the interested reader to Tse and Viswanath [277] on the fundamentals of wireless communication and provide an overview of the surveyed articles in Table 6.

Different ways of drone employment are possible. First of all, drones may be assigned to stationary locations and serve as intermediaries to connect mobile devices to macrocell base stations (Figure 13a). The set of potential locations may be specified in advance. Secondly, instead of staying in a fixed location, a drone may fly, for example, along a cyclic trajectory (Figure 13b). Thirdly, drone-to-drone transmissions may take place so that a mobile device connected to one drone may establish links to a mobile device connected to another drone (Figure 13c).

Research has considered the placement of several drones into stationary positions over some area of interest, which is closely related to the so-called disc coverage problem, but considers communication constraints [156, 160, 177–179, 247]. Coordinates of users may be known in advance [13]. Mozaffari et al. [180] consider a drone providing communication to mobile devices in households. Simultaneously, these households may be making use of device-to-device communication, which causes signal interferences. Given assumptions on the distribution of device-to-device communication channels and of mobile devices, the authors analyze the cases of stationary deployment of a drone and of mobile deployment of a drone that pauses during flight to perform transmission services. Chetlur and Dhillon [46] derive analytic formulas for the coverage probability of an arbitrarily located user (eg, of a mobile cellular phone) by a network of randomly positioned drones.

Alternatively, a set of potential locations for drones may be given and drones must be assigned to a subset of these locations [290]. In Mozaffari et al. [183], the positions of drones are known and fixed. The authors partition a given geographical area into disjoint regions associated with each drone, taking into account the distribution density of the users. Al-Hourani et al. [5] determine an optimal altitude of a drone, positioned at given x, y-coordinates, to maximize radio coverage.

Some researchers take flying trajectories of drones into account [85, 88, 119, 120, 123, 159, 313]. In a number of papers, each user receives particular time slots to exchange information with the drone (so-called time-division multiple access (TDMA)). These papers consider scheduling a drone's communication with ground mobile devices [159] and optimizing the trajectory of the drone [297, 298]. Jeong et al. [119] schedule data computation by a drone serving as a cloudlet as well as data transmission between the cloudlet and a mobile device to minimize the total energy expenditure of the drone given its fixed trajectory. The case of moving mobile user nodes is analyzed in Fotouhi et al. [85] and Jiang and Swindlehurst [123]. Zeng and Zhang [313] point out the importance of considering the propulsion energy spent on flight or hovering as it is usually several times greater than the energy spent on communication. The authors calculate optimal flying trajectories for a fixed-wing drone that has to maintain communication with a stationary ground station. Galkin et al. [88] derive analytic formulas for an optimal altitude of a randomly moving network of drones to maximize the coverage probability for the stationary user.

Serving as flying base stations, several loitering drones may form a multihop communication network, in which a mobile device connected with one drone may transmit data to a mobile device connected to some other drone in the network [77, 98, 99, 248]. Some articles also optimize allocation of limited transmission power between the source node and drones (as relay nodes) to improve communication quality [147, 314].

If drones belong to different providers, they compete with each other for users as selfish strategic players and game-theoretic applications arise. In Koulali et al. [137], mobile devices perform only passive scanning: They wait for welcome messages from drones and establish a link with the sender of the first message received. Knowing the probability distribution for locations of mobile devices, drones have to decide on the duration and starting points of their beaconing intervals: The longer the beaconing intervals are, the larger the probability of encountering users, but energy consumption increases as well.

The most common objectives in this section relate to minimizing cost and maximizing the quality of customer service. The communications provider must assign locations to drones so that the desired mobile connectivity is achieved at minimum cost [290] or with the minimum number of drones [160]. Because data transmission and setup operations to establish links consume the energy of drones, a common objective function is to maximize energy efficiency or minimize energy to achieve the desired communication quality [47]. Alternatively, the number of established communication links [32, 99] and the quality of

TABLE 5 Overview of the surveyed articles: Planning of data gathering and recharging in a wireless sensor network

Publication	Contribution	Subjects of planning	Drone characteristic(s)	Application
[1]	Game P, Game H, Exp	drone	communication constraints (eg, signal strength depends on distance, adaptive modulation)	general
[7]	H, Exp	drone	limited communication range	general
[23]	Exp	drone	discussed: limited recharging capability of the drone	general
[39]	MH, Exp	drone	energy consumption function (depends on data transmission and traveled distance), limited communication range	general
[52]	Control, EmpCS, Exp	drone	equations of motion (minimum turning radius, influence of wind, uncertainty in motion), communication constraints	general
[57]	H, Exp	several drones	limited communication range	other (environmental protection and disaster management)
[67]	H, Exp	drone	communication constraints (eg, limited communication range, data collection with help of mobile agents)	other (rescue)
[100]	M, Exp	several drones	limited buffer size for saving data, communication constraints (eg, limited communication range, limited incoming and outcoming data rates), equations of motion	infrastructure & construction, environmental protection and disaster management
[111]	MH, Exp	drone	equations of motion (minimum turning radius, influence of wind), limited communication range	other (environmental protection and disaster management)
[117]	H, Exp	drone	adaptable travel speed, communication constraints (limited communication range), limited data storage capacity	infrastructure & construction, security
[148]	M, H, Exp	several drones	communication constraints (eg, given set of possible modulation levels for message transmission, maximum transmit power), parameters of energy consumption	other (environmental protection and disaster management)
[150]	H, Exp	drone	limited flight distance, limited communication range	general
[169]	M, H, Exp	several drones	limited buffer size for saving data, limited communication range	general
[181]	M, P, LR, H, Exp	several drones	communication constraints (eg, probability of successful transmission depends on distance, limited communication range), energy consumption function (limited energy, energy consumption depends on velocity vector)	telecommunications
[189]	Control, MH, Exp	drone	limited energy, communication constraint (eg, limited communication range, message interferences are possible, communication delays)	other (utilities)
[221]	Exp	drone	limited communication range	general
[237]	MH	several drones	drone's trajectory is a smooth (Bezier) curve, limited communication range, upper and lower bound on the number of sensor, from which a drone can collect the data	general

(*Continued*)

TABLE 5 (Continued)

Publication	Contribution	Subjects of planning	Drone characteristic(s)	Application
[259]	M, MH, Exp	drone	limited flight time, communication constraints (limited communication range, limited communication rate)	general
[260]	M, H, Exp	drone	minimum turning radius, limited communication range	general
[267]	M, BnC, Exp	several drones	minimum turning radius, communication constraints (limited communication range, speed to establish a communication link and to transmit data depends on the drone-to-sensor assignment)	general
[293]	P	several drones	communication constraints (eg, time-division multiple access (TDMA) channel access method, exponential law for the path loss)	general
[301]	H, Exp	drone	limited communication range	other (wild life monitoring)
[302]	M, E, Exp	drone	limited flight time, maximum speed, limited communication range, energy transmission constraints (channel power gain depends on the distance between the drone and the energy receiver, given transmission power)	general
[318]	M, H, Exp	drone	communication parameters (distribution of the fading coefficients)	general

communication [229, 316], such as packet transmission delay [147, 182] or the coverage probability [5, 88], should be optimized given limited resources, such as the limited energy of the drone.

4.6 | Operational aspects of a self-organizing network of drones

In some drone operations, in which communication is an issue and the base station needs to obtain recent collected information with the shortest possible delays, we may treat a set of drones as a flying wireless ad hoc network.

A flying ad-hoc network (FANET) is a dynamically self-organizing network of drones that may utilize direct drone-to-drone communication [238]. FANET may be involved in any of the drone operations described in Sections 4.1–4.5. Direct drone-to-drone communication may have several advantages. First, since the speed of direct data transmission between two nodes is usually faster than the flying speed of a drone, multihop transmissions to the base station may increase the recency of the received information from drones that are out of the direct communication range. It may also free up the limited buffer size of the drone for further data collection [100, 101]. Second, communication between drones is important for flying in formation [217]. Third, users can reduce the payload of some drones and economize on cost by equipping only select drones with the hardware enabling direct long-distance communication with the base station or satellites [24]. Fourth, because of the limited communication range, several drones may be required to provide connectivity to mobile devices [77, 98, 99, 248]. Literature surveys on communication protocols in FANETs can be found in Bekmezci et al. [24] and Sahingoz [238]. We refer the interested reader to Jawhar et al. [116] for an overview of communication and networking aspects of drone-based systems.

We do not include articles in this section where FANET performs operations described in Sections 4.1–4.5. For example, Gu et al. [101] describe coverage path planning operations of micro drones in which one of the objective functions is to minimize information delay. Besides deciding on coverage paths of drones, the authors schedule drone dispatch times so that drones occupy optimum locations relative to each other to enable fast message transmission to the base station. Another example is found in Vilar and Shin [288], who considers recognition and mapping of important facilities in urban environments. Communication between drones is limited by the communication range and is only possible within visual line of sight. The authors formulate the multiple TSP to assign surveillance tasks to a subset of drones and place the remaining drones as relays to establish communication links with the ground station.

TABLE 6 Overview of the surveyed articles: Allocating communication links and computing power to mobile devices

Publication	Contribution	Subjects of planning	Drone characteristic(s)	Application
[5]	E, Exp	drone	communication constraints (eg, path loss depends on the distance between the drone and the receiver, probability of line-of-sight communication depends on distribution of buildings' heights, density of buildings, distance between transmitter and receiver, threshold on the path loss)	other (disaster management)
[13]	M, E, Exp	drone	communication constraints (eg, path loss depends on the distance between the drone and the receiver, probability of line-of-sight communication depends on drone's altitude and the distance between transmitter and receiver, threshold on the path loss, given transmission power of the drone)	telecommunications
[32]	M, E, Exp	several drones	communication constraints (eg, limited communication range, threshold for the signal-to-noise ratio, given transmission power, altitude-dependent probability of line-of-sight communication)	telecommunications
[46]	P, Exp	several drones	communication constraints (eg, Nakagami-*m* fading for wireless links, signal-to-noise ratio depends on transmission power, distance between source and sink of the transmission and interferences from other transmissions)	general
[47]	E, H, Exp	drone	minimum turning radius, equations of motion, communication constraints (eg, limited communication range), energy consumption equations, signal-to-noise equations	general
[77]	Control, EmpCS, Exp	several drones	communication restrictions (eg, adaptive modulation scheme, transmitted signal depends on distance)	other (disaster management)
[85]	Game H, H, EmpCS, Exp	several drones	communication constraints (eg, limited communication range, fixed transmission power, interference is possible, probability of having a line-of-sight connection depends on the elevation angle of the transmission link, scenarios of the bandwidth allocation (equal, greedy)) constant speed, minimum turning radius	telecommunications
[88]	P, Exp	several drones	communication constraints (eg, Nakagama-*m* fading, building density, drone antenna beamwidth, transmission power, interference is possible)	telecommunications
[98]	M, Decentral H, Exp	several drones	limited communication range, communication loss depending on the transmission distance, equations of motion	general
[99]	M, Exp	several drones	limited communication range, equations of motion, fuel consumption depends on velocity, acceleration, altitude	infrastructure & construction, environmental protection and disaster management
[119]	M, LR, E, Exp	drone	communication constraints (limited communication range, limited bandwidth, information loss depends on distance), energy consumption equations (it depends, eg, on CPU frequency, amount of transmitted information)	telecommunications

(*Continued*)

TABLE 6 (Continued)

Publication	Contribution	Subjects of planning	Drone characteristic(s)	Application
[120]	M, BnB, H, Exp	drone	limited energy, maximum speed, energy consumption depends on data transmission and processing, flying speed and acceleration, limited communication range	telecommunications
[123]	M, P, Bnd, H, Exp	drone	communication constraints (eg, space-division multiple access (SDMA) or time-division multiple access (TDMA) channel access methods, correlated Rician fading for wireless links, mutual interference depends on the correlation between the users' channel vectors, maximum number of active uplink users), minimum turning radius	general
[137]	Game P, Game H, Exp	several drones	limited energy capacity, energy consumption function (eg, depends on the length of the beaconing interval), limited communication range	telecommunications
[147]	M, P, E, Exp	several drones	communication constraints (Rayleigh fading model for both desired signal and interference, transmission success between mobile device and drone is a random variable)	telecommunications
[156]	E, Exp	several drones	communication constraints (eg, given transmission power, path loss depends on the distance between the user and the drone, no interference)	telecommunications
[159]	P, Exp	drone	limited communication range, instantaneous channel capacity from the drone to a sensor depends on the distance between them	general
[160]	H, Exp	several drones	limited communication range	general
[177]	P, Exp	drone, several drones	communication constraints (eg, path loss depends on the distance between the drone and the receiver, altitude-dependent probability to have a line-of-sight connection, cases of no interference and full interference, threshold for the signal-to-noise ratio)	general
[178]	M, P, H, Exp	several drones	communication constraints (eg, downlink coverage probability that depends on altitude and on the antenna gain, random shadow fading coefficients for line-of-sight and non-line-of-sight links)	general
[179]	P, H, Exp	several drones	communication constraints (eg, no interference between drones, transmission rate depends on transmission power, average path loss and transmission power)	general
[180]	P, Bnd, H, Exp	drone	communication constraints (eg, Rayleigh fading channel model for device-to-device transmissions, required signal-to-noise ratio threshold, given transmission power, random additional attenuation factor in case of the non-lign-of-sight connection, FDMA technology for establishing links with drone in parallel)	general
[182]	M, E, Exp	several drones	communication constraints (eg, frequency division multiple access, path loss depends on the distance and obstacles along the path)	telecommunications
[183]	M, P, E, Exp		limited flight time, communication constraints (limited communication range, interferences, signal quality depends on distance)	general

(*Continued*)

TABLE 6 (Continued)

Publication	Contribution	Subjects of planning	Drone characteristic(s)	Application
[229]	MH, Exp	several drones	communication constraints (eg, random frequency hopping, signal-to-noise ratio depends on the distance between the drone and the receiver as well as the distance to the macro cell base station, free space propagation)	telecommunications
[247]	H, Exp	several drones	communication constraints (eg, signal-to-noise ratio depends on transmission power, distance between source and sink of the transmission and interferences from other transmissions)	telecommunications
[290]	M, MH, Exp	several drones	limited communication range, limited capacity on the number of (down)links	general
[298]	M, P, H, Exp	drone	communication constraints (eg, time-division multiple access (TDMA) channel access method, free-space path loss model for channel gain, given transmission power), motion constraints (eg, given altitude, maximum speed)	telecommunications
[313]	P, E, Exp	drone	communication constraints (free-space path loss model), propulsion energy consumption (eg, depends on speed and acceleration)	general
[297]	M, P, H, Exp	several drones	communication constraints (eg, time division multiple access (TDMA), free-space path loss, interferences are possible), maximum speed	general
[314]	M, P, H, E, Exp	drone	constant speed, communication constraints (free-space path loss model for the channel power)	general
[316]	E, Control, EmpCS, Exp	several drones	minimum turning radius, communication constraints (eg, limited communication range, signal strength depends on distance)	general

Several articles examine *general* problems of FANETs that are not related to any specific operation described in Sections 4.1–4.5 (see an overview of these articles in Table 7). For instance, Oliveira [201] and Díaz-Báñez et al. [65] schedule relative positioning of drones in a FANET to maximize the total connection time, whereas Navaravong et al. [187] minimize total traffic (traffic intensity multiplied by the transmission distance). Aloul and Kandasamy [10] and Koupaei and Abdechiri [138] optimize fault diagnoses of the nodes of the FANET. Indeed, to maintain a stable spatial formation, drones should regularly exchange information on their positions and velocities. In case of hardware failures, some of these messages may be false. Therefore, in Koupaei and Abdechiri [138], velocities and positions of each drone should be verified by the given number of neighbors. Since

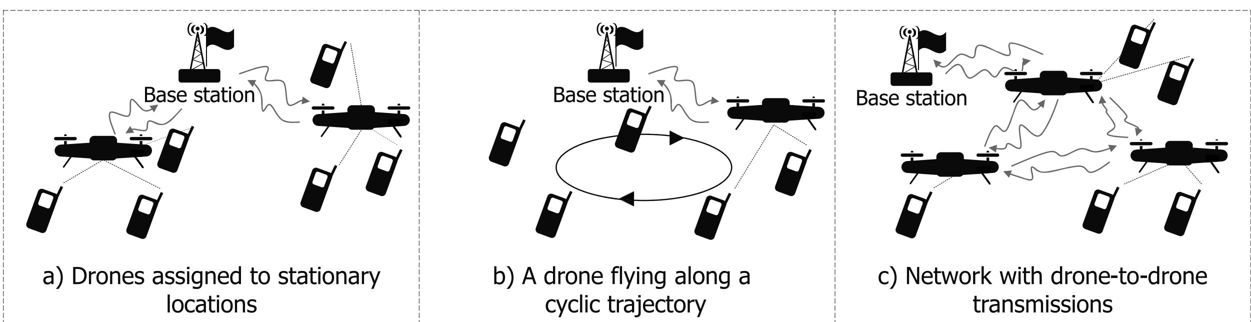

FIGURE 13 Illustration of drone operations to allocate communication links and computing power to mobile devices

TABLE 7 Overview of the surveyed articles: Operations of a self-organizing network of drones

Publication	Contribution	Subjects of planning	Drone characteristic(s)	Application
[10]	M, Exp	several drones	testing range	general
[65]	P, H, EmpCS, Exp	several drones	limited communication range	general
[138]	MH, Exp	several drones	limited communication range, limited testing range	general
[187]	H, BnB, Exp	several drones	communication constraints (limited communication distance), limited energy	general
[201]	M, P, DP, H, Exp	several drones	limited flight distance	general

communication and sensing ranges of drones differ, a problem of optimal assignment of drones to the given set of potential positions arises.

5 | PLANNING COMBINED OPERATIONS OF DRONES WITH OTHER VEHICLES

Micro, mini, and small drones, which are popular in civil applications, can spend only a very limited time airborne. Therefore, combining drones with other robots or means of transportation leads to a significant increase of efficiency and effectiveness in performing the desired operations. For the sake of brevity, we refer to robots and means of transportation other than drones as *vehicles* in this section.

Most of the surveyed articles that involve combined operations examine routing for a set of locations (see Section 4.3). Routing operations may take place in uncertain, dynamic environments, such as monitoring of disaster regions or suppression of wildfires [212, 287, 296]. Only a few articles consider other operations, such as area coverage [262, 274] (see Section 4.1) and use of drones to expand connectivity of ground vehicles [122, 141, 200, 248] (see Section 4.5). Presumably, this situation can be explained by the prominence of delivery applications in the media, which may overshadow some other interesting applications. Indeed, in the future, drones may potentially be supported, for instance, by ships in search operations [70] (see Section 4.2) and in gathering data from sensors monitoring underwater pipes (see Section 4.4). Such operations, in which the ships will serve as carriers and moving refueling depots, will also require combined operations planning.

In this section, we classify articles according to the roles assigned to drones and vehicles in combined operations. For instance, both drones and vehicles may work in parallel and their operations may have (almost) equal priority. Alternatively, either drones (or vehicles) may serve as the main performance driver in combined operations. In this case, optimization problems on combined operations will often describe only the drone's (or vehicle's) objectives—since they have priority—and model vehicle (or drone) operations as constraints because they play a supporting role. In hierarchical planning, operations of the main performance driver (the drone or the vehicle) will be optimized first and taken as given in planning operations of the other working unit (the vehicle or the drone).

In the combined operations of drones and vehicles, synchronization may or may not be required. In many applications, some synchronization is necessary, for example, when a drone has to wait for its low-speed carrier. No synchronization is required, on the other hand, if drones and vehicles perform independent tasks, such as independent deliveries from the central warehouse [186] or if operations of either drones or vehicles are fixed as input data in the model [165, 274]. Overall, many new optimization problems seem to arise from the need to synchronize operations of drones and other vehicles.

Also in this operation type, most common objectives aim at minimizing the makespan (eg, completion time of a route) [3, 41, 186, 243, 271, 292] and the cost [37, 167, 271], such as energy consumption [287] or the number of required drones [122]. Campbell et al. [37] introduce fixed costs for each truck and for each drone stop. Several articles aim at optimizing customer service, in particular via the number of delivered customer orders [244], number of performed sensor measurements [274], and, in the case of drones serving as relays, communication performance [141, 296]. Objective functions may regulate cooperation of drones and other vehicles. For example, Viguria et al. [287] penalizes situations when a single task (eg, observation) is shared among several robots.

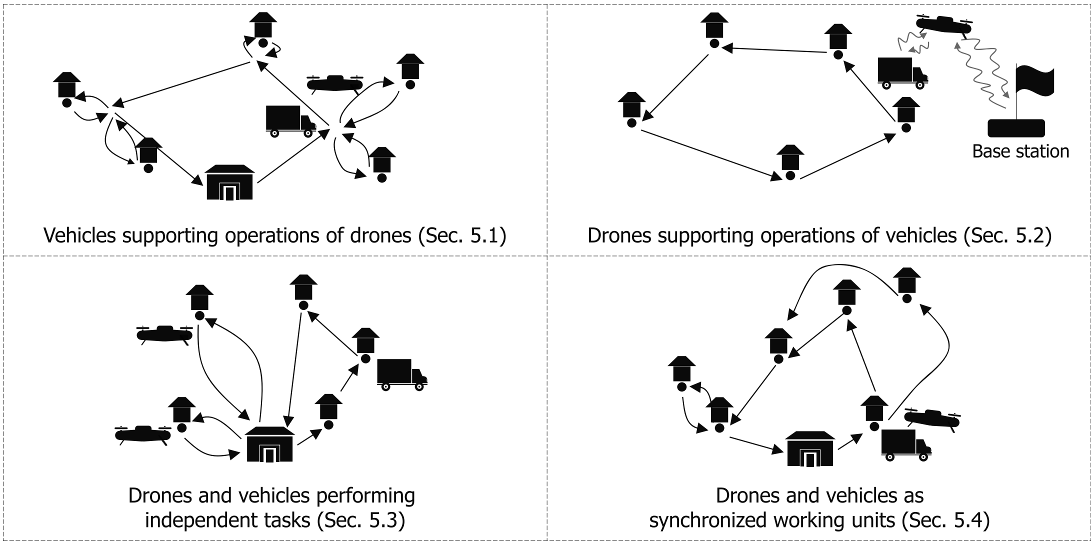

FIGURE 14 Illustrative examples of different types of combined operations. Straight arrows depict trajectories of the vehicle, bending arrows depict trajectories of the drones, small homes correspond to customer locations, larger facilities correspond to depots

In Sections 5.1 and 5.2, we survey problems in which either drones or vehicles, respectively, serve as the main performance driver in combined operations. Afterward, we look at articles where drones and vehicles perform tasks in parallel, either without (Section 5.3) or with synchronization (Section 5.4) (see Figure 14).

Table 8 lists articles according to the roles of drones and vehicles in combined operations and Table 9 provides an overview of the surveyed articles.

5.1 | Vehicles supporting operations of drones

Combined operations with vehicles as supporting units fit a variety of applications, including precision agriculture, package delivery, rescue operations, oceanographic sampling, and forest fire or oil spill monitoring. As a rule, the support vehicle is slower, but can travel for a longer time than the drone. In a common modeling approach, the drone may land on the support vehicle to traverse some distance without expending energy. For example, in Tokekar et al. [274], an unmanned ground vehicle (UGV) can carry a drone, which has to take aerial images of as many points of interest as possible to gather information for classification of soils based on nitrogen level. In this scenario, the drone does not refuel or recharge on the UGV. The UGV's speed is assumed to be enough to pick up the drone at any location and at the most suitable time, so that the drone does not have to wait for the UGV. The authors model the resulting problem as an orienteering problem (see Section 4.1.2).

Other studies consider different drone/vehicle relationships. In Luo et al. [158], Mathew et al. [167] and Garone et al. [89], a drone recharges each time it lands on the support vehicle. In a common setting in delivery operations, a drone delivers one package per sortie to customers located at the nodes of a graph [81, 167]. The support truck cannot perform deliveries; it just transports the drone to some nearby street node within the drone's range of flight. The objective of Mathew et al. [167] is to find paths for the drone and the truck that minimize the total delivery cost; thus, possible waiting times of the drone for the truck are not relevant. The authors transform the resulting problem into the asymmetric TSP. Garone et al. [89] describe a sea rescue scenario in which a drone has to visit a given set of visit points. The authors model the resulting problem in continuous space, where the low speed of the carrier restricts its possible meeting points with the drone. They prove that if the sequence of

TABLE 8 Surveyed articles according to the roles of drones and vehicles in combined operations

	Drones as the main performance driver (Section 5.1)	Vehicles as the main performance driver (Section 5.2)	Drones and vehicles as equally important working units (Sections 5.3–5.4)
Synchronization	[89,158,312]	[262]	[3,37,41,58,106,140,186,215,287,292]
No synchronization	[81,165–167,274]	[78,122,141,200,243,244,248]	[82,186,212,271,281,296]

TABLE 9 Planning combined operations of drones with other vehicles

Publication	Contribution	Subjects of planning	Drone characteristic(s)	Application
Vehicles supporting operations of drones ***(Section 5.1)***				
[81]	MH, H, Exp	several drones, truck	delivery of 1 package per sortie	transport
[89]	M, P, H, Exp	drone, carrier	limited flight time	other (rescue)
[158]	M, H, Exp	drone, truck	limited flight time	general
[165]	M, P, Exp	drones, recharging robots	limited energy	general
[166]	M, P, H, Exp	drones, recharging robots	limited energy	general
[167]	P, Exp	drone, UGV	limited flight time, delivery of 1 package per sortie	transport
[274]	P, H, EmpCS, Exp	drone, UGV	limited flight time, setup times for landing and takeoff	agriculture
[312]	P, EmpCS, Exp	drone, UGV	limited energy	transport
Drones supporting operations of vehicles ***(Section 5.2)***				
[78]	P, Exp	several drones, several passenger vehicles	limited communication range	telecommunications
[122]	E, Exp	drone, several drones, several rescue vehicles	communication constraints (eg, limited communication range, required connectivity threshold, given transmission power, shadow fading with normal distribution that depends on the elevation angle)	other (environmental protection and disaster management)
[141]	Decentral MH, Exp	several drones, ground vehicles	equations of motion, communication constraints (probability of successful communication depends on, eg, noise and distance)	general
[200]	M, Decentral H, H, Exp	several drones, ground vehicles	minimum turning radius, limited flight time	general
[243]	MH, H, Exp	drone, truck		general
[244]	MH, H, Exp	drone, truck	limited flight distance	general
[248]	MH, Exp	several drones, UGVs	communication constraints	general
[262]	H, Exp	drone, several autonomous underwater vehicles	limited flight time	other (environmental protection and disaster management)
Drones and vehicles performing independent tasks ***(Section 5.3)***				
[82]	M, H, MH, Exp	several drones, several off-load trucks	1 package per delivery	other (environmental protection and disaster management)
[186]	M, H, Exp	several drones, truck	limited flight time, delivery of 1 package per sortie	transport
[212]	M, Control	drones, UGVs, airship	limited water tank	other (environmental protection and disaster management)

(*Continued*)

TABLE 9 (Continued)

Publication	Contribution	Subjects of planning	Drone characteristic(s)	Application
[271]	M, Exp	drone, several trucks	limited payload	transport
[281]	DP, Exp	several drones, trucks	limited payload, limited energy	transport
[296]	Decentral MH, Decentral H, Exp, Control	several drones, airships, satellites	limited flight distance, limited energy	other (environmental protection and disaster management)
Drones and vehicles as synchronized working units *(Section 5.4)*				
[3]	M, P, H, Exp	drone, truck	limited flight time, delivery of 1 package per sortie	transport
[37]	P, Exp	drone or several drones, truck	delivery of 1 package per sortie	transport
[41]	P, Exp	drone, truck	delivery of 1 package per sortie	transport
[58]	MH, Exp	several drones, trucks	delivery of 1 package per sortie, limited flight distance	transport
[106]	M, H, MH, Exp	drone, truck	delivery of 1 package per sortie	transport
[140]	H, Exp	drone, truck	one package per sortie, function of energy expenditure (depends on the velocity vector of the wind and on the velocity vector of the drone), limited energy	transport
[186]	M, H, Exp	drone or several drones, truck	limited flight time, delivery of 1 package per sortie	transport
[215]	P	several drones, trucks	limited flight time, delivery of 1 package per sortie	transport
[287]	Decentral H, EmpCS, Exp	several drones, UGVs	a general framework: no specific drone characteristics are formulated	other (environmental protection and disaster management)
[292]	P	several drones, several trucks	limited flight time, delivery of 1 package per sortie	transport

visits is given as well as the positions of the landings/takeoffs of the drone within this sequence of visits, a convex optimization problem arises. In Yu et al. [312], a battery recharge takes some time, and, while the UGV is traveling, a drone may recharge its battery after landing on the UGV.

Mathew et al. [165, 166] consider drones supported by a set of mobile recharging robots. Motions of the drones are taken as given, and recharging may occur only within some time window specified for each drone. The objective is to find paths of the recharging robots with minimum total cost so that each drone meets one of the robots exactly once within its specified time window. The authors discretize time and space to transform the resulting problem into a one-in-a-set VRP.

5.2 | Drones supporting operations of vehicles

Drones may serve as support units for a mobile depot. In Savuran and Karakaya [243, 244], the trajectory and speed of the mobile carrier is taken as a given (ie, it has priority). A drone takes off from the mobile carrier, serves as many customers as possible, and has to land on the mobile carrier at the end of its sortie. If the flight range of the drone is long enough, the objective could be to minimize the total cost of the drone's tour [243]; otherwise the number of customers served must be maximized [244]. Although the formulated problem seems very restrictive, it may find important applications in future planning of floating warehouses [171].

In Sujit et al. [262], a drone supports operations of autonomous underwater vehicles (AUVs) exploring the ocean. The drone periodically performs a tour from the base to visit all the AUVs, collecting information and instructing them on their next exploration paths and the next meeting points. A trade-off arises between selecting AUV paths with the largest information collection potential and adhering to a set of feasible meeting points limited by the endurance in time of the drone.

Drones may also provide communication to ground vehicles. For instance, as communication relays, they may connect vehicles, for example, rescue vehicles, to the ground control station and with each other [78, 122, 141, 200, 248].

5.3 | Drones and vehicles performing independent tasks

In some delivery applications, drones and vehicles perform independent tasks without the need of synchronization [82, 186, 281]. One example is a study by Murray and Chu [186], who set up a delivery problem with customers located in close proximity to a warehouse. Drones and a truck pick up packages at the warehouse to deliver them to customers. Packages may be delivered either by drone, which transports a maximum of one package per sortie, or by truck, which can transport several packages but moves at a slower speed. Drones cannot land on the truck and must return to the warehouse to pick up another package. The objective is to determine the required number of drones and find tours for the truck and for the drones that minimize makespan. Ulmer and Thomas [281] investigate the same-day delivery setting, in which randomly arriving customer orders should be accepted or declined for same-day delivery by the logistics provider. Deliveries can be performed either by vehicles or by drones. Tavana et al. [271] consider parallel operations of trucks and drones in cross-docking with the objective of minimizing completion time. Drones may deliver orders directly from a supplier to a customer, but can carry only a very limited payload. As an alternative, trucks have a much larger carrying capacity, but they have to transport the orders indirectly via an interim warehouse, called cross-dock, where goods are unloaded, re-bundled into vehicle loads based on their destination, and loaded onto new vehicles (see [34] on cross-docking), which takes much time because of the reloading of the goods and the limited capacity of the cross-dock.

Several articles examine task assignment to heterogeneous vehicles in disaster management applications [212, 296]. For example, Wu et al. [296] propose a coordination framework to assign observational tasks to drones, airships, and satellites while taking strengths and constraints of each observational resource into account. In Phan and Liu [212], a set of drones and a set of unmanned ground vehicles controlled by an airship must cooperatively predict fire spread rates and drop water to extinguish the fire.

5.4 | Drones and vehicles as synchronized working units

Synchronization is usually required whenever a drone needs to land on a truck. Because of limited speeds of the drone and the truck, situations arise in which one vehicle must wait for the other one.

Murray and Chu [186], Agatz et al. [3], and Ha et al. [106] formulate the TSP with a drone, or a flying sidekick TSP. A truck equipped with a drone performs a tour to deliver packages from a central warehouse to customers. From time to time, the drone takes a package, delivers it to one of the customers and returns to the truck to recharge its batteries [140]. The maximum flight time of the drone's flight is limited. Because of the required setup operations performed by the driver, the drone can take off and land only while the truck visits a customer node. Murray and Chu [186] demonstrate in computational experiments that the latter requirement may result in substantial synchronization costs when the drone and the truck have to wait for each other.

Wang et al. [292] and Poikonen et al. [215] extended the problem setting to the VRP with a drone. They perform worst-case analyses; for example, they estimate the best possible reduction in delivery completion time if truck operations are combined with drone operations compared to truck operations only. The authors prove that even if each truck is equipped with only one drone, if drones and trucks follow the street network and if the drone speed is the same as the speed of the truck, combined operations of delivery trucks and drones may halve the delivery time in some applications. The derived bounds are similar to Amdahl's law on the maximum speed-up potential for computer programs via parallelization [14]. Poikonen et al. [215] also examine maximum potential savings in the case of different distance metrics for trucks and drones, in the case of a limited battery life, and for a general objective function that considers not only the makespan, but also variable costs of truck and drone deployment per unit of time. The authors also establish connections between the VRP with a drone and the well-studied min–max vehicle routing and the min–max close-enough VRPs.

Carlsson and Song [41] and Campbell et al. [37] use continuous approximation methods to derive analytical formulas for the *expected* delivery cost and times by assuming a continuous distribution of customer locations in 2D space. Campbell et al. [37] model truck travel with the L1 (Manhattan) metric and drone travel with the L2 (Euclidean) metric. For the case of the random and independent distribution of customers in space (ie, the Poisson distribution), the authors have demonstrated substantial savings on delivery cost (of about 10% to 40% in a realistic setting) if deliveries are performed by a truck equipped with a drone.

In Daknama and Kraus [58], drones may land on any truck, provided this truck is parking in one of the specified safe locations (nodes of the graph). The authors test several metaheuristics that schedule delivery trucks and drones. Viguria et al. [287] consider fire detection and extinguishing operations, where ground robots can provide a lift for a drone.

6 | STRATEGIC, TACTICAL, AND OPERATIONAL ISSUES LINKED TO DRONE OPERATIONS

To enable successful operations of drones, a number of strategic and operational decisions have to be made (see Figure 15). *Strategic decisions* include decisions on the integration of drone into the civil airspace (Section 6.1) and decisions on physical infrastructure, such as on positioning of depots and recharging stations (Section 6.2). Logistic operators and disaster response teams have to decide on fleet compositions, such as the number, design, and equipment of drones, as well as of other robots and vehicles. *Tactical and operational decisions* include decisions on the scheduling of refueling, recharging or battery swap processes at recharging stations, scheduling of drone servicing in depots and warehouses, scheduling human experts who will assess the collected critical information on the fly, and scheduling (predictive) maintenance of drones. In the years to come, we expect that widespread use of drone technology in civil applications will lead to a substantial amount of research on optimization problems related to these decisions. Table 10 provides an overview of the surveyed articles.

6.1 | Integration of drones into the civil airspace

Proposed concepts for integration of drone operations within civil airspace include drone-only zones or corridors and shared airspace with piloted aircraft. In any of these cases, integration of drones into the civil airspace will require development of suitable air traffic rules and management concepts, as well as collision and dynamic automated path replanning capabilities for individual drones. These approaches, for instance, may specify a set of conflict-resolving rules (eg, right-of-way rules), types of surveillance (eg, aircraft positions are determined by central radar or based on information broadcasted by aircraft), and types of coordination (ie, whether aircraft can communicate with each other in case of conflict). We refer the interested reader to the surveys of Jenie et al. [118] on conflict detection and resolution approaches and of Pham et al. [211] on collision avoidance systems.

Chen et al. [45] investigate drone-only air highways. The authors argue that although air highways will potentially increase the travel distances for drones, they offer major advantages by avoiding (reducing) multiway conflicts and, thus, reducing the likelihood of collisions. Chen et al. [45] offer a methodology to determine location of an air highway and propose control strategies for drones when they join the highway traffic and travel as leaders or followers of emerging platoons. Richert and

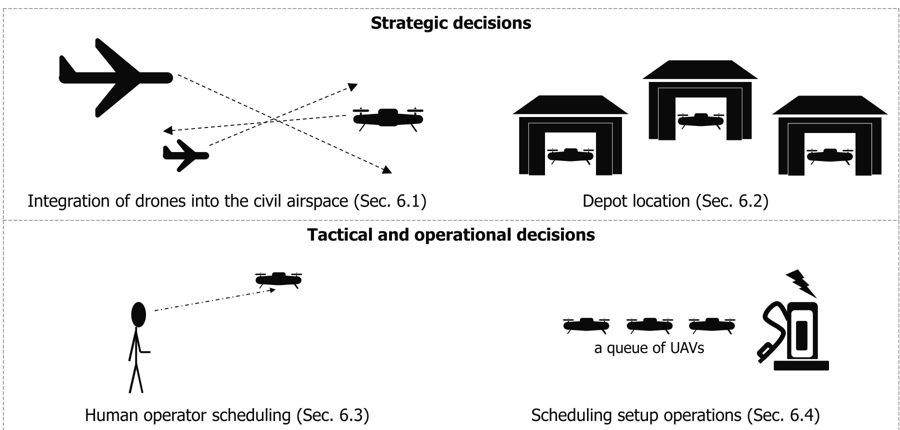

FIGURE 15 Strategic, tactical, and operational issues linked to drone operations: Visual guidance to Section 6

TABLE 10 Strategic, tactical, and operational issues linked to drone operations

Publication	Contribution	Subjects of planning	Drone characteristic(s)	Application
Integration of drones into the civil airspace ***(Section 6.1)***				
[45]	M, Game P, Exp	several drones	equations of motion	other (air traffic management)
[86]	M, H, BnC, CP, Exp	drone	maximum rate of climb, maximum rate of descent	other (air traffic management)
[209]	MH, Exp	drone	equations of motion	other (air traffic management)
[225]	M, P, Exp	several drones	fuel consumption function (eg, less fuel consumption in wind shadow)	general
Location of physical infrastructure ***(Section 6.2)***				
[50]	M, H, Exp	several drones, several trucks	energy expenditure depends on acceleration, payload, turning, kind of movements (climbing, descending, hovering), limited flying distance	other (disaster management)
[82]	M, H, MH, Exp	several drones, several off-load trucks	1 package per delivery	other (disaster management)
[93]	M, MH, Exp	several drones	limited flight distance, limited payload	other (disaster management)
[113]	M, MH, Exp	several drones	limited energy, energy consumption is higher if the drone is carrying a package, delivery of 1 package per sortie	transport
[131]	M, BnB, H, Exp	several drones	limited flight time	general
[133]	LR, H, Exp	several drones	limited flight distance	transport
[263]	M, BnC, Exp	drone	equations of motion (angular velocities), limited sensing range, GPS-denied environment - the drone has to be able to localize itself with help of the landmarks	general
Human operator scheduling ***(Section 6.3)***				
[202]	M, H, Exp	several drones, human operators	minimum turning radius, sensors with a limited footprint	general
[210]	M, H, Exp	several drones, human operators		general
Scheduling setup operations ***(Section 6.4)***				
[126]	DP, H, Exp	several drones	limited energy	general, military
[232]	M, H, EmpCS, Exp	several drones		general, military

Cortes [225] observe that, similar to platooning for conventional trucks [27, 31], flying in a formation enables the drones that are following the lead drone to consume less energy. Since these benefits are asymmetric, Richert and Cortes [225] examine a game with two strategic independent drones and design a scheme in which one drone proposes a schedule of leader–follower switches to make breaking out from the formation unattractive for both drones at any point in time.

Persiani and Bagassi [209] and Furini et al. [86] assume shared airspace. The authors consider path replanning for a drone as the lowest priority participant in air traffic. Given scheduled routes of piloted aircraft, the drone adjusts its route in order to avoid collisions. These two studies each formulate a time-dependent TSP to sequence a drone's visit points, and determine its trajectory in space and time, considering important properties of motion such as possible ascent and descent angles. Furini et al. [86] formulate a mixed-integer program and work out several well-performing cuts for this problem.

6.2 | Location of physical infrastructure

The existing articles mostly examine the placement of distribution and transfer centers in disaster regions to supply emergency commodities via drones [50, 82, 93]. For example, Golabi et al. [93] study the location of emergency supply facilities given budget limitations and a set of possible disaster scenarios and their probabilities. The scenarios specify possible damage to infrastructure after some disaster, such as an earthquake. Inhabitants living along intact roads (edges of the graph) can travel by themselves to the nearest aid facility, but inhabitants on damaged edges must be supplied by drones. In this case, the limited flight distance of drones poses a major restriction in the problem. Working with similar scenarios, Chowdhury et al. [50] formulate an integrated facility location and VRP. The authors assume that deliveries from emergency supply centers are generally performed by trucks, and drones are involved only if the road infrastructure is damaged. Fikar et al. [82] consider the placement of a limited number of transfer points operated by relief organizations. Such transfer points, equipped with off-road vehicles and drones, dispatch supplies over regions with damaged infrastructure, so that first- and last-mile deliveries are performed with conventional means of transportation over intact roads. Interestingly, off-road vehicles proved to be more beneficial than drones in detailed simulations of two rather densely populated disaster regions in Austria because of the longer unloading and loading duration of the drones. The authors modeled the speed of off-road vehicles and drones to be 45 and 135 km/h and set the loading and unloading operations at 3 and 6 minutes, respectively.

Hong et al. [113] study the placement of recharging stations for delivery drones, and Kim and Morrison [131] consider automatic service centers for drones in a general context. In the latter paper, the authors simultaneously plan tours of drones to perform a given set of tasks and decide on the placement of automatic service centers where the drones can replenish their energy. Sundar et al. [263] decide on positioning of the landmarks, that is, recognizable building structures, to enable localization of drones in a GPS-denied environment. Kim et al. [133] formulate the facility location problem to position drone depots; drones serve patients in the rural area by delivering medicines and picking up blood samples and urine.

Most articles aim at minimizing total cost [50, 133], taking both the fixed cost of opening an additional facility [50, 263] and inventory holding cost [50] into account. In disaster applications, urgency-related objectives, such as average lead time for deliveries [82] and total travel time for people and vehicles [93], gain importance.

6.3 | Human operator scheduling

A number of important civil surveillance applications, such as search and rescue or maintenance inspection, require a human operator who examines the sensory information sent by a drone on the fly. In this case, the drone's operations should consider possible idle time of the human operator, and the operator should have enough time to examine information on each point of interest (PoI). Ortiz et al. [202] propose a heuristic algorithm for path planning for drones in this setting assuming the sequences of PoI visits for each drone are given.

Further, cognitive under- and overloading of human operators is to be avoided by alternating demanding and less demanding tasks appropriately as well as by providing enough rest breaks. In the given time horizon, Peters and Bertuccelli [210] schedule as many monitoring tasks to several operators as possible, given routes and speeds of drones, while penalizing situations of cognitive under- and overloading.

6.4 | Scheduling setup operations

Most publications on scheduling setup operations are motivated by military applications, but their salient points can potentially be extended to civil applications. Since we expect many articles on scheduling civil setup operations in the future, we mention a few articles on military applications in this section to suggest possible research directions to the reader. According to the existing literature, the main trade-off in scheduling setup or maintenance operations of drones, such as refueling, launching, and repair, is to consider the drone's priority to return to its tasks while not burning up fuel by exceeding its maximum waiting time [126, 232]. Jin et al. [126] optimize the refueling sequence for drones at an automatic refueling tank. Ryan et al. [232] collect data on experience-based planning rules applied at aircraft carrier decks and compare them to optimal solutions from integer programming. Similar planning problems may emerge at (mobile) warehouses servicing a fleet of drones, such as *Amazon's* floating warehouse or *Ford's* autolivery [84, 171].

7 | DRONE OPERATIONS: A SOURCE OF NEW OPTIMIZATION PROBLEMS OR A NEW APPLICATION FOR WELL-STUDIED ONES?

Some features of drones, such as the limited payload or the limited flight time, have already been extensively studied in research on capacitated vehicle routing and vehicle routing in the presence of refueling depots [94]. However, based on our survey, we can identify a number of model extensions, as well as new problems motivated by drone research. Examples of these new and challenging problems include, but are not limited to, the TSP with drones (see, eg, Agatz et al. [3], describing combined delivery operations of a drone and a truck) and the cyclical multiple access data transmission scheme (see, eg, Lyu et al. [159], describing a drone collecting information from a set of ground sensors while cycling along a specified trajectory). Instead of listing such problems, we summarize some characteristics of drones in the following that require new operations research methods. Note that such a list cannot be complete, if only because of an ongoing high degree of innovation in drone technologies.

- *Novel modeling aspects related to the specifics of motion*. A number of novel aspects are related to the specifics of flight. A significant difference between operating vehicles and drones is that drones operate in three dimensions while vehicles are restricted to movements on the ground, specifically, to the road network. Furthermore, drones are more sensitive to weather conditions than regular trucks. Thus, the weather adds dynamics and complexity to these emerging optimization problems and drones add flexibility in terms of constructing vertical tours for delivery or inspection.

  In Section 4, we have also discussed the importance of considering equations of motion of the drone and energy consumption, such as the minimum turning radius (Section 4.3) and the number of (sharp) turns (Section 4.1).
- *Novel modeling aspects related to energy consumption and payload*. Energy consumption of the drone heavily depends on the payload, and the weight of the battery (or fuel) contributes a significant share to the total weight of the drone. Interesting novel planning problems may arise from exploiting modularity in the drone's design, and examining tradeoffs in the flight range and the payload of the drone, such as how to equip a team of drones with sensors (of different weights and capabilities) and batteries (of different weights and capacities) (see Section 4.3).
- *Novel modeling aspects related to energy consumption and the quality of sensing*. Observations may be performed from a number of alternative observation points often with trade-offs between the flight distance, the energy consumption, the number of required drones, and the quality of sensing. Recall, for instance, the trade-off between the altitude of flight and the size of the sensor footprint described in Section 4.1.
- *Novel modeling aspects related to communication*. Communication is an essential component of many drone operations, such as data gathering from sensors (Section 4.4), serving as communication relays and flying cloudlets (Section 4.5), especially when a team of drones acts as a FANET (Section 4.6). Incorporating communication aspects into the routing and positioning of drones is a further potential source of methodological innovations.
- *Combined operations with other vehicles*. Drones have to collaborate with other robots and means of transportation in a number of operations (Section 5), which may pose challenging synchronization problems (such as coordination of meeting points).
- *Novel modeling aspects related to the drones as part of the civil airspace*. A number of issues arise in adopting traffic rules and in planning for the civil airspace to incorporate drones, especially if drones are to share the airspace already reserved for aircraft and passenger flights (see Section 6.1).
- *Novel modeling aspects related to the specifics of particular drone deployments*. A number of novel optimization problems will be driven by emerging applications that would be impossible or too expensive without drone technology. These are, for example, path planning for coverage of disconnected, nonconvex areas for the purposes of mapping or surveillance (Section 4.1), energy replenishment and energy-aware data gathering in sensor networks (Section 4.4), and estimating motion of icebergs and ice concentration in the sea (Section 4.2).

8 | CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

In this article, we provide a literature survey on optimization approaches to civil applications of drones. Our goal is to provide a fast point of entry into the topic for interested researchers and operations planning specialists.

As we have discussed in Section 2, drones represent an emerging technology and new ideas and innovations continually appear, such as floating (flying) warehouses [171], automated battery switching [269, 275], and in-flight payload transfer from one drone to another [246]. Although drones are not likely to replace existing technologies, they emerge as yet another option to supplement and complement available vehicles and robots. As unmanned technology, drones open up a number of applications that are currently unattractive because of a high labor cost, such as wildlife monitoring or iceberg tracking. As aerial vehicles, drones may access remote areas quickly notwithstanding the state of the roads. And as flying computers, drones may serve as communication relays or cloudlets. Overall, according to several experts, the largest market potential may be related to drone applications in monitoring of infrastructure and construction sites, agriculture, and delivery applications. In some civil applications, like disaster management, transport of medical supplies or environmental monitoring, drones may even help reduce human injuries and save lives.

It is, therefore, not surprising that planning of drone operations has recently attracted considerable interest and research. Thus, more than 75% of the surveyed articles have been published in the last 5years.

Articles on drone operations primarily belong to engineering-, informatics-, and operations research-oriented outlets. This underscores the high degree of interdisciplinarity of this topic. One important aim of this survey is to bring these communities together. With an eye to an interdisciplinary readership, we provide a short overview of the technical peculiarities of drones (in Section 3) as well as references to some relevant topics in optimization and information technologies (in Sections 4–6).

Based on the literature surveyed, we believe that the following research directions will have the most impact in the coming years:

- As we have discussed in Section 7, drone operations pose new optimization problems and new methodological challenges, which should be addressed in future research. By leveraging state-of-the-art optimization and operations research model formulations and solution methodologies, researchers can obtain better solutions and deeper insights into the emerging problems.
- As discussed above, among the most valuable features of drone technology, and of automated technology in general, is the flexibility of deployment. Therefore, future research should work out *dynamic planning schemes* for a range of relevant drone operations fulfilling a set of desired criteria on average or with a certain guarantee. Future research should also develop *approaches to deal with data uncertainty* [35, 206]. One important source of data uncertainty is the specifics of the drone's motion, susceptibility to weather conditions, and the necessity of dynamic path replanning to avoid collisions.
- More work is needed on strategic and tactical planning issues, such as determination of fleet size and fleet composition. Furthermore, future studies should focus on strategic questions of *drone design* to optimize performance, practicality, and economics. Optimization is a valuable tool to examine the best-case and the expected potential of emerging innovations, and it, thus, can help guide engineers and managers in investment and research decisions. First of all, future studies should evaluate design options for the drones themselves, such as an automatic battery switch. Second, they should analyze alternative designs for systems of drones, other robots and vehicles, and humans, such as an automatic landing capability on a moving truck. Finally, future research should provide guidance on infrastructure development, such as layout of depots and battery recharging stations.
- Whereas the majority of existing studies focus on minimizing completion time [186, 241, 243] or total travel distance [90, 199, 242], operations planning may significantly benefit from *incorporating demand into planning models*. Future research should develop suitable revenue management approaches (such as segmentation and smart pricing) that may shift demand to the most attractive services and, thus, increase the profitability of commercial drone applications.
- It is essential to understand the *economic and social value* of drones in various applications and work out detailed business cases. In particular, future studies should examine how individual beliefs and experience impact purchasing decisions of drone technology and drone services, and the ways in which drones are used as well as the perceived benefits. These inquiries should suggest which types of the drones (eg, fixed-wing drones vs. rotorcrafts, expensive large ones vs. cheap small ones) are most suitable for specific tasks. In a number of

applications, such as delivery of vaccines to children in developing countries, quantifying the trade-offs will be particularly challenging. However, without an in-depth understanding of costs and benefits related to the drone technology, widespread use will be slow to happen.

- More generally, it is important to work out *technological and regulatory solutions that will address public concerns of privacy and safety* without impeding value-creating drone deployment. Overly strict and rigid regulations may drive promising start-ups out of the market and lead to the loss of significant benefits; however, overly lax regulations may risk major accidents when certain drones are allowed to perform operations they are not yet up to. The latter could lead to the erosion of public confidence in this emerging, promising technology. Current challenges, for instance, include development of low cost sense-and-avoid systems that enable drones to "see" unexpected hindrances and safety mechanisms to speedbrake the falling drone in case of an engine failure. Future research should suggest and analyze alternative technological and regulatory solutions. As widespread use of drone technology is impossible without *public acceptance*, honest discussions of the pros and cons of drones should be initiated through the public media to foster understanding and appreciation of the emerging technology.

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