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The Drone Scheduling Problem: A Systematic State-of-the-Art Review

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***Abstract*— Drones are receiving popularity with time due to their advanced mobility. Although they were initially deployed for military purposes, they now have a wide array of applications in various public and private sectors. Further deployment of drones can promote the global economic recovery from the COVID-19 pandemic. Even though drones offer a number of advantages, they have limited flying time and weight carrying capacity. Effective drone schedules may assist with overcoming such limitations. Drone scheduling is associated with optimization of drone flight paths and may include other features, such as determination of arrival time at each node, utilization of drones, battery capacity considerations, and battery recharging considerations. A number of studies on drone scheduling have been published over the past years. However, there is a lack of a systematic literature survey that provides a holistic overview of the drone scheduling problem, existing tendencies, main research limitations, and future research needs. Therefore, this study conducts an extensive survey of the scientific literature that assessed drone scheduling. The collected studies are grouped into different categories, including general drone scheduling, drone scheduling for delivery of goods, drone scheduling for monitoring, and drone scheduling with recharge considerations. A detailed review of the collected studies is presented for each of the categories. Representative mathematical models are provided for each category of studies, accompanied by a summary of findings, existing gaps in the state-of-the-art, and future research needs. The outcomes of this research are expected to assist the relevant stakeholders with an effective drone schedule design.**

***Index Terms*— Drone delivery, drone recharge, drone scheduling, flight path, monitoring, UAV.**

I. Background

AIRCRAFTS that have the ability to fly with no pilot on board are referred to as "*drones*". Several terms are commonly used for drones, such as "*unmanned aerial vehicle* (UAV)," "*unmanned aircraft system* (UAS)," "*remotely piloted aircraft* (RPA)," "*remotely piloted vehicle* (RPV)," etc. However, the term "*drone*" will be used in this study due to its popularity in the scientific community and in public [1], [2]. Drones are becoming more and more popular with time due to their mobility and flexibility, accompanied by rapid developments in the field of information technology, machine learning, and artificial intelligence. Although drones were initially developed for defense operations (e.g., bombing, combat, surveillance, spying), they have a wide range of applications in numerous civilian and environmental fields, including transportation, infrastructure, disaster management, air quality monitoring, agriculture, media, healthcare, and others [2]–[9] – see Fig. 1. Various challenges in ground transportation (e.g., congestion, restrictions in lead time, infrastructure vulnerability, extensive labor cost) have led to increasing uses of drones, especially in freight transportation and logistics. A growing number of companies, including Amazon, Google, UPS, FedEx, and DHL, have started deploying drones, especially for last-mile delivery [10], [11]. For instance, Amazon has launched "*Prime Air*", where drones deliver packages directly to customers within 30 minutes [12], [13]. Google has an autonomous, eco-friendly delivery drone service named "*Wing*" [11], [14]. In addition, a recovery of the global economy is expected after the COVID-19 pandemic, which can be bolstered with innovative solutions (e.g., Internet of Things, drones). Hence, drones may be utilized at a significantly greater extent in the near future.

Drones are typically smaller than traditional aerial vehicles. There are different classifications of drones based on their size. In particular, the size of drones may range from a minuscule class of drones named "*smart dust*", which is minimum 1 mm long and weighs 0.005 gm (consisting of micro-electro-mechanical systems, e.g., robots, sensors), to vast fixed-wing drones, which may have a wingspan of up to 61 m and weigh 15,000 kg [3], [15]. Between smart dust and vast fixed-wing drones, there are micro-unmanned air vehicles, micro-air vehicles, nano-air vehicles, and pico-air vehicles [3], [15]. A detailed classification of drones based on weight and range is shown in **Table I** [15], [16]. Drones may have a wide array of propulsion systems, such as battery-based systems, electric motor-based systems, gas turbine engines, reciprocating piston engines, propeller-based systems, Wankel rotary engines, rocket propulsion, proton exchange membrane fuel cells, ultracapacitors, photovoltaics, etc. [17]. Among these systems, battery-based systems, electric motor-based systems, and gas turbine engines are the most widely used [3], [15]. Moreover, the types of drone wings vary between fixed-wing, rotary-wing, flapping-wing, and hybrid-wing [15], [18].

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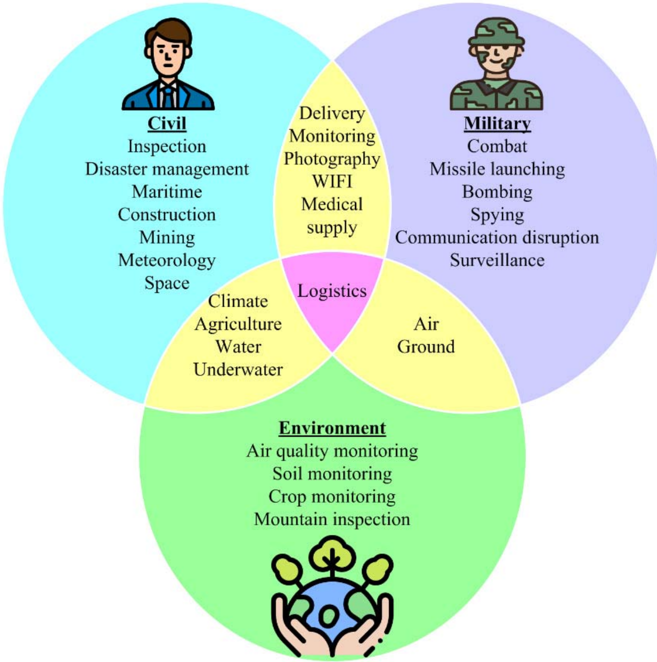

Fig. 1. Drone applications in various domains.

TABLE I
CLASSIFICATION OF DRONES BASED ON WEIGHT AND RANGE

Type	Characteristics		
	Maximum Weight (kg)	Maximum Range (km)	Wing Type
Nano	0.20	5	Fixed wing, multirotor
Micro	2	25	Fixed wing, multirotor
Mini	20	40	Fixed wing, multirotor
Light	50	70	Fixed wing, multirotor
Small	150	150	Fixed wing
Tactical	600	150	Fixed wing
MALE	1,000	200	Fixed wing
HALE	1,000	250	Fixed wing
Heavy	2,000	1,000	Fixed wing
Super heavy	2,500	1,500	Fixed wing

Drone technology has experienced a number of advancements over time. Innovative patents, such as autonomous recharge, hydrogen power, advanced computer vision, etc., may further facilitate the development of future drones. Newer models with improved features are being added to fleets of drones. Nonetheless, drones have a fairly restricted use because of current limitations in battery, flying range, size, etc. Specifically, drone batteries greatly curb the flying ranges and weight carrying capacities of drones. If the weight carrying capacities or flying ranges are exceeded, drones may be subject to failures and accidents. Hence, substantial research efforts have been made to optimize the efficiency of drones under battery constraints. Such efforts are evidenced by a significant number of operations research studies published in the 21st century, which have focused on various problems revolving around drones, such as planning, routing, and scheduling.

Drone scheduling is one of the key problems that have received increasing attention over the last decade. Drone scheduling is associated with several features, such as launch points, customer visits, delivery of goods, monitoring, and battery capacities. Under this problem, a given number of drones are deployed from a launch point or a ground vehicle (e.g., truck) to serve some customer nodes. Due to limited battery capacity, the drones can fly for only a limited amount of time. They are expected to serve the designated customers and return to the launch point (or the ground vehicle) within this limited amount of time. Flying from one node to another reduces battery levels and may hinder the drones from completing their service. Hence, the flight paths of the drones are optimized, so that the drones can safely return to the launch point after serving all or most of the customers. In addition to optimization of flight paths, drone scheduling may be associated with several other features (e.g., time windows, delivery deadlines, prioritization of service requests). Each customer node could be assigned an arrival time window. Then, the arrival and departure times at different nodes are also determined. Based on the nature of the problem, various operational constraints may be enforced.

A number of studies have been dedicated towards drone scheduling, which have created a need for literature surveys on drone scheduling. Several literature surveys can be found on drone operations, drone routing, and other decision problems associated with the deployment of drones [2], [3], [19]–[23]. A summary of the most relevant survey studies on the deployment of drones is presented in **Table II** with an emphasis on the following aspects: (i) specific drone scheduling focus; (ii) review of application areas; (iii) presentation of the relevant mathematical formulations; (iv) analysis of solution approaches; (v) task assignments; and (vi) categorical future research needs for different variations of the drone scheduling problem. It can be observed that there is still a lack of a systematic literature survey that provides a holistic overview of the drone scheduling problem, existing tendencies, main research limitations, and future research needs (see **Table II**). To address this gap in the state-of-the-art, this study presents a comprehensive survey of the research efforts, which assessed different aspects of drone scheduling. The contributions of this study can be summarized as follows:

- ✓ A recent and detailed survey of the studies on drone scheduling is conducted. Specifically, this survey provides a comprehensive review of 145 studies that assessed drone scheduling and various factors, which could affect drone scheduling decisions.
- ✓ Representative mathematical formulations for different variants of the drone scheduling problem are provided, which could serve as foundations for future research.
- ✓ A special focus is given to the model formulations, model objectives, time windows, drone characteristics, number of ground vehicles, solution approaches, and major considerations of the collected studies on drone scheduling.

TABLE II
SUMMARY OF THE RELEVANT SURVEY STUDIES ON THE DEPLOYMENT OF DRONES

Survey Study	Focus on Drone Scheduling	Application Areas	Mathematical Formulations	Analysis of Solution Approaches	Task Assignments	Categorical Future Research Needs
Otto et al. (2018) [19]	–	√	–	√	√	–
Khoufi et al. (2019) [20]	–	√	–	√	√	–
Chung et al. (2020) [2]	Partial	√	–	√	√	–
Macrina et al. (2020) [3]	–	√	–	√	√	–
Thibbotuwawa et al. (2020) [21]	Partial	√	√	–	–	–
Moshref-Javadi and Winkenbach (2021) [22]	–	√	–	√	–	–
Rojas Viloria et al. (2021) [23]	–	√	–	√	√	–
Current study	Full	√	√	√	√	√

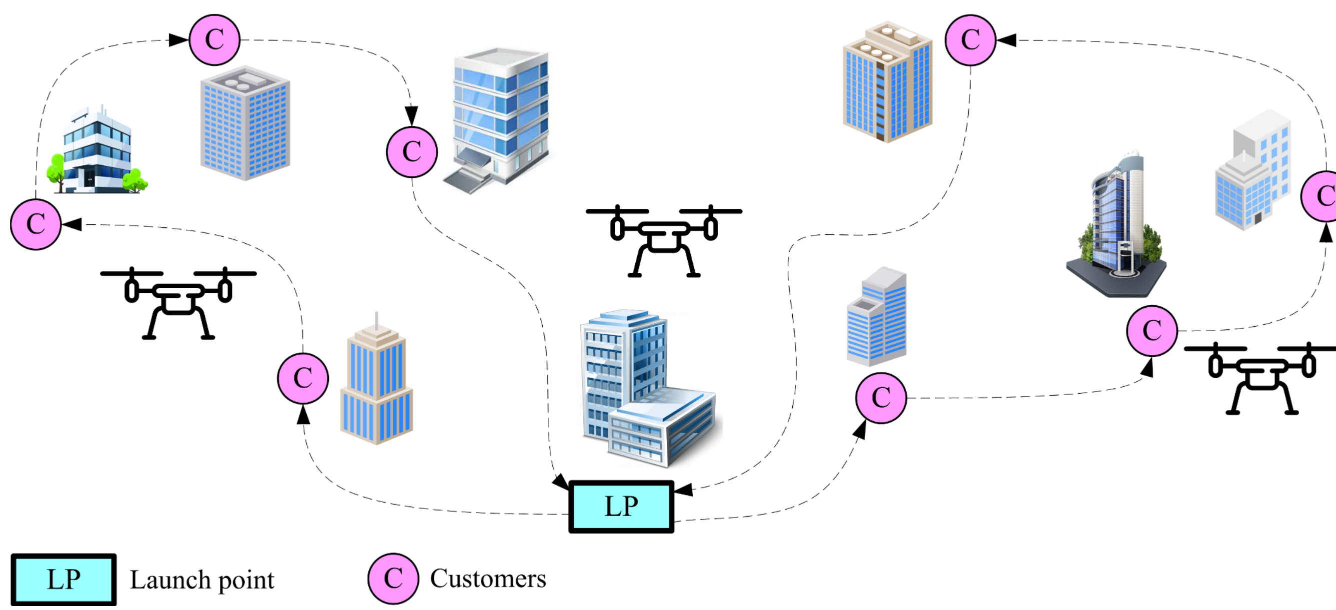

Fig. 2. Typical flight paths of drones.

- ✓ The latest trends in drone scheduling are discerned, while limitations of the prior and recent studies on drone scheduling are identified. Based on these limitations, future research needs in drone scheduling are outlined.

The remainder of this manuscript is structured as follows. A detailed description of the generic drone scheduling problem is presented in the following section. The third section describes the literature search methodology that was used to gather and select drone scheduling studies, while the fourth section provides a detailed review of the selected studies. This research is concluded in the fifth section.

II. DESCRIPTION OF THE DRONE SCHEDULING PROBLEM

A description of the generic drone scheduling problem is provided in this section of the manuscript. Drones may be deployed from launch points, depots, trucks, and other locations to perform the requested type of service. Their flight time depends on their battery capacity [24]–[27]. Typically, a commercial drone battery requires for the drone to return to its launch point within one hour after initiating its flight [26], [28]. Therefore, drone flights can be scheduled on an hourly basis. Let $C = \{1, \ldots, N_C\}$ denote the set of launch points. A set of available drones $K = \{1, \ldots, N_K\}$ will be deployed from the launch points. They will serve the set of customer nodes $I = \{1, \ldots, N_I\}$ and then return to the respective launch points. Some typical flight paths of drones are illustrated in Fig. 2.

When a drone is launched, an operating cost $p_k, k \in K$ is incurred, which is associated with maintenance, personnel, operation of control center, depreciation cost, among others [26]. The operating cost is assumed to be fixed and not dependent on the flight duration/distance between nodes $d_{ij}, i \in I \cup C, j \in I \cup C$. Generally, a drone has a fully charged battery upon launch. However, it must return to its initial launch point within its maximum allowable flight duration $D_k, k \in K$, as its battery level declines along the path. Drone scheduling aims to optimize the flight paths of drones. Hence, a binary decision variable $\boldsymbol{x}_{ijk}, i \in I \cup C, j \in I \cup C, k \in K$

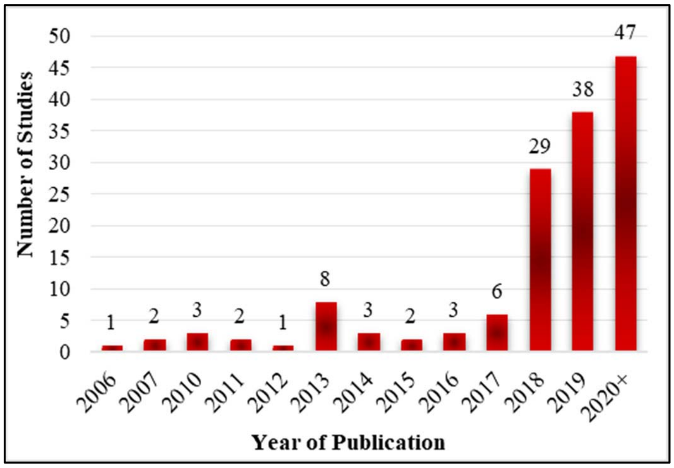

Fig. 3. Distribution of the selected studies by the year of publication.

is used. The value of $\boldsymbol{x}_{ijk}$ is 1 if drone k travels from node i to node j, and 0 otherwise. Let a binary auxiliary variable $\boldsymbol{h}_k, k \in K$ be 1 if drone k is launched, and 0 otherwise. Moreover, the arrival time of a drone at each node is recorded through a positive auxiliary variable $\boldsymbol{t}_{ik}, i \in I \cup C, k \in K$. Several objective functions can be associated with the drone scheduling decision problem, such as minimization of the total operating cost, minimization of the total travel duration, minimization of the maximum completion time, and others (more details will be provided in the following sections of the manuscript).

III. Literature Search

The content analysis method was used in the study to perform a systematic review of the literature on drone scheduling. The content analysis method is viewed as a well-established methodology that has been widely used over the years to conduct systematic reviews of the scientific literature and draw the key insights [29]. This study accessed the major scientific publishers (e.g., IEEE, Springer, Elsevier, Wiley, Sage) to conduct a literature search for the drone scheduling problem. The following keywords were used to guide the search process: drone scheduling, UAV scheduling, unmanned aerial vehicle scheduling, UAS scheduling, RPA scheduling, RPV scheduling, drone task scheduling, UAV task scheduling, unmanned delivery, and remote surveillance. After performing the structured keyword search, the identified studies were evaluated, and a total of 145 studies were found to be the most closely aligned to the theme of this literature survey. The present survey specifically captured the studies written in English and published in peer-reviewed journals, conference proceedings, and book chapters. The studies written in other languages were not considered.

A distribution of the selected studies by the year of publication is illustrated in Fig. 3, which indicates that the drone scheduling problem has been garnering growing attention from the scientific community. Especially, a substantial number of studies have been published over the last three years. Such a tendency can be elucidated by rapid improvements in information technology, congestion, increase in delivery demand, vehicle cost, labor cost, along with other reasons. A distribution of the selected studies by journal is shown in Fig. 4, which reveals that a significant number of the drone scheduling studies were published in reputed journals, including IEEE Access, IEEE Transactions on Vehicular Technology, IEEE Internet of Things Journal, and Journal of Intelligent & Robotic Systems. Note that apart from journal publications (a total of 107 studies or 73.8%), some of the selected drone scheduling studies were published in conference proceedings (a total of 35 studies or 24.1%) and book chapters (a total of 3 studies or 2.1%).

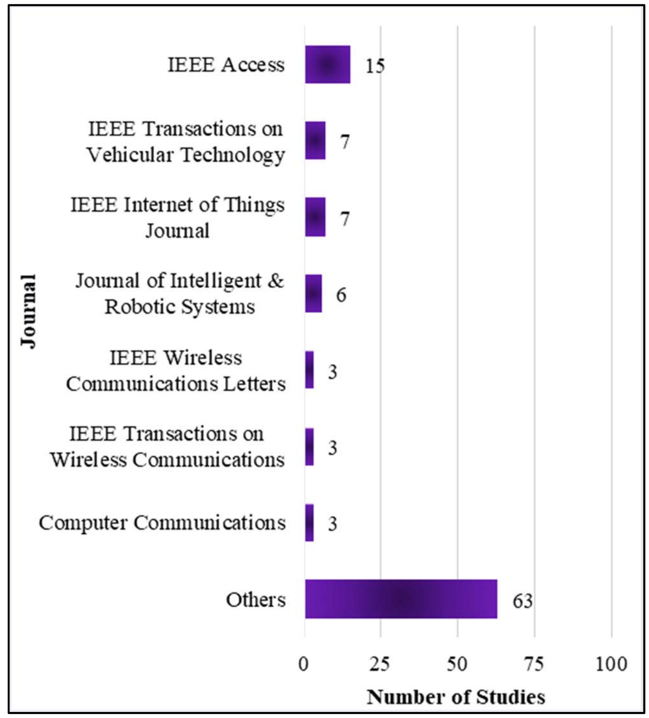

Fig. 4. Distribution of the selected studies by journal.

The collected studies were then grouped into the following categories for a detailed review:

1) *General Drone Scheduling* – this group of studies focuses on basic attributes of the drone scheduling problem, including utilization of drones, determination of drone flight paths, and arrival times of drones at nodes;
2) *Drone Scheduling for Delivery of Goods* – this group of studies specifically focuses on the deployment of drones for delivery of goods to the designated customer locations;
3) *Drone Scheduling for Monitoring* – this group of studies specifically focuses on the deployment of drones for non-military monitoring and inspection purposes; and
4) *Drone Scheduling with Recharge Considerations* – this group of studies specifically captures recharging operations of drone batteries in the drone scheduling problem.

If a study had an overlap between multiple categories, it was grouped based on its primary area of focus. A distribution of the selected studies by study category is delineated in

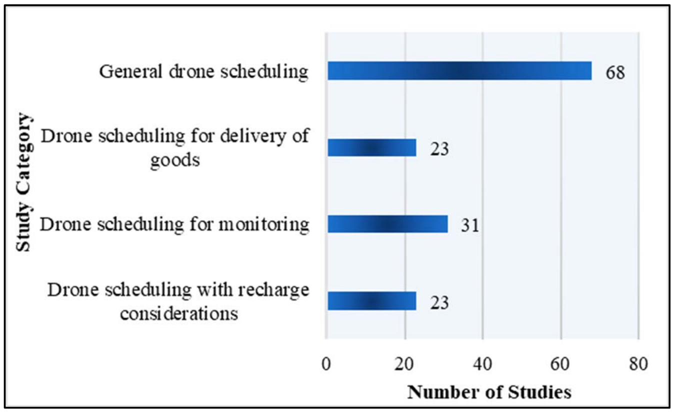

Fig. 5. Distribution of the selected studies by study category.

Fig. 5, where it can be observed that the majority of the collected studies were related to the general drone scheduling problem (68 studies or 46.9% of the total number of studies). Moreover, a significant amount of studies were related to drone scheduling for monitoring purposes (31 studies or 21.4% of the total number of studies). There is an assortment of studies in the literature that deal with drone routes and drone schedules. While a number of studies have incorporated time components of drones (e.g., arrival times at nodes) as variables, many studies have formulated models that determine drone flight paths or trajectories with limited or no focus on time components. Such models have been generally referred to as "*drone routing models*" by the studies. The present survey primarily concentrated on review of the studies that presented drone scheduling models.

IV. Review of the Existing Literature

A detailed review of the studies, collected from the literature search, is presented in this section. Each of the four aforementioned study categories will be analyzed, and the following aspects will be highlighted: (i) a detailed scope of each study category accompanied by a representative mathematical model; (ii) review and evaluation of the pertinent studies; (iii) a summary of findings from the conducted studies; and (iv) existing state-of-the-art limitations along with future research needs.

A. General Drone Scheduling

The general drone scheduling problem is assessed in this section of the manuscript. Several drone scheduling decisions, such as utilization of drones, determination of drone flight paths, arrival times of drones at nodes, etc., have been captured by the studies that focused on the general drone scheduling problem. Note that the studies under this category do not specifically focus on delivery of goods and monitoring or incorporate recharge considerations (which are the attributes related to other study categories classified in this manuscript). The general drone scheduling studies are inclined towards the aforementioned basic drone scheduling decisions and may have other considerations, such as data dissemination. A mathematical formulation for the general drone scheduling problem can be presented as follows:

General Drone Scheduling Problem (**GDSP**)

$$min \sum_{k\in K} p_k \boldsymbol{h}_k \tag{1}$$

Subject to :

$$\sum_{i\in I\cup C}\sum_{k\in K}\boldsymbol{x}_{ijk}=1 \quad \forall j\in I \tag{2}$$

$$\sum_{j\in I\cup C}\sum_{k\in K}\boldsymbol{x}_{ijk}=1 \quad \forall i\in I \tag{3}$$

$$\boldsymbol{x}_{iik}=0\forall i\in I\cup C, k\in K \tag{4}$$

$$\sum_{j\in I}\boldsymbol{x}_{cjk}=\sum_{i\in I}\boldsymbol{x}_{ick} \quad \forall c\in C, k\in K \tag{5}$$

$$\sum_{c\in C}\sum_{j\in I}\boldsymbol{x}_{cjk}=\boldsymbol{h}_k \quad \forall k\in K \tag{6}$$

$$\sum_{i\in I}\sum_{c\in C}\boldsymbol{x}_{ick}=\boldsymbol{h}_k \quad \forall k\in K \tag{7}$$

$$\sum_{j\in I\cup C}\boldsymbol{x}_{\upsilon jk}=\sum_{i\in I\cup C}\boldsymbol{x}_{i\upsilon k} \quad \forall \upsilon\in I, k\in K \tag{8}$$

$$\sum_{i\in I\cup C}\sum_{j\in I\cup C}d_{ij}\boldsymbol{x}_{ijk}\le D_k \quad \forall k\in K \tag{9}$$

$$\boldsymbol{t}_{ik}+d_{ij}-M\left(1-\boldsymbol{x}_{ijk}\right)\le \boldsymbol{t}_{jk} \;\forall i\in I\cup C, j\in I\cup C, k\in K \tag{10}$$

$$\boldsymbol{x}_{ijk},\boldsymbol{h}_k\in\{0,1\},\boldsymbol{t}_{ik}\ge 0 \;\forall i\in I\cup C, j\in I\cup C, k\in K \tag{11}$$

The objective function (1) of the **GDSP** mathematical formulation minimizes the total drone operating cost. Constraint sets (2) and (3) guarantee that each customer node is visited once by only one drone. Constraint set (4) ensures that a drone cannot travel from one node to the same node directly. Constraint set (5) indicates that each drone returns to the launch point where it departed from. Constraint sets (6) and (7) show the utilization of drones (i.e., how many drones are required to provide a specific service for the existing customer locations). Flow conservation of the drone flights is guaranteed by constraint set (8). Constraint set (9) ensures that the total flight duration of a drone does not exceed its maximum allowable flight duration. Constraint set (10) functions as a time conservation constraint (as well as a sub-tour elimination constraint), where M is a large positive number. In particular, if a drone flies from node i to node j, then the arrival time of the drone at node j should not be less than the sum of the arrival time of the drone at node i and the flight duration between nodes i and j. If a certain amount of time is to be spent at the customer nodes (e.g., due to data transfer), it can be added to the left-hand side of this constraint set. Constraint set (11) defines the nature of the variables in the **GDSP** mathematical formulation.

1) Description of the Relevant Studies: Bertuccelli *et al.* [30] stated that supervision duties of drone operators (e.g., task scheduling, information management) could be overwhelming, especially for an environment with a large number of drones. In order to improve the operator performance, the study presented a scheduling model that had the objective of maximizing the reward for operators due to completing tasks. A time window was defined for each task. Comparisons with a greedy scheduling method using Monte Carlo Simulation demonstrated the efficiency of the developed methodology. Zeng *et al.* [31] studied drone resource scheduling for battlefield applications, especially for clusters of targets through synchronization of missions. A total of three objective functions, which were consolidated later into one objective function with weights, were outlined. The three objective functions included: (1) maximization of the attack benefit; (2) minimization of the attack cost; and (3) maximization of the synchronization benefit. Mission time windows along with arrival time windows were incorporated. An exhaustive algorithm was designed for small-scale instances of the problem. Khosiawan and Nielsen [32] argued that schedulers were required to ensure collision-free operations of drones in an indoor environment. Therefore, a drone application system with a scheduler was designed. A phased manner was incorporated by the scheduler's components in order to achieve abstraction as well as efficiency in computational time.

Kim and Lee [33] studied the extension of network coverage, where drones delivered data from mobile devices to base stations. Due to the limited transmission range of drones, the service area was divided into multiple sections. Scheduling of the sections was performed to maximize the network throughput. Simulation results showed that the proposed methodology could derive the optimal number of sections, considering the transmission opportunity and channel error rate. Cai *et al.* [34] deployed a pair of drones for data dissemination with secrecy. One of the drones communicated with ground users, while the other drone protected communications by jamming intruders. A mathematical model was formulated to maximize the minimum worst-case secrecy rate among users through joint optimization of drone flight paths and user schedules. Equality constraints were imposed to reduce the complexity of the nonlinear model. Cheng *et al.* [35] deployed drones to offload data for cell-edge users within a mobile network. Drone trajectories were optimized in order to maximize the sum rate of edge users. At the same time, base station-drone interferences were avoided, and mobile users' rate requirements were fulfilled. The proposed non-convex model was disintegrated into two convex models, and an iterative algorithm was used for solution.

Chowdhery and Jamieson [36] argued that wireless networks could be hindered by emergencies (e.g., disasters), which could lead to failure in meeting user demand or coverage. Therefore, the study deployed mobile drone hotspots to improve wireless networks. Under the system, a mobile drone would provide coverage to a set of clients. A channel prediction algorithm along with a client scheduling algorithm were used for solution. Hua *et al.* [37] used drones to communicate with nodes within a wireless sensor network. A scheduling model was outlined to minimize the energy consumption due to transmission and propulsion. In particular, decisions regarding flight paths, communication schedules, and energy allocation were provided. Kim *et al.* [26] argued that the maximum flight time of a drone was susceptible to air temperature, as the battery capacity of a typical drone declined by 25% when the air temperature was −10 °C. It was advised that either drones with higher battery capacities should be deployed, or the number of drones should be increased at temperatures below 20 °C. The study employed a total of three uncertainty sets (i.e., box, polyhedral, and ellipsoidal) to assess uncertainties in battery capacity due to air temperature. Numerical experiments indicated that the applied robust optimization method was able to reduce drone failures as compared to deterministic optimization methods.

Zeng *et al.* [38] employed drones as relay nodes to disseminate data within vehicular ad-hoc networks. A scheduling strategy was presented to maximize the total throughput of such a network and to minimize the overall delay in transmission. A recursive least squares algorithm was used to predict vehicular information, while a maximum vehicle coverage algorithm was employed for scheduling vehicular movements. Khosiawan *et al.* [39] discussed that only a few studies designed drone scheduling models for indoor environments. However, various industries, such as green houses, hospitals, wind turbine factories, etc., could benefit from such models. Hence, the system architecture for indoor applications of drones was delineated. A mixed-integer nonlinear programming model was developed to minimize the total makespan, and the model was solved with a heuristic in conjunction with Particle Swarm Optimization. Lyu *et al.* [40] assessed wireless communication through drones to meet the shortage of resources for dynamic Internet of Vehicles. Drones were deployed to ensure throughput quality of service. A scheduling scheme was designed, which incorporated the following tasks: (1) monitoring of resource shortage; (2) deployment of minimal drones; and (3) returning of drones with empty batteries. Simulations were conducted to showcase the efficiency of the proposed scheme.

Shi *et al.* [41] employed drone base stations for radio access networks. A system was contemplated, where drone base stations flew over areas of interest in order to assist with communication between an area of interest and a base station. A mixed-integer nonlinear programming model was proposed to minimize the average path loss between a drone base station and a user. After decomposing the studied problem into multiple sub-problems, a multi-drone base station 3-dimensional trajectory planning and scheduling algorithm was used as the solution approach. A cluster of drones may perform different tasks simultaneously. Tasks are ceased when some drones in the cluster run low on battery. Yang *et al.* [42] applied reinforcement learning for real-time task scheduling of a drone cluster. Through calculation of task performance efficiency, the cluster of drones was able to take autonomous behavioral decisions in order to facilitate a decentralized network. Fan *et al.* [43] studied data scheduling with drones for vehicular networks. A data scheduling problem, which encompassed priority of data transmission, network fairness, link connection time, and link quality, was examined. The data scheduling problem was reduced to a maximum weighted matching problem, and a data scheduling scheme was proposed, which was inspired by the Blossom Algorithm.

Jin *et al.* [44] assessed charging a wireless rechargeable sensor network with a drone. Charging deadlines for sensors and energy levels of drones were incorporated for the charging system. A drone scheduling model was formulated to maximize the number of sensors charged by the drone. An approximation algorithm was developed to solve the proposed model, and simulation results found that the proposed solution methodology had several benefits over the Greedy Replenished Energy Algorithm. Li *et al.* [45] analyzed data capture scheduling with drones in order to facilitate wireless sensor networks at areas with no or limited cellular infrastructure. It was underlined that buffer overflows at ground sensors could be caused by drone maneuvers. A mathematical model was presented to minimize the overall data loss. Furthermore, an absorbing Markov chain was formulated to model data collection. Pu and Carpenter [46] developed a priority-based service scheduling method for data upload and download. Moreover, a service request balancing method was presented for data upload and download. Several considerations were incorporated, such as data popularity, data size, and data request deadline. The general drone scheduling problem has been addressed by a number of other studies as well [12], [28], [47]–[94].

2) Summary of Studies: A summary of findings from the collected studies, which addressed the general drone scheduling problem, is presented in **Table III**. The table provides a concise summary on the model formulations, model objectives, time windows, drone characteristics, number of ground vehicles, and solution approaches for the respective mathematical models along with certain important notes and major considerations. It was found that a significant number of the studies on general drone scheduling formulated mixed-integer non-linear programming (MINLP) models, did not enforce time windows, and deployed multiple drones. The developed mathematical models had a variety of different objective functions (e.g., maximize the total benefit, minimize the total operating cost, and maximize the network utility). Moreover, the general drone scheduling studies typically did not deploy any ground vehicles in synchronization with drones. Heuristics were found to be common solution approaches for the general drone scheduling problem. In addition, many studies on general drone scheduling deployed drones for data dissemination.

3) Future Research Needs: Limitations and future research needs in the area of general drone scheduling include the following:

- Drone operators may face difficulties if drone schedules do not follow a consistent pattern (i.e., frequent changes are observed from day to day). Therefore, new methods that could facilitate the development of more consistent drone schedules over a given planning horizon should be designed [48], [49], [134], [137], [147].
- Several studies assume that drones will fly at their maximum speed. In the real world, however, the maximum drone flying speeds could be shortened by additional air resistance and result in larger flying times. Hence, future studies should consider the drone flying speed as an additional variable [2], [3], [26], [128].
- Due to the requirement of comparatively lower energy to stay afloat, balloon-based drones could be more energy-efficient as compared to traditional drones. Hence, new mathematical formulations capturing the operational features of balloon-based drones should be explored in the future studies [36], [56], [84], [121].
- Comprehensive flight behaviors of drones may be incorporated by drone scheduling models [32], [167], [170].
- Some real-world systems may include a human in the loop of drone service. Therefore, human behavior should be captured for modeling such services. The effects of potential human errors (e.g., drone operator errors) on the drone operations could be further investigated as well [49], [134], [136], [140], [149].
- Drone failure is a common phenomenon. Based on virtual or physical tests, a distribution of drone failures could be modeled and directly incorporated within the existing mathematical models [81], [92], [138], [167].
- Multiple drone base stations may exist in a network for data dissemination. Communication and resource allocation for such networks could be more explicitly modeled in the future [60], [123], [145].
- Various solution approaches have been presented in the literature to address the general drone scheduling problem (i.e., exact optimization methods, heuristics, and metaheuristics) [19], [22], [23]. The future research should explore customized hybrid algorithms that directly account for specific problem features and deploy local search mechanisms [95]–[98]. Such algorithms are expected to provide promising solutions to the general drone scheduling problem in a timely manner.

B. Drone Scheduling for Delivery of Goods

An emerging application of drones is delivery of goods. Over the recent years, drones have been employed by a number of organizations to replace or complement ground vehicles for delivery of goods. Hence, a significant portion of the drone scheduling literature has focused on delivery of goods. Even though drones boast a number of advantages, their weight carrying capacity is very limited. Let Q_k be the weight carrying capacity of drone k. The demand of customer j is denoted by $q_j, j \in I$. Then, a mathematical formulation for the drone scheduling problem for delivery of goods can be presented follows:

Drone Scheduling Problem for Delivery of Goods (**DSPDG**)

$$min \sum_{i \in I \cup C} \sum_{j \in I \cup C} \sum_{k \in K} d_{ij} \boldsymbol{x}_{ijk} \tag{12}$$

Subject to :

Constraint sets (2) − (5), (8) − (10)

$$\sum_{i \in I \cup C} \sum_{j \in I} q_j \boldsymbol{x}_{ijk} \leq Q_k \quad \forall k \in K \tag{13}$$

$$\boldsymbol{x}_{ijk} \in \{0, 1\}, \boldsymbol{t}_{ik} \geq 0 \quad \forall i \in I \cup C, j \in I \cup C, k \in K \tag{14}$$

TABLE III
SUMMARY OF FINDINGS: STUDIES ON GENERAL DRONE SCHEDULING

References	Formulation Types	Model Objectives	Time Windows	Drone Characteristics	Number of Ground Vehicles	Solution Approaches	Notes/Major Considerations
Bertuccelli et al. (2010) [30]	MINLP	Maximize the total reward	N/A	MD	N/A	Monte Carlo Simulation; Heuristic	Supervision of drones
Zeng et al. (2010) [31]	IP	Maximize the attack benefit; minimize the attack cost; maximize the synchronization benefit	Strict	MD; ECC	N/A	Exhaustive Algorithm	Mission time window and arrival time window
Khosiawan and Nielsen (2016) [32]	N/A	N/A	N/A	MD	N/A	N/A	Indoor scheduling
Kim and Lee (2017) [33]	N/A	Maximize the throughput	N/A	SD	N/A	Heuristic	Data dissemination
Cai et al. (2018) [34]	INLP	Maximize the minimum worst-case secrecy rate	N/A	MD	N/A	Heuristic	Data dissemination
Cheng et al. (2018) [35]	MINLP	Maximize the sum rate of edge users	N/A	MD	N/A	Heuristic	Data dissemination
Chowdhery and Jamieson (2018) [36]	N/A	Maximize the network utility	Soft	MD	N/A	Heuristic	Data dissemination
Hua et al. (2018) [37]	MINLP	Minimize the energy consumption	N/A	SD; ECC	N/A	Heuristic	Data dissemination
Kim et al. (2018) [26]	MIP	Minimize the total operating cost	N/A	MD	N/A	CPLEX	Air temperature
Zeng et al. (2018) [38]	N/A	Minimize the overall transmission delay; maximize the throughput	N/A	MD	N/A	Heuristic	Data dissemination
Khosiawan et al. (2019) [39]	MINLP	Minimize the maximum completion time	N/A	MD; ECC	N/A	Heuristic; Particle Swarm Optimization	Indoor scheduling
Lyu et al. (2019) [40]	N/A	N/A	N/A	MD	N/A	N/A	Data dissemination
Shi et al. (2019) [41]	MINLP	Minimize the average drone base station to user path loss	N/A	MD	N/A	Heuristic	Data dissemination
Yang et al. (2019) [42]	N/A	N/A	N/A	MD	N/A	N/A	Real-time scheduling
Fan et al. (2021) [43]	N/A	Maximize the network utility	N/A	MD	N/A	Heuristic	Data dissemination
Jin et al. (2021) [44]	N/A	Maximize the number of charged sensors	Strict	SD; ECC	N/A	Approximation Algorithm	Wireless rechargeable sensor network
Li et al. (2021) [45]	N/A	Minimize the data loss	N/A	SD; ECC	N/A	Deep Learning	Data dissemination
Pu and Carpenter (2021) [46]	N/A	Maximize the total benefit	Strict	MD; ECC	N/A	Heuristic	Data dissemination

Notes: IP – Integer Programming; INLP – Integer Non-Linear Programming; MIP – Mixed-Integer Programming; MINLP – Mixed-Integer Non-Linear Programming; SD – Single Drone; MD – Multiple Drones; ECC – Energy Consumption Considerations.

The objective function (12) of the **DSPDG** mathematical formulation minimizes the total travel duration, as timely delivery is essential for each customer served by the assigned drone. Constraint set (13) implies that a drone can carry a limited quantity of goods. Constraint set (14) defines the nature of the variables in the **DSPDG** mathematical formulation. Some examples of flight paths of drones that can be obtained using the **DSPDG** mathematical model for delivery of goods are depicted in Fig. 6.

1) Description of the Relevant Studies: Zhang *et al.* [99] developed a drone scheduling scheme for delivery within an area to minimize the overall delivery delay. Moreover, an allocation scheme was presented for delivery within multiple areas in order to maximize the probability of successful completion of delivery requests. Murray and Chu [100] conducted one of the pioneering studies on the traveling salesman problem with drones. It was stated that drones might not be able to deliver all packages due to the size or weight of packages or the limited flight ranges of drones. Hence, two routing and scheduling models were proposed for drones and trucks. The first model, called the "flying sidekick traveling salesman problem," involved cooperation between a truck and a drone.

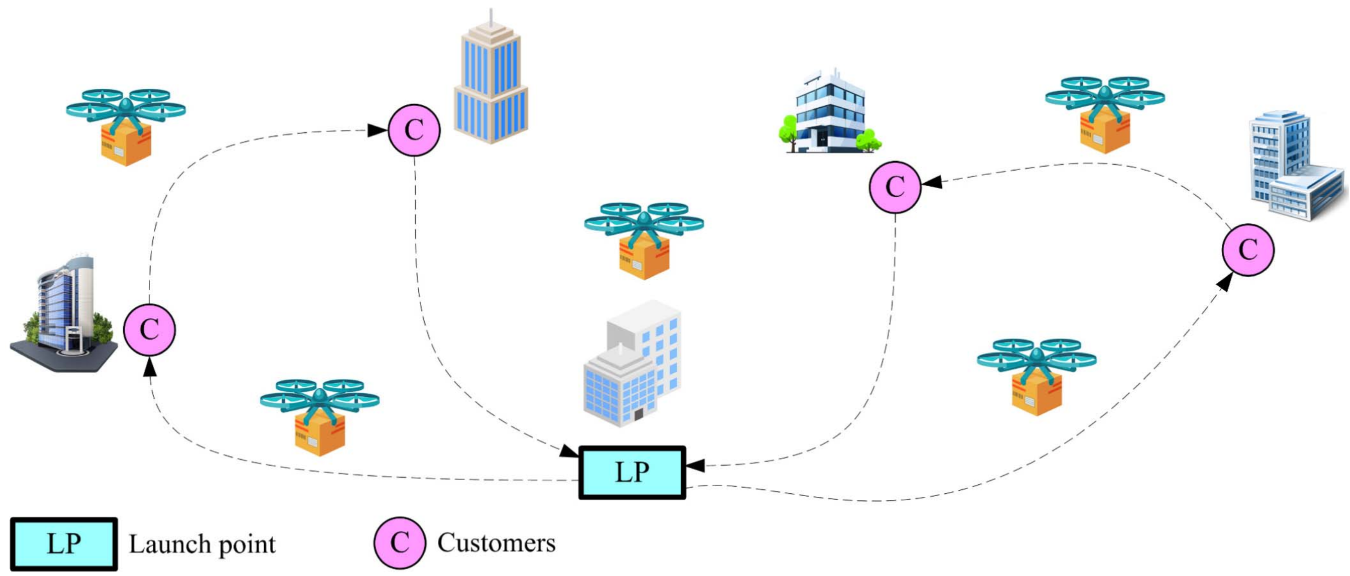

Fig. 6. Flight paths of drones for delivery of goods.

The truck carried the drone and was deployed from the depot. The drone would then be launched from the truck, visit/serve customers, and return to the truck. A customer could also be directly served by a truck. The second model, named the "parallel drone scheduling traveling salesman problem," deployed a truck and a fleet of drones from the depot. A customer could be served by either the truck or one of the drones, and all of them had to return to the depot after serving the customers. Ham and Kim [101] presented a material transfer drone scheduling model for semiconductor factories. The objective of the model was to minimize the maximum completion time of delivery tasks, which were characterized by priority. Precedence relationships were also defined for the tasks, since drones had to compete for a limited number of ports.

Boysen *et al.* [10] discussed that the last-mile delivery with drones could be an effective solution to reduce roadway traffic. The study developed two drone scheduling models for delivery with drones along a given truck route. The models weighted several considerations, such as use of a single drone vs. multiple drones and identical vs. non-identical stops. GUROBI was employed to solve the proposed mixed-integer programming models. Numerical experiments revealed that one of the models was able to handle up to 100 customer nodes within a short time. Chen *et al.* [102] implied that drones should deliver packages in a minimal time and reduce late arrivals. A hybrid block-based edge recombination algorithm was proposed, which was contrasted with the generic edge recombination algorithm. Numerical experiments showed that the proposed algorithm could obtain better results. Ham [103] assessed the use of drones for last-mile delivery. In particular, a fleet of trucks, a fleet of drones, and a set of depots were considered. Moreover, each drone completed two types of tasks: drop-off and pick-up. Initially, a drone dropped a parcel at a customer location. Then, it could go to another customer location to pick up a returned parcel or travel to a depot in order to drop the next parcel at the respective customer location. A constraint programming technique was used to solve the problem. Results indicated that the proposed solution approach could achieve optimality for most of the tested problem instances.

Liu *et al.* [104] studied collaboration between trucks and drones, where drones were transported by trucks. The study modeled the demand point to be far from the warehouse. The impacts of payload or battery weight on the energy consumption of drones were not directly accounted for. Saleu *et al.* [105] assessed the parallel drone scheduling traveling salesman problem. A two-step heuristic algorithm was developed to solve the studied problem, which employed Dynamic Programming in order to split the set of customers between the set of drones and the truck. Numerical experiments indicated that the proposed heuristic was able to return promising results. Shi and Ng [106] exhibited a path planning algorithm to avoid collision during drone deliveries. It was demonstrated that the proposed algorithm could provide optimal results, when a waiting penalty was added. Torabbeigi *et al.* [107] discussed that drones could be faster and cheaper as compared to the conventional modes of transportation. However, they should be reliable as well. Therefore, the study proposed a two-staged model to improve the reliability of drones in the form of minimizing the expected loss of demand. Drone failures were modeled with an exponential distribution.

Kim and Moon [108] stated that the flight range of drones around a distribution center was limited. Hence, a parallel scheduling scheme was proposed between a truck and a set of drones. A mixed-integer programming model, which was later divided into two models, was proposed to minimize the delivery time of the truck and drones. It was demonstrated that the proposed approach could eliminate route distortion. Peng *et al.* [109] studied a cooperative service between drones and vehicles. In that study, a vehicle acted as a mobile base station for a fleet of drones, which could serve customers within a short distance due to battery limitations. The vehicle moved between selected anchor points, and then the drones were deployed to serve the customers near those points. When all the customers near an anchor point were served, the vehicle moved to another point. The proposed model was inspired by several basic optimization problems, including the facility location problem, vehicle routing problem, traveling salesman problem, and bin packing problem. A hybrid version of the Genetic Algorithm, which employed heuristic procedures for population initialization, was used for solution. The developed solution approach was found to be more efficient when comparing to some of the solution approaches found in the literature.

Sawadsitang *et al.* [110] proposed a three-stage, stochastic, multi-objective optimization model for drone delivery. The model aimed to minimize the total cost of delivery as well as the percentage of packages unsuccessfully delivered and to maximize the total reward for the on-time delivery. The e-constraint method was employed to handle the proposed model, whose performance was evaluated by using real-world data from a Singapore-based logistics company. Seakhoa-King *et al.* [111] designed a scheduling algorithm to optimize a time-sensitive delivery service provider's revenue. The inputs to the proposed algorithm included a function that captured service agreements with customers and an expected distribution of flight times. It was demonstrated that the algorithm was successful in increasing revenues. Wang *et al.* [112] studied simultaneous use of independent drones, truck-carried drones, and trucks for a hybrid parcel delivery system. The numbers of truck-carried drones and trucks were assumed to be equal, i.e., each truck carried a single drone. Numerical experiments revealed that the proposed hybrid delivery system outperformed the alternative approaches that employed only independent drones or truck-carried drones.

Cheng *et al.* [113] proposed a drone delivery system considering time windows. A mathematical formulation was presented to minimize the travel cost and the energy consumption. The employed energy consumption function incorporated the impact of payload and battery weight. A Branch-and-Cut Algorithm was used as a solution methodology. Dell'Amico *et al.* [114] employed the traveling salesman problem framework for the parallel drone scheduling problem, where customers were shared between a truck and a set of drones. During each trip, which started and ended at the depot, the truck was allowed to serve multiple customers. The drones, on the other hand, served only one customer during each trip. A mixed-integer programming model was formulated to minimize the maximum working time of all the vehicles. A set of matheuristic algorithms were developed to solve the proposed model, including Fast Heuristics and Random Restart Local Search. Ham [115] presented a material transfer drone scheduling model for a robotic mobile fulfillment facility. Time windows and precedence relationships were assigned to the tasks to be completed. Moreover, pick-ups and drop-offs were facilitated by the employed drones.

Huang *et al.* [116] proposed two delivery methods involving drones along with public transportation vehicles (e.g., trams, trains). Under one of the methods, packages were directly delivered by drones, while collaboration between public transportation vehicles and drones was established under the other method. Several practical considerations, such as consumption of energy, replenishment of battery, and trip time, were captured. Torabbeigi *et al.* [27] employed a bi-level approach for delivery of parcels with drones. At the strategic planning level, a set covering approach was used to minimize the initial depot opening cost. At the operational planning level, on the other hand, delivery schedules were determined in order to minimize the number of drones deployed. Specific considerations for drones were incorporated, including the impact of payload on flight duration as well as remaining battery level. It was also stipulated that payload had a linear relationship with battery consumption. Liu *et al.* [11] discussed that it was challenging for decision-makers to determine the optimal number of drones to ensure that all parcels could be delivered before the corresponding deadlines. A mathematical model was formulated, where each parcel was assigned a release time, a deadline, and a distance to the depot. A Genetic Algorithm was developed to solve the model.

Torabbeigi *et al.* [117] implied that failures in drone delivery systems could result in unmet demand as well as loss of customer satisfaction. A Weibull distribution was used to model drone failures, while a mixed-integer programming model was proposed to minimize the expected loss of customer demand. Simulated Annealing was employed to solve the proposed model. A comparison with a traditional makespan model revealed that the proposed approach could offer more reliability. Yuan *et al.* [118] deployed a heterogeneous fleet of drones for delivery of goods in an urban setting. Several drone scheduling considerations were incorporated, including weight carrying capacity, maximum allowable flight duration, and flying speed. A Genetic Algorithm was developed for solution, which included a weight-based loading technique. Comparisons with two existing solution algorithms demonstrated the superiority of the developed algorithm.

2) Summary of Studies: A summary of findings from the collected studies, which captured drone scheduling for delivery of goods, is presented in **Table IV**. It was found that a significant number of the studies on drone scheduling for delivery of goods formulated mixed-integer programming (MIP) models, did not enforce time windows, and deployed multiple drones. The developed mathematical models had a variety of different objective functions (e.g., minimize the maximum completion time, minimize the total delivery cost, and minimize the overall delay). Moreover, a significant number of the studies on drone scheduling for delivery of goods deployed either single or multiple ground vehicles in synchronization with drones. Heuristic and metaheuristic algorithms were found to be common solution approaches for the drone scheduling problem with delivery of goods. In addition, a significant number of the studies considered parallel drone scheduling and vehicle-drone cooperation.

3) Future Research Needs: Limitations and future research needs in the area of drone scheduling for delivery of goods include the following:

TABLE IV
SUMMARY OF FINDINGS: STUDIES ON DRONE SCHEDULING FOR DELIVERY OF GOODS

References	Formulation Types	Model Objectives	Time Windows	Drone Characteristics	Number of Ground Vehicles	Solution Approaches	Notes/Major Considerations
Zhang et al. (2014) [99]	N/A	Minimize the overall delay; maximize the probability of successfully handling service requests	N/A	MD	N/A	Dynamic Programming	Prioritization of service requests
Murray and Chu (2015) [100]	MIP	Minimize the completion time	N/A	SD/MD	Single	GUROBI; Heuristic	Parallel drone scheduling; vehicle-drone cooperation
Ham and Kim (2017) [101]	N/A	Minimize the maximum completion time	N/A	MD	N/A	IBM ILOG CP Optimizer	Pick-up and delivery
Boysen et al. (2018) [10]	MIP	Minimize the completion time	N/A	MD	Single	GUROBI; Simulated Annealing	Vehicle-drone cooperation
Chen et al. (2018) [102]	N/A	Minimize the completion time; minimize the tardiness	N/A	SD	N/A	Hybrid Block-Based Edge Recombination Algorithm	Late arrival
Ham (2018) [103]	CP	Minimize the maximum completion time	Strict	MD	Multiple	Constraint Programming	Parallel drone scheduling; pick-up and delivery
Liu et al. (2018) [104]	IP	Minimize the total cost	N/A	SD	Single	Enumeration; Heuristic	Vehicle-drone cooperation
Saleu et al. (2018) [105]	MIP	Minimize the completion time	N/A	MD	Single	Heuristic	Parallel drone scheduling
Shi and Ng (2018) [106]	N/A	N/A	N/A	MD	N/A	Hybrid A* Algorithm	Drone failure
Torabbeigi et al. (2018) [107]	MIP	Minimize the expected loss of demand	N/A	MD	N/A	CPLEX; Heuristic	Drone failure
Kim and Moon (2019) [108]	MIP	Minimize the completion time; minimize the number of drones	N/A	MD	Single	XPRESS-MP; Heuristic	Parallel drone scheduling
Peng et al. (2019) [109]	IP	Minimize the total distance cost; minimize the completion time	N/A	MD	Single	Hybrid Genetic Algorithm	Vehicle-drone cooperation
Sawadsitang et al. (2019) [110]	LP	Minimize the total delivery cost; minimize the percentage of unsuccessful delivered packages; maximize the reward of on-time delivery	Soft	MD	N/A	E-Constraint Method	Outsourcing to carrier
Seakhoa-King et al. (2019) [111]	N/A	Maximize the revenue	Soft	MD	N/A	Heuristic	Time-sensitive delivery
Wang et al. (2019) [112]	N/A	Minimize the maximum completion time	N/A	MD; ECC	Multiple	Heuristic	Parallel drone scheduling; vehicle-drone cooperation
Cheng et al. (2020) [113]	MINLP	Minimize the travel cost and the energy consumption	Strict	MD; ECC	N/A	Branch-and-Cut Algorithm	Payload; time windows
Dell'Amico et al. (2020) [114]	MIP	Minimize the maximum completion time	N/A	MD	Single	Matheuristic	Parallel drone scheduling
Ham (2020) [115]	MIP; CP	Minimize the maximum completion time	Strict	MD	N/A	IBM OPL	Pick-up and delivery; time windows
Huang et al. (2020) [116]	MIP	Minimize the completion time	N/A	SD; ECC	Multiple	Dynamic Programming	Vehicle-drone cooperation; recharge considerations

TABLE IV
(Continued.) SUMMARY OF FINDINGS: STUDIES ON DRONE SCHEDULING FOR DELIVERY OF GOODS

Torabbeigi et al. (2020) [27]	MIP	Minimize the initial depot opening cost; minimize the number of drones	N/A	MD; ECC	N/A	Variable Preprocessing Algorithm; Primal and Dual Bound Generation Methods	Payload
Liu et al. (2021) [11]	MIP	Minimize the number of drones	N/A	MD	N/A	Genetic Algorithm	Time-sensitive delivery
Torabbeigi et al. (2021) [117]	MIP	Minimize the expected loss of demand	N/A	MD	N/A	Simulated Annealing	Drone failure
Yuan et al. (2021) [118]	MIP	Minimize the maximum completion time	N/A	MD	N/A	Genetic Algorithm	Heterogeneous fleet

Notes: CP – Constraint Programming; IP – Integer Programming; LP – Linear Programming; MIP – Mixed-Integer Programming; MINLP – Mixed-Integer Non-Linear Programming; SD – Single Drone; MD – Multiple Drones; ECC – Energy Consumption Considerations.

- Even though drone scheduling for delivery of goods is becoming a popular research topic, there is a lack of benchmarks in solutions for drone scheduling models involving delivery of goods. Hence, significant efforts should be made in order to establish benchmarks [92], [93].
- Battery consumption rate is affected by payload. Therefore, payload should be incorporated in the battery consumption function by the future studies [27], [166]–[168], [171].
- Replacement of trucks with public transportation vehicles could be more profitable for vehicle-assisted drone deliveries. Hence, incorporation of public transportation vehicles along with a consideration of their routes into the drone scheduling models should be further explored [44], [116].
- Many of the existing models involve one vehicle assisting one or multiple drones. Collaboration between multiple vehicles and multiple drones could be more profitable [103], [112].
- A comprehensive analysis of the advantages and disadvantages of vehicle-assisted drone deliveries could be taken as a future research direction [10], [100], [103]–[105].
- Dynamic placement of delivery orders is often captured in real-world systems with ground vehicles. Such services should also be proposed for drone deliveries.

C. Drone Scheduling for Monitoring

At earlier times, drones were used for military purposes, such as surveillance and attack. With time, drones have been employed by public and private entities for non-military monitoring and inspection purposes (e.g., disaster management, fault detection). Nonetheless, a number of drone scheduling studies can be found that aim to employ drones for surveillance. This study category includes the studies that involve either security- or non-security-oriented monitoring. Under the scope of the drone scheduling problem for monitoring, the group of customers (or objects) are treated as targets to be monitored. Each target or customer is allocated a specified monitoring time $s_i, i \in I$. Then, a mathematical formulation for the drone scheduling problem for monitoring can be presented as follows:

Drone Scheduling Problem for Monitoring (**DSPM**)

$$min(\max_{ik} \boldsymbol{t}_{ik}) \quad \forall i \in I \cup C, k \in K \tag{15}$$

Subject to :

Constraint sets (2) – (5), (8) – (9), (14)

$$\boldsymbol{t}_{ik} + s_i + d_{ij} - M\left(1 - \boldsymbol{x}_{ijk}\right) \leq \boldsymbol{t}_{jk} \quad \forall i \in I \cup C, j \in I \cup C, k \in K \tag{16}$$

The objective function (15) of the **DSPM** mathematical formulation minimizes the maximum completion time of the monitoring tasks. Constraint set (16) functions as a time conservation constraint (i.e., if a drone travels from one node to another, then, the arrival time at the destination node cannot be less than the sum of the arrival time at the origin node, the monitoring time at the origin node, and the travel duration between the two nodes). Some examples of flight paths of drones that can be obtained using the **DSPM** mathematical model for various monitoring purposes are shown in Fig. 7.

1) Description of the Relevant Studies: Weinstein and Schumacher [119] scheduled drones using the framework of the vehicle routing problem with time windows. Three objective functions were examined: (1) minimization of the total travel distance; (2) minimization of the maximum completion time; and (3) minimization of the total travel time. The study indicated that minimization of the maximum completion time could be more precise for military applications (e.g., attack, surveillance); however, it was associated with greater computational time. Li *et al.* [120] assessed a drone scheduling method to survey an area after a disaster had passed. After a real-time tracking of the locations of the available fleets of drones, the arrival times of drones at a meeting point were estimated. Afterwards, they were deployed to inspect the disaster zone. Koulali *et al.* [121] studied drone scheduling for disaster relief and similar circumstances. Beaconing periods of competing drones were modeled under a sub-modular game perspective. The equilibrium beaconing strategy of each drone was assessed

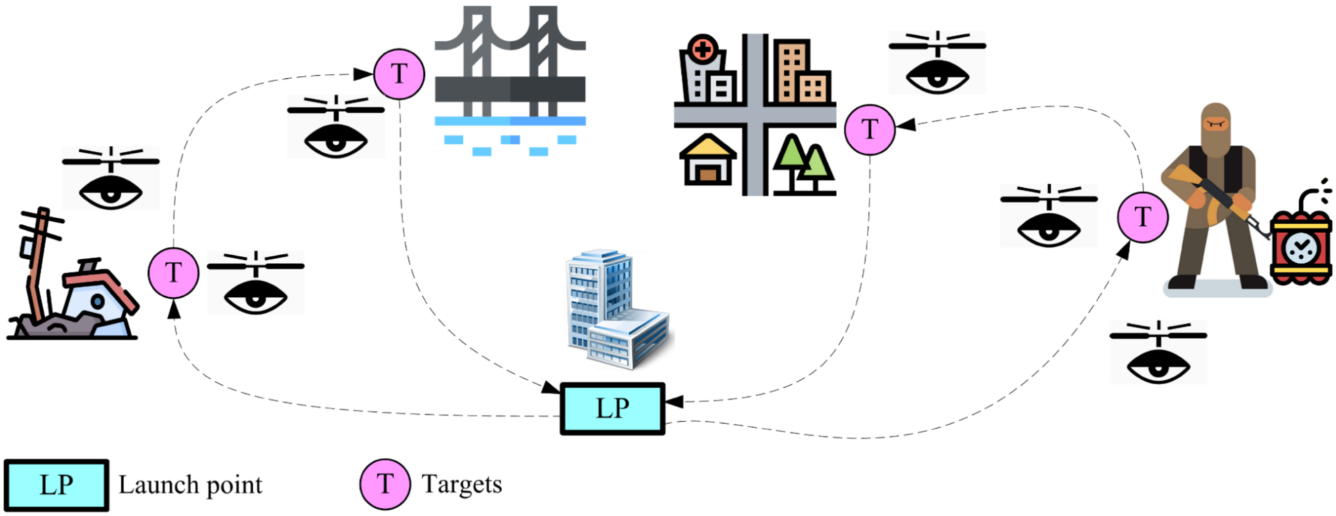

Fig. 7. Flight paths of drones for monitoring.

without prior knowledge of its opponent drone's schedule. Ghazzai *et al.* [122] studied parallel and sequential scheduling of drones for an extended time period to cover events, which were distributed temporally and spatially. Technical attributes, such as battery capacity, were incorporated to schedule drones that had to return to a docking station on a regular basis. It was found that the total energy consumption, which consisted of the energy consumption for covering events, waiting, and flying, decreased, when a high-capacity battery was used.

Gu *et al.* [123] asserted that surveillance of small moving targets was a challenging issue. Therefore, a sky-ground surveillance network, including drones and wireless sensor networks, was developed. Moreover, a task scheduling model for multiple drones within the network was proposed by the study. Cao *et al.* [124] discussed that wind turbines would become a major energy source in the future, especially for energy internet. However, installing and using wind turbines at remote areas might incur significant costs. Hence, an inspection and computing model, equipped with drones, was proposed. The model was based on mobile edge computing and jointly optimized the computation and trajectory operations of drones. Chen *et al.* [125] envisaged a scheme to inspect air pollution from oceangoing vessels. The scheme involved several aspects related to inspection of pollution, including drone schedules. The drone schedules provided two major decisions: (1) assignment of drones to vessels; and (2) time of inspection. Hu *et al.* [126] argued that vehicle-drone cooperative surveillance had significant merit due to long driving ranges of vehicles and extensive mobility of drones. A routing and scheduling problem that involved a number of drones, carried by a vehicle, to sense various targets in a parallel fashion was formulated. A solution algorithm was developed, which involved joint optimization of tour assignment, anchor point selection, and path planning. Hu *et al.* [127] allowed recycling of drones at multiple locations in order to minimize time wastage. Several decisions were considered, such as determination of launching and recycling points, synchronization, time scheduling, and others for inspection of wide areas.

Drones have a significant potential in monitoring emissions from vessels in emission control areas (i.e., areas where vessels are required to use less harmful fuel). Hence, Xia *et al.* [128] formulated a drone scheduling model in order to maximize the total revenue generated from monitoring vessels by drones. A Lagrangian Relaxation-based technique was employed to solve the mixed-integer programming model that incorporated time-dependent locations of vessels. Numerical experiments conducted for the Pearl River Delta demonstrated that the proposed approach could provide compact upper bounds for instances comprising up to 100 vessels. Ejaz *et al.* [129] employed an energy-aware task scheduling framework to collect data from a ground Internet of Things network to be used by first responders after a disaster had passed through an area. The proposed framework aimed to minimize the total energy consumption of drones. The optimal trajectory of drones was determined by using a Genetic Algorithm. Moreover, the health risk of the affected people was estimated with a decision tree classification algorithm. Jung *et al.* [130] aimed to reduce overlaps between the monitoring areas of different drones within a surveillance system. The problem was formulated as a maximum weight independent set problem. A solution algorithm was developed, which was able to conserve energy efficiently.

Jung *et al.* [131] analyzed a drone-based surveillance system. Under the system, a number of drones equipped with cameras monitored an area, but some of the surveillance cameras were turned off at overlapping zones to obtain energy efficiency. Moreover, unscheduled drones travelled to charging stations. It was indicated that the proposed methodology was applicable to drone taxi services as well. Zhang *et al.* [132] formulated a game theory-based scheme to derive a balance between minimization of energy consumption and maximization of reputation of drones. Energy consumption of drones was modeled considering the working state along with scheduling strategies, while the reputation gain model was based on practical scenarios. The game theory-based scheme was employed to incorporate both models in order to maximize the operator's payoff. Yi and Sutrisna [133] explored drone scheduling for monitoring of construction sites. A mixed-integer nonlinear programming model was formulated to direct drones to spend more time at areas that required greater attention. Hence, the model incorporated the minimum monitoring time and the actual monitoring time at different segments. A Dynamic Programming Algorithm was used to optimize the flying speed of drones. A real-world case study indicated that the optimal flying speed along a given segment was dependent on the minimum monitoring requirements of that segment and its nearby segments. Drone scheduling for monitoring has been captured by several other studies [134]–[149].

2) Summary of Studies: A summary of findings from the collected studies, which captured drone scheduling for monitoring, is presented in **Table V**. It was found that a significant number of the studies on drone scheduling for monitoring formulated mixed-integer programming (MIP) and mixed-integer non-linear programming (MINLP) models, did not enforce time windows, deployed multiple drones, and incorporated energy consumption considerations. The developed mathematical models had a variety of different objective functions (e.g., minimize the completion time, minimize the energy consumption, and maximize the total surveillance benefit). Moreover, a significant number of the studies on drone scheduling for monitoring did not deploy any ground vehicles in synchronization with drones. Heuristics were found to be common solution approaches for the drone scheduling problem with monitoring.

3) Future Research Needs: Limitations and future research needs in the area of drone scheduling for monitoring include the following:

- Multiple drones could be deployed to inspect a site more effectively. However, that could incur additional costs. Therefore, inspection of a site with multiple drones along with related trade-offs in multi-objective settings could be further examined [51], [110].
- Collaboration between drones could reduce or eliminate overlaps between monitored areas. This could be another future research avenue [130], [131].
- Reactive solution methodologies (e.g., consensus-based algorithms) could be used for drone scheduling in order to deal with unplanned events [49], [122], [163].
- Geographical features of monitored areas could be incorporated for effective scheduling of drones [56], [78], [88], [165].
- Sudden events and disruptions can happen at any place and any point of time. Such events may influence the operations of drones that are assigned for monitoring of specific objects. Advanced methodologies, such as machine learning, could be employed to predict when and where the upcoming events could happen.
- Remaining battery capacities may drop below a threshold value because of environmental and other reasons, especially at disaster-affected monitored zones. Alternative methodologies for developing drone schedules are needed in such cases [2], [3], [81], [146].

D. Drone Scheduling With Recharge Considerations

This section of the manuscript focuses on the drone scheduling problem with recharge considerations. Note that the studies, which captured recharge of devices other than drone batteries (e.g., wireless sensor nodes), are not included in this category. Recharge of drones has been modeled in a wide variety of ways by researchers. Several aspects of recharge (e.g., split jobs with recharge, recharge speed, battery assignment, recharge capacity, charging station slots) along with various energy functions have been captured by different models. A representative mathematical model for the drone scheduling problem for split jobs with recharge considerations is presented in this section of the manuscript, where different drones are allowed to process different segments (or portions) of a customer's job. Hence, the customers are divided into a set of split jobs $I = \{1, \ldots, N_I\}$. Various charging stations are used to launch the set of drones $K = \{1, \ldots, N_K\}$. The drones process split jobs and stop at charging stations for recharge. After recharge, they are launched again to process split jobs. Hence, the drones commence multiple flights $R = \{1, \ldots, N_R\}$.

Due to multiple flights, a starting index and an ending index are assigned to a charging station. Hence, the set of charging stations is treated as a set of starting charging stations $CS = \{1, \ldots, N_{CS}\}$ and a set of ending charging stations $CE = \{1, \ldots, N_{CE}\}$. Furthermore, an index for the flight number is added to the variables. Therefore, a binary decision variable $\boldsymbol{x}_{ijkr}, i \in I \cup CS \cup CE, j \in I \cup CS \cup CE, k \in K, r \in R$ is used. The value of $\boldsymbol{x}_{ijkr}$ is 1 if drone k flies from split job i or charging station i to split job j or charging station j during flight r, and 0 otherwise. Another positive auxiliary variable $\boldsymbol{t}_{ikr}, i \in I \cup CS \cup CE, k \in K, r \in R$ is used to record the start time of split job i or the start time of recharge at charging station i for drone k during flight r. Moreover, the time parameter $s_i, i \in I \cup CS \cup CE$, in this case, indicates either the processing time of split job i or the recharge time at charging station i. Then, a mathematical formulation for the drone scheduling problem with recharge considerations can be presented as follows [150]:

The objective function (17) of the **DSPRC** mathematical formulation minimizes the total travel duration. A total of three groups of constraints are included in this model. The first group of constraints [i.e., constraints (18) to (22)] applies some basic routing rules for the **DSPRC** mathematical formulation. Constraint set (18) implies that each drone is initially launched from its designated starting charging station $CS'_k, k \in K$. Constraint set (19) indicates that each drone is launched from a starting charging station and flies to either a split job or an ending charging station. Constraint set (20) guarantees that each flight of a drone is finished at an ending charging station. Constraint set (21) indicates that a drone is not allowed to end its flight at the starting index of a charging station. Constraint set (22) ensures that each drone starts a flight from the charging station where its previous flight ended. The second group of constraints [i.e., constraints (23) to (25)] monitors split jobs. Constraint set (23) ensures that a drone's flight is not ended at a split job. Constraint set (24) requires that each split job is processed. Constraint set (25) implies that each split job

TABLE V

SUMMARY OF FINDINGS: STUDIES ON DRONE SCHEDULING FOR MONITORING

References	Formulation Types	Model Objectives	Time Windows	Drone Characteristics	Number of Ground Vehicles	Solution Approaches	Notes/Major Considerations
Weinstein and Schumacher (2007) [119]	MIP	Minimize the total travel distance; minimize the maximum completion time; minimize the total travel time	Soft and strict	MD	N/A	GNU Linear Programming Kit	Operator-imposed time windows
Li et al. (2014) [120]	N/A	N/A	N/A	MD	N/A	N/A	Disaster management
Koulali et al. (2016) [121]	N/A	Maximize the payoff	Strict	MD; ECC	N/A	Heuristic	Data dissemination; game theory
Ghazzai et al. (2018) [122]	MINLP	Minimize the energy consumption	Strict	MD; ECC	N/A	GUROBI	Spatially and temporally distributed events
Gu et al. (2018) [123]	N/A	N/A	N/A	MD; ECC	Single	N/A	Moving targets; wireless sensor network
Cao et al. (2019) [124]	N/A	Minimize the completion time; minimize the energy consumption	N/A	MD; ECC	N/A	Heuristic	Mobile edge computing
Chen et al. (2019) [125]	MINLP	Maximize the total weighted number of inspected vessels	Strict	MD	N/A	N/A	Emissions from vessels
Hu et al. (2019) [126]	IP	Minimize the completion time	N/A	MD	Single	Heuristic	Vehicle-drone cooperation
Hu et al. (2019) [127]	N/A	Minimize the time wastage	N/A	MD	Single	Heuristic	Vehicle-drone cooperation
Xia et al. (2019) [128]	MIP	Maximize the weights of all included arcs	Strict	MD	N/A	Lagrangian Relaxation	Emission control areas
Ejaz et al. (2020) [129]	INLP	Minimize the energy consumption	N/A	MD; ECC	N/A	Genetic Algorithm	Disaster management
Jung et al. (2020) [130]	IP	Maximize the summation of weights of all possible independent sets in a conflict graph	N/A	MD; ECC	N/A	Heuristic	Conflict graph
Jung et al. (2020) [131]	MIP	Minimize the energy consumption; maximize the amount of charging energy	N/A	MD; ECC	N/A	Heuristic	Recharge considerations
Zhang et al. (2020) [132]	N/A	Minimize the energy consumption; maximize the reputation	N/A	MD; ECC	N/A	Heuristic	Game theory; mobile edge computing
Yi and Sutrisna (2021) [133]	NLP	Maximize the total surveillance benefit	Strict	SD; ECC	N/A	Dynamic Programming	Fixed path; prioritization of areas

Notes: IP – Integer Programming; INLP – Integer Non-Linear Programming; MIP – Mixed-Integer Programming; MINLP – Mixed-Integer Non-Linear Programming; NLP – Non-Linear Programming; SD – Single Drone; MD – Multiple Drones; ECC – Energy Consumption Considerations.

is started at its designated start time $a_i, i \in I$. The third group of constraints [i.e., constraints (26) to (30)] regulates time. Constraint set (26) indicates that the start time of a drone's flight and the end time of its previous flight are the same. Constraint set (27) functions as a time conservation constraint. Constraint set (28) links the two variables. Constraint set (29) ensures that the total flight duration of a drone does not exceed its maximum allowable flight duration. Constraint set (30) defines the nature of the variables in the **DSPRC** mathematical formulation. Some flight paths of drones with recharge considerations that can be obtained using the **DSPRC** mathematical model are illustrated in Fig. 8.

1) Description of the Relevant Studies: Kim and Morrison [151] developed a scheduling scheme for capacitated drones, where they could replenish their energy levels at several stations and resume service. Split jobs were accommodated (i.e., different drones could complete different segments of a customer's task). The objective of the proposed model was to minimize the sum of the travel cost, drone purchase cost, and station purchase cost. A Branch-and-Bound Algorithm was employed to obtain global optimality for the model, while a heuristic was used for large-size instances of the problem. Kim *et al.* [152] proposed a drone scheduling model that incorporated automated charging

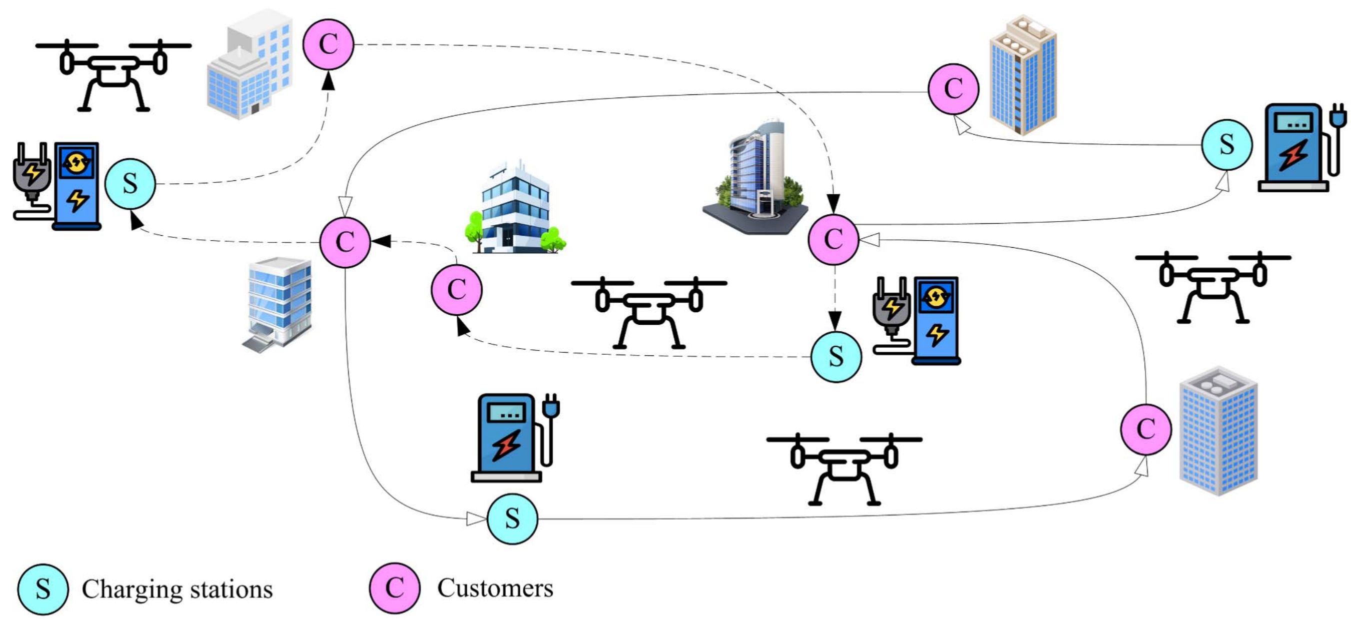

Fig. 8. Flight paths of drones with recharge considerations.

stations along with split job considerations. The proposed mixed-integer programming model was solved with a Genetic Algorithm for large instances that could not be tackled by CPLEX. Results demonstrated the efficiency of the proposed methodology. Song *et al.* [150] designed drone schedules, which allowed split tasks. A mixed-integer programming model was developed, whose aim was to minimize the total travel distance. It was indicated that the developed mathematical model obtained significant improvements in computational complexity, as compared to many of the existing models in the literature. The model was solved with CPLEX for instances with up to 20 split tasks.

Zhou *et al.* [153] demonstrated a cooperative network between drones and ground vehicles. An aerial sub-network, consisting of drones, assisted a sub-network of ground vehicles through air-to-air and ground interactions. The ground vehicle was used for drone energy monitoring and recharging. Such a network architecture could be effective for a number of areas, including pollution inspection, disaster management, and data dissemination. Lim and Jung [154] discussed that geographical conditions (e.g., mountains, islands) might impede conventional vehicles from completing deliveries on time. The study presented a drone delivery scheduling model considering battery capacity, recharge speed, and drone weight. Simulation results based on a case study for remote islands in South Korea, whose delivery lead time was 1-3 days longer than other areas, demonstrated the potential of the proposed approach. Park *et al.* [155] discussed that proper management of drone batteries was not thoroughly explored in the literature. Therefore, the study disintegrated battery management into two sub-problems, including battery assignment and battery scheduling, with the goal to minimize the degradation of drone batteries. Battery assignment was conducted with an assignment algorithm, while battery scheduling was formulated as an integer programming model, which could be tackled with external solvers. It was underlined that the state-of-health degradation of drone batteries was affected by the idle time between charge cycles, while energy consumption of drone delivery services was impacted by battery assignment.

Kim and Lim [156] assessed two different kinds of wireless charging systems, including stationary and dynamic. Under the stationary wireless charging system, a drone could be recharged after landing. On the contrary, the dynamic wireless charging system would require a drone to fly over coiled lines in order to be recharged. A hybrid model was proposed to combine both of the systems to minimize the total cost. Numerical experiments highlighted several merits of the proposed model, including longer flight times along with reduced landing times and uncontrolled times. Trotta *et al.* [157] examined a mesh network of drones to facilitate continuity of service through a ground-based recharge scheme. Game theory-based strategies as well as swarm mobility algorithms were applied for scheduling. In addition, a cost-benefit analysis was performed to promote cooperation among drones for recharge. Ghazzai *et al.* [158] studied drone-based intelligent transportation systems. A drone-based traffic monitoring system was proposed, where the permanent locations of docking and charging stations were determined in order to maximize the coverage efficiency. Afterwards, a scheduling scheme was developed to minimize the total energy consumption.

Shin *et al.* [159] suggested that mobile charging stations had limitations in charging drones due to the number of available stations as well as charging time. Hence, the study examined an auctioning process of charging time slots for such stations through bidding. The proposed approach relied on the distribution of participating drones, which was determined by deep learning. Results indicated that the proposed approach could be efficient for problem instances with multi-drone

Drone Scheduling Problem with Recharge Considerations (**DSPRC**)

$$min \sum_{i\in I\cup CS\cup CE}\ \sum_{j\in I\cup CS\cup CE}\ \sum_{k\in K}\sum_{r\in R} d_{ij}\boldsymbol{x}_{ijkr} \quad (17)$$

Subject to :

$$\sum_{j\in I\cup CE} \boldsymbol{x}_{(CS'_k)jk(1)} = 1\ \forall k\in K \quad (18)$$

$$\sum_{c\in CS}\ \sum_{j\in I\cup CE} \boldsymbol{x}_{cjkr} = 1\ \forall k\in K, r\in R \quad (19)$$

$$\sum_{i\in I\cup CS}\ \sum_{c\in CE} \boldsymbol{x}_{ickr} = 1\ \forall k\in K, r\in R \quad (20)$$

$$\sum_{i\in I\cup CS} \boldsymbol{x}_{ickr} = 0\ \forall c\in CS, k\in K, r\in R \quad (21)$$

$$\sum_{i\in I\cup CS} \boldsymbol{x}_{ickr} = \sum_{j\in I\cup CE} \boldsymbol{x}_{(c-1)jk(r+1)}\ \forall c\in CE, k\in K, r\leq |R|-1 \quad (22)$$

$$\sum_{j\in I\cup CS\cup CE} \boldsymbol{x}_{vjkr} = \sum_{i\in I\cup CS\cup CE} \boldsymbol{x}_{ivkr}\ \forall v\in I, k\in K, r\in R \quad (23)$$

$$\sum_{i\in I\cup CS\cup CE}\ \sum_{k\in K}\sum_{r\in R} \boldsymbol{x}_{ijkr} = 1\ \forall j\in I \quad (24)$$

$$\sum_{k\in K}\sum_{r\in R} \boldsymbol{t}_{ikr} = a_i\ \forall i\in I \quad (25)$$

$$\boldsymbol{t}_{ckr} = \boldsymbol{t}_{(c-1)k(r+1)}\ \forall c\in CE, k\in K, r\leq |R|-1 \quad (26)$$

$$\boldsymbol{t}_{ikr} + s_i + d_{ij} - M\left(1-\boldsymbol{x}_{ijkr}\right) \leq \boldsymbol{t}_{jkr}\ \forall i\in I\cup CS, j\in I\cup CE, k\in K, r\in R \quad (27)$$

$$M\cdot \sum_{j\in I\cup CE} \boldsymbol{x}_{ijkr} \geq \boldsymbol{t}_{ikr}\ \forall i\in I\cup CS, k\in K, r\in R \quad (28)$$

$$\sum_{i\in I\cup CS\cup CE}\ \sum_{j\in I\cup CS\cup CE} d_{ij}\boldsymbol{x}_{ijkr} + \sum_{i\in I}\ \sum_{j\in I\cup CS\cup CE} s_i\boldsymbol{x}_{ijkr} \leq D_k\ \forall k\in K, r\in R \quad (29)$$

$$\boldsymbol{x}_{ijkr}\in\{0,1\}, \boldsymbol{t}_{ikr}\geq 0\ \forall i\in I\cup CS\cup CE, j\in I\cup CS\cup CE, k\in K, r\in R \quad (30)$$

scenarios. Tajrian and Kim [160] developed a scheduling algorithm to facilitate power charging of drones. The algorithm featured a scheduler that decided the order of recharge. Results from simulation demonstrated that the algorithm was effective in reducing the turnaround time and deadline miss ratio. For 5G mobile networks, Tipantuña *et al.* [161] employed a drone scheduling algorithm to promote Network Functions Virtualization, a solution to promote orchestration, management, and automation. The energy-aware solution was inspired by a brute-force search combinatorial algorithm and could estimate the number of drones to be deployed for a given degree of service. Ahani *et al.* [162] considered battery recharge while collecting data from sensor nodes. The latest data were attempted to be collected. Hence, a performance metric, named age of information, was employed that indicated the time passed since the latest data collection. The objective of the study was to minimize the mean age of information cost. The study proved the considered problem to be NP-hard, and a Graph Labeling Algorithm was used for solution. Comparisons with a Greedy Algorithm showcased the superiority of the proposed methodology.

Hassija *et al.* [163] suggested that drones needed to be light-weighted and could not be equipped with large batteries. It was also implied that frequent recharge or battery replacements could hinder the use of drones. Therefore, the study proposed a model to optimize the schedule to charge drones within a network. After entering the network, a drone had to make a request for a charging slot. A scheduling algorithm was used to allocate time slots between competing drones, with a consideration of criticality and deadline. The trading of energy between charging stations and charged drones was determined through game theory. It was revealed that the proposed solution approach was advantageous for both drones and charging stations. Hu *et al.* [164] envisioned a mobile edge computing system that required cooperation between a drone and an access point. The access point was responsible for charging the drone and computing offloaded tasks of user equipment. A mathematical model was proposed to optimize the drone's energy as well as trajectory, time allocation, and task allocation. Some other studies have assessed drone scheduling with recharge considerations as well [165]–[172].

2) Summary of Studies: A summary of findings from the collected studies, which captured drone scheduling with recharge considerations, is presented in **Table VI**. It was found that a significant number of the studies on drone scheduling with recharge considerations formulated mixed-integer programming (MIP) and mixed-integer non-linear programming (MINLP) models, did not enforce time windows, deployed multiple drones, and incorporated energy consumption considerations. The developed mathematical models had a variety of different objective functions (e.g., minimize the total cost, minimize the total travel distance, and maximize the revenue). Moreover, a significant number of the studies on drone scheduling with recharge considerations did not deploy any ground vehicles in synchronization with drones. Heuristics were found to be common solution approaches for the drone scheduling problem with recharge considerations. In addition, data dissemination and split jobs were considered by some studies.

3) Future Research Needs: Limitations and future research needs in the area of drone scheduling with recharge considerations include the following:

- Different drones of a fleet may be equipped with different batteries. Therefore, the same energy function may not be applicable to all drones. Hence, future studies need to consider heterogeneous fleets of drones [46], [49], [118].
- Multiple auctions for the available mobile charging stations could be proposed in order to conduct a larger-scale recharge of drones. However, additional formulations, analyses, and verifications would be required [159], [163].
- Capacitated charging stations with a limited number of drones and limited energy could be modeled by future studies and incorporated within the existing

TABLE VI
SUMMARY OF FINDINGS: STUDIES ON DRONE SCHEDULING WITH RECHARGE CONSIDERATIONS

References	Formulation Types	Model Objectives	Time Windows	Drone Characteristics	Number of Ground Vehicles	Solution Approaches	Notes/Major Considerations
Kim and Morrison (2013) [151]	MIP	Minimize the total cost	N/A	MD; ECC	N/A	Branch-and-Bound Algorithm; Heuristic	Split jobs
Kim et al. (2013) [152]	MIP	Minimize the total travel distance	N/A	MD; ECC	N/A	Genetic Algorithm; CPLEX	Split jobs
Song et al. (2013) [150]	MIP	Minimize the total travel distance	N/A	MD; ECC	N/A	CPLEX; Heuristic	Split jobs
Zhou et al. (2015) [153]	N/A	N/A	N/A	MD; ECC	N/A	N/A	Data dissemination
Lim and Jung (2017) [154]	N/A	N/A	N/A	MD; ECC	N/A	N/A	Charging speed
Park et al. (2017) [155]	IP	Minimize the state-of-health degradation of batteries	N/A	MD; ECC	N/A	Heuristic; Simulation	Battery assignment; battery scheduling
Kim and Lim (2018) [156]	MINLP	Minimize the total cost	N/A	MD; ECC	N/A	BARON	Dynamic wireless charging; stationary wireless charging
Trotta et al. (2018) [157]	N/A	Maximize the network lifetime	N/A	MD; ECC	N/A	Heuristic	Game theory
Ghazzai et al. (2019) [158]	MINLP	Maximize the coverage efficiency; minimize the energy consumption	Strict	MD; ECC	N/A	Penalized Weighted K-Means Algorithm; Particle Swarm Optimization	Placement of charging stations
Shin et al. (2019) [159]	N/A	Maximize the revenue	N/A	MD; ECC	N/A	Deep Learning	Deep learning-based auction
Tajrian and Kim (2019) [160]	N/A	Minimize the ratio of turnaround time and deadline miss	N/A	MD; ECC	N/A	Heuristic	Prioritization for recharge
Tipantuña et al. (2019) [161]	N/A	Maximize the use of available resources	Strict	MD; ECC	N/A	Heuristic	Data dissemination
Ahani et al. (2020) [162]	N/A	Minimize the total cost	N/A	SD; ECC	N/A	Graph Labeling Algorithm	Data dissemination
Hassija et al. (2020) [163]	N/A	Maximize the revenue; maximize the flight time	N/A	MD; ECC	N/A	Heuristic	Consensus timestamp; game theory
Hu et al. (2020) [164]	MINLP	Maximize the weighted sum completed task-input bits of user equipment	N/A	SD; ECC	N/A	Heuristic	Mobile edge computing

Notes: IP – Integer Programming; MIP – Mixed-Integer Programming; MINLP – Mixed-Integer Non-Linear Programming; SD – Single Drone; MD – Multiple Drones; ECC – Energy Consumption Considerations.

mathematical formulations for the drone scheduling problem [118], [139].

- Charging stations may fail due to overuse. Hence, failure of charging stations should be modeled in the mathematical formulations for the drone scheduling problem.
- Advanced technologies for more efficient recharge of drones could be explored.

V. CONCLUDING REMARKS

Public and private applications of drones are still at a primary stage and limited with various restrictions (e.g., battery capacity, limited carrying capacity). Therefore, drone schedules should be optimized to overcome such restrictions. The drone scheduling problem is associated with optimization of drone flight paths and may include other features, such as determination of arrival times at different nodes, considering battery constraints and related limitations (e.g., flight duration and range). This research conducted a comprehensive survey of the studies that focused on the drone scheduling problem. The selected studies were grouped into the following categories: (1) general drone scheduling; (2) drone scheduling for delivery of goods; (3) drone scheduling for monitoring; and (4) drone scheduling with recharge considerations. Representative mathematical models were provided for the considered study categories. Furthermore, for each of the four study categories, a detailed description of the studies was provided, accompanied by a summary of findings, existing gaps in the state-of-the-art, and critical future research needs.

The review of the selected studies revealed that a wide range of mathematical formulations were proposed, including linear programming, non-linear programming, integer programming, integer non-linear programming, mixed-integer programming, mixed-integer non-linear programming, and other formulations. Moreover, various model objectives were considered. The considered minimization objectives include minimization of the completion time, energy consumption, maximum completion time, total cost, number of drones, travel distance, and expected loss of demand. On the other hand, the maximization objectives include maximization of the revenue, throughput, network utility, etc. Most of the studies did not use time windows, while soft and strict time windows were enforced by only a few studies. An overwhelming majority of the reviewed studies deployed multiple drones but did not use ground vehicles in synchronization with them. Moreover, some studies directly considered energy consumption of drones. Several solution approaches were employed by the selected studies to tackle their mathematical models, which comprise exact optimization approaches (e.g., CPLEX, GUROBI), metaheuristics (e.g., Genetic Algorithm, Particle Swarm Optimization, Simulated Annealing), heuristics, and other approaches. Furthermore, a variety of considerations were incorporated by the selected studies, such as vehicle-drone cooperation, parallel drone scheduling, data dissemination, time windows at customer nodes, split deliveries, drone failures, and air temperature effects on the drone battery capacity.

This study is expected to assist decision makers, researchers, and scientists with better understanding of clear trends and directions in the field of drone scheduling. Several extensions may be associated with this study, including the following:

- There are many limitations in the field of drone scheduling, some of which require more urgent attention than the rest. Hence, a prioritization of limitations should be performed in consultation with the appropriate professionals to systematically guide the future research.
- The existing limitations in drone scheduling models could be addressed by means of consultation with the appropriate experts.
- Interviews with the major companies, which deploy drones for service, could be conducted in order to clearly identify the state-of-the-practice.
- More categories and sub-categories focusing on different features of the drone scheduling problem could be created (e.g., collaborative drone scheduling). Representative mathematical models for those categories and sub-categories may also be explored.
- Specific aspects of drone scheduling could be captured by future surveys, including the type of launch point, time components, maximum and selected speeds, continuity of service, etc.
- A more detailed review and classification of the solution approaches that have been used for the drone scheduling problem could be performed. The existing algorithms should be evaluated for their ability of adjusting to rapidly changing environments. Adaptive and self-adaptive algorithms proved their effectiveness for different decision problems [173]–[177] and can be promising for the drone scheduling problem as well.
- Drones may have different kinds of batteries as well as corresponding energy consumption and recharge functions. Hence, a drone scheduling model for a given type of drone battery may not be accurate for another type. Therefore, future surveys should categorize drone scheduling models based on battery type.
- Drone batteries are at a developmental stage, where advancements are being made regularly. Future research should study these advancements more deeply.
- Automation is expected to improve operations efficiency but imposes some legal challenges [178], [179]. Drones can be purchased for private use. However, some regulatory and legal restrictions are associated with the private use of drones. The future review studies could capture these restrictions and propose a set of alternatives that would assist in addressing these issues.

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