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Review

Optimization for drone and drone-truck combined operations: A review of the state of the art and future directions

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ABSTRACT

This paper surveys the state-of-the-art optimization approaches in the civil application of drone operations (DO) and drone-truck combined operations (DTCO) including construction/infrastructure, agriculture, transportation/logistics, security/disaster management, entertainment/media, etc. In particular, this paper reviews ongoing research on various optimization issues related to DO and DTCO including mathematical models, solution methods, synchronization between a drone and a truck, and barriers in implementing DO and DTCO. First, the paper introduces DO and DTCO and their applications, and explores some previous works including survey papers. In addition, this paper surveys the state of the art of DO and DTCO studies and discusses the research gaps in the literature. Furthermore, the detailed review of DTCO models and solution methods are reviewed. Finally, future research directions are discussed.

Contents

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1. Introduction

1.1. Background

A drone is a machine that can fly without the assistance of a human pilot on board, and it becomes very popular because of its capability and potentiality, bolstered by the latest development of information technology including the boom of machine learning. There are different terms used for a drone, such as an unmanned aerial vehicle (UAV), remotely piloted aircraft (RPA), etc. In this paper, we use the term "drone" as it is commonly used in the research community (Ha and Deville, 2015; Ferrandez et al., 2016; Agatz and Bouman, 2018).

1.2. Drone operations (DO)

Drones can play an important role in a variety of application areas such as construction/infrastructure (Phung et al., 2017; Guerrero and Bestaoui, 2013), agriculture (Bandeira et al., 2015; Barrientos et al., 2011), transportation/logistics (Murray and Chu, 2015; Ponza, 2016), security/disaster management (Sandvik and Lohne, 2014; Marin, 2016; Mathew and Smith, 2013; Ortiz and Kingston, 2013), entertainment/media (Guerriero et al., 2014; Huang et al., 2018), and others (Sathyan and Ernest, 2016; Sancı and İşler, 2011; Oh et al., 2014). Indeed, several companies around the world including DHL (Aufgebauer, 2016), FedEx (Levin, 2018), Google (Statt, 2017), Matternet (Dickey, 2018), UPS (Kastrenakes, 2017), Alibaba (Lin, 2018), and Amazon (Johnson, 2017) have shown interest and used drones in the areas that can be broadly defined as last-mile delivery, which is an expensive and labor-intensive part of the logistics operations (Boyer and Prud'homme, 2009). For example, Matternet became the first company to receive full authorization for operating a drone logistics network in Switzerland in March 2017 (Ong, 2017). In addition, UPS partnered with Matternet for delivering medical samples in North Carolina in March 2019, the first FAA sanctioned use of routine revenue flights (Kelleher, 2019). DHL used a completely autonomous drone system to deliver consumer goods between January and March of 2016 in the Bavarian community of Reit im Winkl (Burgess, 2016). Amazon

Table 1
Drone and truck complementary features: Updated from Agatz and Bouman (2018).

Mode	Speed	Weight	Capacity	Range	Energy Consumption
Drone	High	Light	One	Short	Low
Truck	Low	Heavy	Many	Long	High

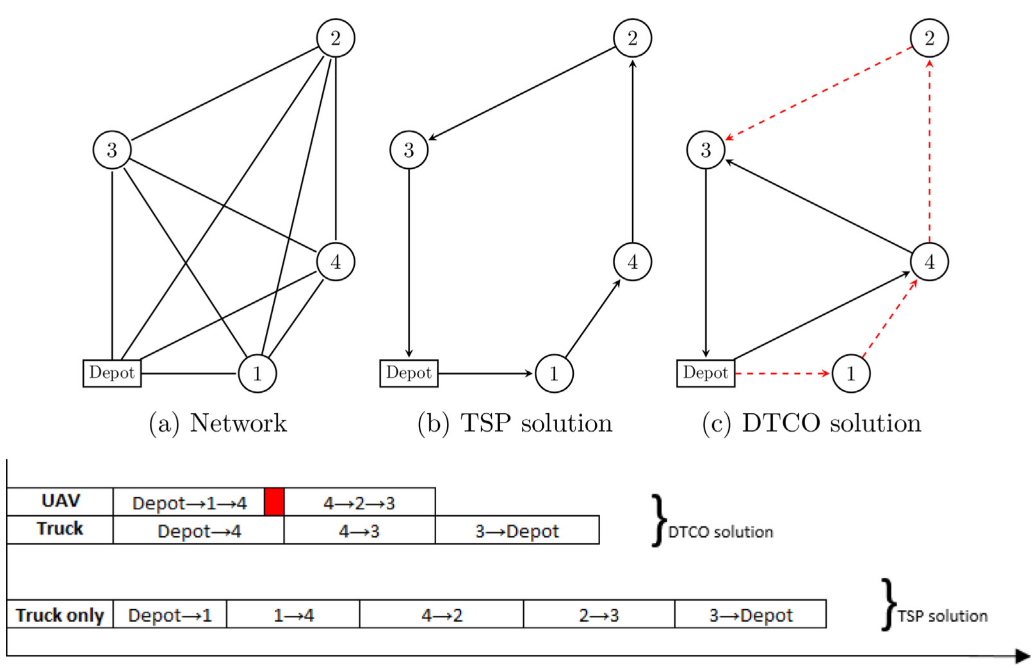
tested drones for Amazon prime air service in 2016, which can deliver packages up to five pounds in 30 minutes or less (Johnson, 2017). In 2019, Amazon added a new drone, MK27, which is apparently more efficient, reliable, stable, and safer compared to previous models in the drone fleet (Snow, 2019). MK27 uses artificial intelligence to operate autonomously in its environment and is able to detect people, animals, etc., and make appropriate maneuvers in response (Snow, 2019). Iceland's largest eCommerce company AHA has partnered with Flytrex to make deliveries using drones in the city of Reykjavik where AHA has been able to significantly reduce parcel delivery times by operating the Flytrex's drone delivery system alongside its existing vehicle-based delivery network (Shu, 2017). In 2019, Wing, the drone company owned by Google's parent company Alphabet, launched its first public drone delivery service in Canberra. Around 100 homes in the suburbs will have access to drone delivery, and there are expansion plans in upcoming months (Porter, 2019). Also in April 2019, Wing became the first company as an airlines to get FAA approval for drone delivery to customers in Virginia, US (Levin, 2019).

1.3. Drone-truck combined operations (DTCO)

There are some advantages and disadvantages of drones (excluding large ones usually used for military purposes, e.g., fixed-wing surveillance drones) when compared to traditionally used trucks when they are used for delivery purposes, as summarized in Table 1. Although many drones may travel faster than trucks and do not have to adhere to a particular route as long as non-permitted flying areas (airspace restrictions) can be avoided, their load capacity and travel range are limited in general. The relatively short travel range and limited capacity issues could be resolved, and the utility of drones can be further enhanced if drones are used with ground vehicles (e.g., trucks) in tandem. Of course, a conventional passenger car or other ground vehicles may be used instead of trucks. In this paper, we use the term, "truck", unless otherwise specified to represent a ground vehicle for the sake of brevity. Then, the drone-truck combined operations (DTCO) is defined as a system in which a drone and a truck work together as a team to achieve tasks such as delivery/collection of items, reconnaissance, inspection, monitoring, etc. We define the term, drone operations (DO), to specify the case where only drones are used.

DTCO has recently attracted the attention of industry as well as academia (Agatz and Bouman, 2018; Andrei, 2017; Bortoluzzi, 2019; Hawkins, 2019; Murray and Chu, 2015; Staff, 2019). For example, UPS tested their drone-truck delivery system in 2017 in which a drone flies off from the roof of the truck, drops the package to the customer, and returns back to the truck (Kastrenakes, 2017). Amazon recently filed a patent in 2018 (Buchmueller and Green, 2018), which suggests using commercial trucks operated by other companies to provide temporary transportation means for drones. This can be seen as drone hitch-hiking rides on trucks to save power.

There are several mathematical models and problems based on the concept of DTCO in the literature, which can be roughly divided into traveling salesman problem with drone (TSPD), see, e.g., Agatz and Bouman (2018), Ha et al. (2018), Murray and Chu (2015), Seifried (2019) and vehicle routing problem with drones (VRPD), see, e.g., Wang et al. (2017), Wang and Sheu (2019). The detailed review of DTCO models and methodologies is provided in Section 4. The most popular application of DTCO in the literature can be seen in logistics, delivery of items in particular, see, e.g., Agatz and Bouman (2018), Gonzalez-R et al. (2020), Ha et al. (2018),



(d) Comparison of delivery schedules of TSP and DTCO (Red box: waiting time)

Fig. 1. TSP vs DTCO solution.

Murray and Chu (2015), Seifried (2019), Wang et al. (2017), Poikonen and Wang (2017). A drone is able to depart from a truck, deliver or pick up a parcel, and return to the truck without any human intervention, while the truck can also deliver items to the customers at the same time or serve as a mobile hub for drones. Once the drone returns to the truck, its battery can be easily replaced, and will be ready for the next trip. The advantages of using a drone in tandem with a truck can be explained with the help of Fig. 1. In Fig. 1a, a simple road network is shown in which customers are located at node 1, 2, 3, and 4, to which a parcel/package needs to be delivered from the depot. A node represents a geographical locus. A simple traveling salesman problem (TSP) solution using the truck only can be seen in Fig. 1b, and a DTCO solution is shown in Fig. 1c in which the truck travels from the depot to node 4, while the drone takes the path $(\text{Depot} - 1 - 4)$ and meets the truck at node 4. After that, the truck takes the path $(4 - 3)$ while drone takes the path $(4 - 2 - 3)$ meeting the truck at node 3. Finally, the truck travels from node 3 to the depot with the drone mounted on top of it. DTCO may lead to significant savings in delivery completion time, as can be seen from Fig. 1d.

1.4. DO and DTCO literature

Research on DO and DTCO is still nascent. In this paper, we review different mathematical models, solution methods, synchronization between a drone and a truck, trade-off between operating cost and responsiveness, and techniques to overcome barriers in DO and DTCO, which can be leveraged to enhance the effectiveness and efficiency operations of DO and DTCO systems. The research questions found in the literature can be summarized as follows.

- What is the effectiveness achieved in terms of responsiveness and efficiency by using drones instead of trucks, and drones in conjunction with trucks?
- What is the need for synchronization between drone and truck?
- What is the reduction in total time achieved using multiple drones and trucks, as opposed to a single drone-truck combination?
- What is the effective way to address the energy consumption and/or equation of motion of a drone?
- What is the optimal way of scheduling and routing for multiple-drone and multiple-truck problems?
- What is the complexity of the problem?
- What are the barriers to DO and DTCO and how to overcome such barriers?

The research on DO and DTCO application is inherently multidisciplinary. Academia and industry are collaborating to make the DO and DTCO based systems a commercial success (Agatz and Bouman, 2018; Andrei, 2017; Bortoluzzi, 2019; Hawkins, 2019; Murray and Chu, 2015; Staff, 2019). Technologies for DO and DTCO application have been improving rapidly, and have already reached a stage where it can be implemented commercially. Thus, systematic investigations pertaining to the operational implications of the DO and DTCO applications are needed. Indeed, there is a high demand for surveys from private sector companies, practitioners, and researchers in addressing the operational challenges posed by DO and DTCO applications, especially to understand the state of the art (Clarke, 2014; Kim et al., 2016; Kunze, 2016). With this work, we aim to present a comprehensive overview of the current research to provide practitioners and researchers with the state-of-the-art information on DO and DTCO based problems. This paper would serve as an entry point for researchers to familiarize themselves with the DO/DTCO and their applications. Researchers will be able to better understand the state of art of the current research and will be able to identify new research directions.

There are a limited number of literature reviews related to drone application, some of which also include information about the DTCO application. Some of the previous survey papers address the following issues:

- Van Blyenburgh (1999) provides a general overview of drones and explores what lies in the future. A classification of drones based on range and altitude is provided. Based on the range, drones are classified as close, short, medium, and long endurance. Based on altitude, drones are classifies as low, medium, and high. The article focuses majorly on the military application of drones; however, some commercial application is discussed as well.
- Nonami (2007) presents the history of the research, development, and civil use of drones in the world with a particular focus on Japan before the year of 2007. The paper also discusses historical events such as New York WTC terror attack in 2001, after which the department of homeland security rapidly increased the budget for drone development. The survey identifies various civil application of drones including observation of ozone layer, air pollution, wild fires, vegetation growth, glaciers, hurricane generation, snow coverage, pipelines, and traffic.
- Chen and Wang (2009) present a review about the autonomous control of drones, introducing the autonomous control level (ACL) and autonomous control concept to measure the degree of autonomy of drones. The paper also presents the architecture of an autonomous drone based on the laws of increasing precision with decreasing intelligence.
- Zhang and Kovacs (2012) present a survey on the use of drones in precision agriculture (PA). In this drone application, techniques such as global positioning system (GPS), geographic information systems (GIS), and remote sensing are utilized to identify the variations in the field. Drones can be used for low altitude remote sensing to provide high spatial and temporal resolution with high flexibility in image acquisition programming. The paper reviews a wide variety of application areas related to drones for PA.
- Nex and Remondino (2014) review the state of the art of drones for geomatics applications including the latest developments in the 3D image processing using drones. In particular, the paper surveys different drone geomatics application areas such as agriculture, forestry, archaeology, environment management, and traffic monitoring.
- Sujit and Saripalli (2014) provide a survey for path following algorithms for fixed-wing drones. Path-following algorithms ensure that a drone follows a predefined path in three or two dimensions at a constant height. The paper compares the carrot-chasing algorithm, nonlinear guidance law (NLGL), vector-field (VF)-based path following, LQR-based path following, and pure pursuit with line-of-sight-based path following algorithm under different parameter settings and wind disturbances. The paper shows that the VF path-following algorithm performs the best, followed by the NLGL algorithm, than the other techniques, with the least control effort.
- Bhardwaj et al. (2016) provide a survey on the use of drones for monitoring glaciers and snowfields. The paper also discusses the significant glaciological studies in which drones are used. It also examines the alpine and polar application of drones and present the future prospects.
- Jawhar et al. (2017) review the state of the art in drone-to-drone communication and with existing networking infrastructures using drone-to-infrastructure communication. They analyze the requirements for a drone-based communication system in terms of functions and services needed. The paper also discusses the role of drones in collecting data from wireless sensor networks (WSNs).

- Coutinho and Battarra (2018) investigates the characteristics of the UAV routing and trajectory optimization problems, performs taxonomic review of 70 selected papers, and provide an overview of methods and algorithms employed in the surveyed papers based on problem characteristics.
- Otto et al. (2018) provide an extensive review of optimization approaches for the civil application of drones, which includes disaster management, transport of medical supplies, and environmental monitoring. The reviewed papers are categorized based on different types of problem specifics such as area coverage, search operations, routing, data gathering, communication links, etc. This paper also covers the brief review of DTCO, which, however, omits the introduction of important mathematical models and methodologies that are unique to DTCO.
- Khoufi and Laouiti (2019) survey the UAV problems from the point view of the variants of TSP and VRP, while focusing on path optimization. The paper also reviews multiple truck and multiple drone cases, and associates such cases to the variants of TSP and VRP using their taxonomy. However, this paper also omits the important details of mathematical models and methodologies.

Each of these survey papers presents a discussion on the drones, application areas, and an overview of the current development in drone systems. However, DTCO and its application have not been covered extensively in the literature, despite its advantage over drone only systems. A plausible reason for this could be: the concept of DTCO is still new to researchers and practitioners; DTCO models are complex in nature; and the technology is still in the emerging phase. Therefore, there is a need for identifying well-defined research issues as well as standardizing necessary terms and definitions. Accordingly, in this paper we survey DTCO research extensively in addition to DO to fill the identified gap in the literature. In particular, we review different mathematical models for DTCO, discuss different approaches to handle DTCO in detail, review methodologies to solve DTCO models, and present new research ideas and directions for future DTCO research.

The rest of the paper is organized as follows. Section 2 surveys the most up-to-date DO studies, especially for the ones published in the last three years. Section 3 surveys the state of the art in DTCO research, and summarize papers based on problem specifics. Section 4 reviews the DTCO models and methodologies in more detail. We review the DO and DTCO implementation barriers discussed in the literature in Section 5. Section 6 addresses future research directions, and Section 7 finally concludes this paper.

2. Review of the DO literature

In this section, we provide a review of recent DO research. In particular, we survey the key papers published in 2016–2020, which include journal articles, conference proceedings, and some articles in open-source archives to be current. We also include several earlier papers (published more than three years ago) if they are necessary to understand the DO study. The survey of DO is not meant to be complete, and we focus more on optimization methods for DTCO and its applications in this paper. However, we believe the reviewed papers are sufficient to provide an overview of the DO research and understand the current trend even though it is not possible to include all the published papers. We refer interested readers to Otto et al. (2018) for more thorough DO survey.

First, we introduce a set of abbreviations for classification purposes and provide their categorized list in Table 2. The first category is the contribution; the second is the application areas; and the third is the vehicle (drone) characteristics. Next, we organize the reviewed papers based on the problem specifics (i.e., topics), instead of application areas. This is because a particular problem type, e.g., routing for a set of locations, can be used for multiple application areas, e.g., logistics, security, and entertainment. The problem specifics are divided into: 1) routing for a set of locations, 2) area coverage, 3) search operations, 4) scheduling for DO, 5) task assignment, and 6) other problems, which are summarized in Table 3, Table 4, Table 5, Table 6, Table 7, and Table 8, respectively. Other problems include data gathering, allocating communication links, path planning, etc. Note that, unlike Otto et al. (2018), we

Table 2
List of abbreviations.

Category	Abbreviation	Details
Contribution	M	Mathematical modeling
	P	Theoretical studies: proofs, complexity analysis, convergence analysis, etc
	E	Exact solution and closed-form solution
	MH	Metaheuristics development or application
	H	Heuristics development or application
	CS	Case studies, empirical results, experiments, computational studies
	C	Control theory and algorithms
Application areas	CI	Construction & Infrastructure
	AG	Agriculture
	TL	Transportation & Logistics
	SM	Security & Disaster management
	EM	Entertainment & media
	GA	General application areas
	OA	Other application areas
Vehicle characteristics	SD	Single drone
	MD	Multiple drones
	LF	Limited flight time/distance/target/payload/max speed/climb (descent) rate
	EqM	Equations of motion including minimum turning radius
	EC	Energy consumption consideration
	CC	Communication consideration
	SC	Sensor related consideration (e.g., limited footprint)
	SF	Safety concerns
	HG	Heterogeneous vehicles, heterogeneous capabilities
	GF	General framework: no special vehicle characteristic

Table 3
Summary of surveyed papers: routing for a set of locations.

Reference	Contribution	Application	Drone characteristics
Altmann et al. (2014)	H, CS	EM	MD, EqM, SC
Babel (2017)	H, CS	SM	SD, EqM
Bae and Rathinam (2015)	M,P, H, CS	GA	MD, LF, EqM, HG
Bandeira et al. (2015)	H, CS	AG	SD, LF, SC
Bellingham et al. (2003)	M, H, CS	GA	MD, LF
Caraballo et al. (2017)	M,P, H, CS	CI	MD, HG
Coelho et al. (2017)	M, H, CS	TL	MD, LF, HG
Cohen and Epstein (2017)	M, H, CS	GA	SD, EqM
Dorling et al. (2017)	M, H, CS	TL	MD, LF, EC
Enright et al. (2009)	P, H, CS	GA	MD, EqM
Furini and Persiani (2016)	M, H, CS	OA	SD, LF
Gottlieb and Shima (2015)	M, H, CS	GA	MD, EqM
Guerrero and Bestaoui (2013)	H, CS	CI	SD, LF,EqM
Guerriero et al. (2014)	M, CS	EM	MD, LF
Kahale and Castillo (2014)	M, CS	SM	SD, EqM
Kim et al. (2017)	H, CS	TL	MD, LF
Lee (2017)	H, CS	TL	MD, GF
Liu et al. (2014)	M, MH, CS	SM	MD, LF
Mersheeva and Friedrich (2012)	MH, H, CS	SM	MD, LF
Niu et al. (2015)	M, CS	SM	SD, LF
Phung et al. (2017)	M, MH, CS	CS	SD, LF
Rathinam and Sengupta (2006)	M, P, H	GA	MD, GF
Roberge and Tarbouchi (2013)	M, H, CS	GA	SD
Sancı and İşler (2011)	MH, CS	GA	SD, GF
Sanjab and Saad (2017)	M, P, CS	TL	SD, GF
Sathyan and Ernest (2016)	MH, CS	GA	MD, SC
Song et al. (2016)	M, H, CS	GA	MD, LF, SC
Sundar and Rathinam (2017)	M, H, CS	GA	MD, EqM
Tseng et al. (2017)	M, P, H, CS	GA	SD, EqM, EC
Venkatachalam and Sundar (2017)	M, P, H, CS	GA	MD, EC
Wen et al. (2016)	M, MH, CS	TL	MD, LF
Woods et al. (2017)	P, E	GA	SD, LF
Yu et al. (2018)	P, H, CS	TL	SD, EC

Table 4
Summary of surveyed papers: area coverage.

Reference	Contribution	Application	Drone characteristics
Avellar et al. (2015)	M, CS	AG	MD, LF
Balampanis and Maza (2017)	H, CS	SM	MD, SC, HG
Barrientos et al. (2011)	H, CS, C	AG	MD, LF, SC
Barna and Solymosi (2019)	H, CS	AG	SD, LF, SC
Çakıcı et al. (2016)	MH, CS	GA	MD, LF, SC
Dille (2013)	H, CS	GA	SD, LF, SC
Ergezer and Leblebicioglu (2013)	MH, CS	GA	SD, LF, SC
Evers et al. (2014)	M, H, CS	GA	SD, LF
Gramajo and Shankar (2017)	CS, C	GA	SD, LF
LLi and X.i and X. Wang (2016)	MH, CS	GA	SD,EC, SC
Li et al. (2011)	H, CS	GA	SD, EC, SC
(Ma (2017))	P, H, CS	AG	SD, EqM, SC
(Maza and Ollero (2007))	H, CS	SM	MD, LF, SC
Moon and Shim (2009)	H, CS	AG	SD, LF, SC
Mufalli and Batta (2012)	M, H, CS	GA	MD, LF, SC
Nedjati et al. (2016)	M, CS	SM	MD, LF, SC
Penicka et al. (2017)	MH, CS	GA	SD, LF, EqM
Pugliese et al. (2016)	M, H, CS	EM	MD, LF, EC, SC
Saeed et al. (2017)	P, H, CS	GA	MD, LF, SC
Savkin and Huang (2020)	H, CS, C	SM	MD, LF, SC
Torres et al. (2016)	H, CS	GA	SD, SC
Tu et al. (2020)	H, CS	AG	SD, SC
Zorbas et al. (2016)	M, H, CS	GA	MD, LF, EC, SC

include scheduling and task assignment as separate topics to classify the reviewed papers because those problems play a critical role in a variety of drone applications. Note also that there is not always a clear-cut difference between the topics, and there are studies that combine several problems at the same time. For example, routing methods are used for scheduling drones to complete tasks such as refueling (Shetty and Sudit, 2008; Weinstein, 2007). In such a case, the primary purpose of the study (e.g., scheduling for Shetty and Sudit (2008) and Weinstein (2007)) is used to organize the papers.

Note that in drone operations, one may need to consider the minimum turning radius of drones, which results in a so-called Dubins path (Ny and Feron, 2011; Penicka et al., 2017; Song and Hu, 2017). In some area coverage problems, the Dubins path is necessary to be considered for certain types of drones (Penicka et al., 2017). Furthermore, the TSP- or VRP-based drone routing problems

Table 5
Summary of surveyed papers: searching operations.

Reference	Contribution	Application	Drone characteristics
Albert and Leira (2017)	H, CS	SM	MD, EqM, SC
Darbari and Gupta (2017)	C, CS	GA	SD, EqM, LF, SC
Haugen and Imsland (2015)	M, CS	SM	MD, EqM, SC
Ho and Ouaknine (2015)	P	GA	MD
Ji et al. (2015)	H, CS, C	GA	MD, SC
Lanillos et al. (2014)	H, CS	GA	MD, LF, SC
Nguyen et al. (2016)	H, CS	GA	SD, EC, SC
Oh et al. (2014)	M,H,CS	GA	MD, LF, EqM
Raap et al. (2017)	M, CS	SM	SD, EqM, SC
Raap et at. (2017)	M, H, CS	SM	SD, EqM, SC
Sujit and Ghose (2004)	H, CS	GA	SD, MD, LF, SC
Sujit and Ghose (2010)	H, CS	GA	MD, LF, SC
Tisdale et al. (2009)	H, CS	GA	SD, MD, EqM, SC
Xu and Doğançay (2017)	H, CS	GA	SD, MD, CC, SC
Yang et al. (2002)	H, CS	GA	SD, MD, EqM, SC
Yao et al. (2017)	H, CS	GA	SD, MD, EqM, SC

Table 6
Summary of surveyed papers: scheduling for DO.

Reference	Contribution	Application	Drone characteristics
Jin and Shima (2006)	H, CS	GA	MD, LF, EC
Kim and Morrison (2014)	M, H, CS	GA	MD, LF, EC
Kim and Song (2013)	M, MH, CS	GA	MD, LF, EC
Ortiz and Kingston (2013)	M, H, CS	EM	MD, EqM, SC
Peng and Lin (2017)	H, CS	GA	MD, LF, EC
Peters and Bertuccelli (2016)	M, H, CS	GA	MD, EC
Shetty and Sudit (2008)	M, CS	GA	MD, LF, EC
Song et al. (2014)	M, H, CS	GA	MD, LF, EC
Song and Park (2018)	M, H, CS	TL	MD, LF, EC
Torabbeigi et al. (2020)	M, H, CS	TL	SD, LF, EC
Weinstein (2007)	M, CS	SM	MD, LF, CC
Xia et al. (2019)	M, H, CS	SM	MD, LF, CC

Table 7
Summary of surveyed papers: task assignment.

Reference	Contribution	Application	Drone characteristics
Choi and Kim (2011)	M, H, CS	GA	MD, EqM
Jiang and Zhou (2017)	M, MH, CS	TL	MD, LF
Karaman and Inalhan (2008)	M, H, CS	GA	MD, GF
Khosiawan (2017)	M, MH, H, CS	OA (manufacturing)	MD, LF, EC
Krakowczyk et al. (2018)	M, H	TL	MD, LF
Thi et al. (2012)	M, H, CS	GA	MD, GF
Miao et al. (2017)	MH, CS	SM	MD, LF
Moon and Oh (2013)	H, CS, C	GA	MD
Oh et al. (2018)	H, CS	TL	MD

Table 8
Summary of surveyed papers: other problems.

Reference	Contribution	Problem	Application	Drone characteristics
Ali et al. (2020)	M, H, CS	Communication links	SM	MD, EC, CC
Alzenad et al. (2017)	M, E, CS	Communication links	OA	SD, EC, CC
Choi and Kim (2014)	E, H, CS	Communication links	GA	SD, EqM, EC, CC
Mozaffari et al. (2016)	M, P, H, CS	Communication links	GA	MD, EC, CC
Alemayehu and Kim (2017)	H, CS	Data gathering	OA	SD, SC, LF
Ho et al. (2015)	MH, CS	Data gathering	OA	SD, EC, SC, CC
Sahingoz (2014)	H, CS	Data gathering	OA	MD, SC, CC
Xu et al. (2016)	M, H, CS	Data gathering	OA	SD, SC, CC
Golabi and Shavarani (2017)	M, H, CS	Facility location	SM	MD, LF
Hong and Kuby (2015)	M, MH, CS	Facility location	TL	MD,LF
Claesson et al. (2017)	E	Healthcare delivery	OA	SD, LF
Haidari et al. (2016)	E	Healthcare delivery	OA	SD, LF
Chen et al. (2017)	M, CS	Platooning	OA	MD, EqM
Stipanović et al. (2004)	M, CS	Platooning	OA	MD, EqM

that consider the Dubins path are called Dubins TSP or Dubins VRP (Savla and Frazzoli, 2005; Savla and Frazzoli, 2008).

2.1. Routing for a set of locations

In applications such as delivery and surveillance, a drone has to visit a set of locations to complete a task. Indeed, the drone routing problem can be useful in most application areas including construction & infrastructure, agriculture, transportation & logistics, security & disaster management, entertainment & media, etc. Table 3 presents a summary of reviewed papers on drone routing for a set of locations. As the routing of drones for a set of locations may be considered as a generalized version of TSP and VRP, the most popular modeling approach for this problem is TSP- and/or VRP-based. For some early studies for TSP and VRP, see Lawler et al. (1985), Lin (1965), Reinelt (1991), Toth and Vigo (2002). Some other modeling approaches include real-time routing (Coelho et al., 2017), dynamic programming (Lee, 2017), and game theory (Sanjab and Saad, 2017) for a drone routing problem to address the dynamic environment and uncertainty.

Routing and path planning may seem to be similar concepts, but there are notable differences between the two. In routing, one has to find an optimal route to realize a given objective, e.g., minimize the travel distance, while path planning is related to how the steering is controlled for every, e.g., 2 m to follow a predetermined path, avoid obstacles, minimize battery consumption, etc. In addition, routing for a set of locations may have an overlap with an area coverage problem as indicated in Otto et al. (2018) because a discretized version of the area coverage problem can be formulated as a routing problem.

As the drone routing problems give rise to additional challenges such as the consideration of more vehicle characteristics and constraints, new modeling approaches have been proposed. For example, the battery specific issues (recharging and/or swapping), drone capacity, and payload weight on energy consumption are common considerations that are usually addressed as constraints in the optimization model (Bae and Rathinam, 2015; Coelho et al., 2017; Dorling et al., 2017; Furini et al., 2016; Guerriero et al., 2014; Kim et al., 2017; Liu et al., 2014; Mersheeva and Friedrich, 2012; Niu et al., 2015; Phung et al., 2017; Song et al., 2016; Wen et al., 2016; Woods et al., 2017; Tseng et al., 2017; Venkatachalam and Sundar, 2017; Yu et al., 2018). In the applications such as traffic monitoring, drones may have to visit the places within specific time windows (Song et al., 2016).

While heuristic approaches have been popular for tackling drone routing problems, not every heuristics method designed for TSPs and VRPs is sufficient for planning drone routing because of the additional conditions and constraints. For example, multiple trips to a depot are not permitted in most VRPs, but drones are permitted to visit the depot multiple times in many cases, mostly because of their limited range and capacity. Various heuristic approaches are proposed including the extended variable neighborhood search for rescue mission routing (Mersheeva and Friedrich, 2012), updated simulated annealing for drone delivery (Dorling et al., 2017), modified column generation for multiple drone routing for complex missions (Mufalli and Batta, 2012), and particle swarm optimization for drone routing with time windows (Jiang and Zhou, 2017).

2.2. Area coverage

In the area coverage problems, a drone or multiple drones cover various shapes of area with some objectives (e.g., minimize the cost/distance/number of turns/energy consumption while satisfying constraints). Most popular application areas include agriculture (e.g., spraying agricultural chemicals or creating digital terrain maps) and security/disaster management (e.g., post disaster survey). The area coverage problem using drones can be divided into roughly three categories: 1) full coverage (Avellar et al., 2015; Balampanis and Maza, 2017; Barrientos et al., 2011; Dille, 2013; LLi and X.i and X. Wang, 2016; Li et al., 2011; Maza and Ollero, 2007; Moon and Shim, 2009; Mozaffari et al., 2016; Nedjati et al., 2016; Torres et al., 2016), 2) maximum information with limited coverage (Çakıcı et al., 2016; Evers et al., 2014; Gramajo and Shankar, 2017; Ma, 2017; Mufalli and Batta, 2012; Penicka et al., 2017, and 3) continuous observation Pugliese et al., 2016; Saeed et al., 2017; Zorbas et al., 2016).

It is worth noting that most drone area coverage problems involve consideration/constraints related to a flight height because the coverage capacity (e.g., picture resolution, information quality, spray range) and the energy consumption may depend on the height. Other important constraints are related to the shape of the covered region and limited energy capacity. The surveyed papers are summarized in Table 4.

2.3. Search operations

Drones can play a critical role in search operations such as environmental monitoring, and search and rescue missions (e.g., finding a mission person), where the target area is usually divided into cells with different probabilities of finding an object. The objectives often include maximizing the finding probability under time constraint or minimizing the time to find a target under given probability.

While the search operations using drones have similarities with traditional search problems that are covered extensively in the literature (see Benkoski and Monticino (1991) and Roberge and Tarbouchi (2013) for the survey), several aspects specific to drone search operations must be considered. First, due to the limited battery capacity, drones have to be recharged, which may result in more frequent search for cells (areas) close to a depot (Sujit and Ghose, 2004; Sujit and Ghose, 2010). In addition, drone sensors have limitations and have different characteristics than the ones used for traditional search operations that utilize piloted aircraft or ground vehicles (Ji et al., 2015; Lanillos et al., 2014; Nguyen et al., 2016; Tisdale et al., 2009). Furthermore, the communication concerns (e.g., between drones, between a drone and a depot, between a drone and a ground vehicle) may arise in certain applications (Ji et al., 2015; Sujit and Ghose, 2010; Yang et al., 2002).

Papers related to search operations problem are presented in Table 5. It is worth noting that most papers in this problem consider the sensor related constraints (e.g., limited footprint).

2.4. Scheduling for DO

There are various scheduling decisions to be made by, e.g., logistics operators and disaster response teams when using drones for their operations. Such decisions may include scheduling the drones for recharging, maintenance, safety checks, etc. The primary goals of drone scheduling problem are to enable persistent drone operations (Jin and Shima, 2006; Kim and Morrison, 2014; Kim and Song, 2013; Peng and Lin, 2017) and to assign appropriate drones for different tasks (Peters and Bertuccelli, 2016; Torabbeigi et al., 2020; Weinstein, 2007). In monitoring problems, an objective is to maximize the number of objects monitored or maximize the information gathered (Xia et al., 2019) for a fixed time constraint, which can be achieved by scheduling multiple drones (Xia et al., 2019). It is common to consider multiple drones for scheduling problems as scheduling is needed when there are multiple drones. The drones to be scheduled could be homogeneous as well as heterogeneous. Most papers consider energy consumption and/or payload weight as one of the important vehicle characteristics because it is directly related to scheduling constraints such as flight time restriction, frequency of recharge, etc. Note that a human operator is required for some drone related applications such as surveillance, search and rescue, and maintenance inspection because some important information needs to be reviewed by the human. Accordingly, the schedule of human operators are taken into account for the drone path planning (Ortiz and Kingston, 2013) and for the monitoring tasks (Peters and Bertuccelli, 2016). An overview of surveyed drone scheduling papers is shown in Table 6.

As in the general scheduling problem case, the drone scheduling problems are frequently modeled using a MILP formulation (Kim and Morrison, 2014; Kim and Song, 2013; Shetty and Sudit, 2008; Song et al., 2014; Weinstein, 2007), which can then be solved using a solver such as CPLEX and Gurobi or by using a heuristic method. For example, Kim and Morrison (2014) use an MILP to formulate the scheduling problem of multiple resources for persistent drone operations. Kim and Song (2013) develop an MILP model for scheduling a system of drones and multiple shared bases in disparate geographic locations. Song et al. (2014) develop an improved MILP formulation of the persistent drone scheduling problem and develop a vision-based guidance system that directs the drones. Shetty and Sudit (2008) formulate an MILP for the drone surveillance mission. A variety of heuristic methods are proposed to solve the MILP problem, which includes a branch and bound-based method (Kim and Morrison, 2014), a genetic algorithm (Kim and Song, 2013), and a tabu search method (Shetty and Sudit, 2008).

Other modeling and solution techniques for solving the scheduling problem include a dynamic programming-based approach for optimal scheduling for refueling multiple autonomous drones (Jin and Shima, 2006), an online rectangle based scheduling algorithm (RSA) to decide the number of drones to be assigned (Peng and Lin, 2017), and a robust task scheduling approach (Peters and Bertuccelli, 2016).

2.5. Task assignment

The drone task assignment is a problem to assign a set of tasks (or targets, deliveries) to a set of drones according to certain environmental knowledge and task requirements. The number of tasks do not necessarily need to be equal to the number of drones (Miao et al., 2017). The drone task assignment is an important problem in application areas such as drone logistics, military missions, and disaster relief operations. The common objective is to minimize the cost (Choi and Kim, 2011; Jiang and Zhou, 2017; Karaman and Inalhan, 2008; Khosiawan, 2017; Thi et al., 2012; Miao et al., 2017; Moon and Oh, 2013) while satisfying the given set of constraints.

Similar to the conventional task assignment problems, an MILP formulation is a common modeling approach for drone task assignment problems. Several methods used to tackle the drone task assignment problem are genetic algorithm (Choi and Kim, 2011), column generation (Karaman and Inalhan, 2008), particle swarm optimization (Khosiawan, 2017), cross-entropy (CE) method in conjunction with a branch and bound algorithm (Thi et al., 2012), high performance artificial immune system (Miao et al., 2017), and hierarchical framework in a dynamic environment (Moon and Oh, 2013). The surveyed papers are summarized in Table 7.

2.6. Other problems

In this section, we briefly introduce other drone problems that are not covered so far. In particular, the problems regarding establishing communication links (Alzenad et al., 2017; Mozaffari et al., 2016), data gathering (Alemayehu and Kim, 2017; Ho et al., 2015; Sahingoz, 2014), facility location (Golabi and Shavarani, 2017; Hong and Kuby, 2015; Mackle et al., 2020), healthcare delivery (Claesson et al., 2017; Haidari et al., 2016), and platooning (Chen et al., 2017) are discussed. We present the summary of reviewed papers in Table 8.

Drones can be used to establish a communication link between a base station and mobile devices. When the drone deployment decisions are made, locations that minimize the communication interference should be considered where probability theory is often involved (Alzenad et al., 2017; Choi and Kim, 2014; Mozaffari et al., 2016). In addition, energy consumption (Alzenad et al., 2017; Choi and Kim, 2014; Mozaffari et al., 2016) and equations of motion (Choi and Kim, 2014) are typical drone characteristic considerations. In a recent study, the deployment of drones to provide a communication structure in a disaster area is proposed using a matching game algorithm (Ali et al., 2020). We refer readers to Tse and Viswanath (2005) for the thorough survey of fundamentals of wireless communications and to Otto et al. (2018) for more detailed review of drone usage as a communication link in wireless communications.

Drones can be also useful at data gathering in a wireless sensor network (WSN) where stationary wireless sensors need to transmit environmental data to the base station through drones. The drone routing operations need to consider the number of direct information transmissions, which is called hop, between nodes (sensor or drone) or base station. Due to the limited communication range, sensors either perform two-hop transmission (sensor-drone-base

(a) A drone departing from a truck

(b) A HorseFly drone

Fig. 2. A HorseFly drone with the electric truck (Hallett, 2018).

station) (Alemayehu and Kim, 2017; Sahingoz, 2014) or hierarchical data transmission (sensors-sink node-drone-base station) (Ho et al., 2015; Xu et al., 2016). Multiple-hop in a cluster of sensors improves data recency by minimizing drone visits while using more memory and energy at each sensor in the cluster. We refer readers to Otto et al. (2018) for detailed review of data gathering with drones.

The problem of locating the facilities such as drone stations is relevant to drone operations because drones can take off from, land on, and recharge at such stations. Golabi and Shavarani (2017) use a genetic algorithm to tackle the facility location problem for drones in response to disaster events such as an earthquake. Hong and Kuby (2015) use simulated annealing (SA) to solve the facility location problem to find recharging stations for delivery drones for logistics.

For problems related to healthcare, Claesson et al. (2017) provide statistical comparisons of the time to delivery of an automated external defibrillator (AED) using fully autonomous drones for simulated out-of-hospital cardiac arrests (OHCAs) vs. emergency medical services (EMS). Haidari et al. (2016) use simulation modeling to compare the vaccine availability and efficiency achieved when using drones vs. when using conventional transport systems.

Several research work about the efficient air transportation problems where multiple drones that fly together by a specific formation have been reported (Chen et al., 2017; Stipanović et al., 2004). Stipanović et al. (2004) provide a mathematical framework for the drone platoon formation problem. Chen et al. (2017) extend the scope of drone platoon operations at air highway to safety issues while anticipating heavy air traffic in the near future.

Table 9
List of abbreviations for DTCO.

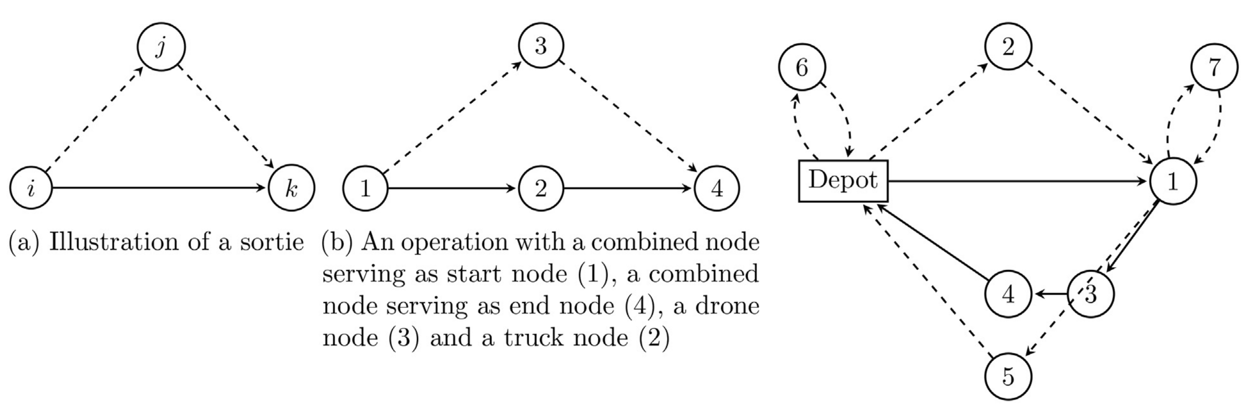
Category	Abbreviation	Details
Vehicle characteristics	ST	Single truck
	MT	Multiple trucks
	UT	Unmanned truck
	CapT	Truck capacity is limited or finite
	UD	Drone capacity is unity
	CapD	Drone capacity is finite (more than one)
Vehicle roles	SW	Drone and truck as synchronized, coordinating working units
	IV	Independent vehicles
	DP	Drone primary, truck supporting
	TP	Truck primary, drone supporting

3. Review of the DTCO literature

In this section, we provide a survey of DTCO research. Recall that in this paper we call the counterpart of a drone a *truck* for the sake of brevity because the truck is the most widely used means of transportation for DTCO in the literature. However, it could even be an underwater vehicle when DTCO is used for ocean explorations (Sujit et al., 2009).

As drones have limited airborne time, it is logical to utilize a ground vehicle or a robot (that is, any means of transportation, either automated or not) in tandem for enhanced capacity, efficiency, and effectiveness of DO. DTCO has been tested for a commercial launch. For example, the HorseFly drone delivery system, shown in Fig. 2, can be fully integrated with a delivery vehicle, which is also designed to meet the FAA guidelines (Dektas, 2018). Similarly, UPS has tested a drone-truck combined delivery system in which a drone can be launched from the roof of a truck to deliver parcels to customers, and then it autonomously returns to the truck without any intervention from the driver (Kastrenakes, 2017). As these examples imply, one of the most well-known DTCO problems is the delivery of items (via routing for a set of locations) but there are other ones including area coverage (Mathew and Smith, 2013; Sujit et al., 2009; Tokekar et al., 2016), scheduling (Boysen et al., 2018; Ham, 2018; Mbiadou Saleu et al., 2018; Tavana et al., 2017), task assignment (Phan and Liu, 2008; Wu et al., 2016), enhancing communication connectivity (Fawaz et al., 2017; Jia and Zhang, 2017; Ladosz and Oh, 2018; Oh et al., 2015; Sharma et al., 2017), and facility location (Chowdhury et al., 2017).

DTCO poses a wide variety of challenging optimization problems. To review the DTCO literature, we first provide a summary of terms and definitions in Section 3.1. Importantly, the DTCO literature can be classified based on the vehicle roles as there are two types of vehicles unlike the DO case. Accordingly, we review and classify the DTCO papers based on the vehicle roles (e.g., primary



(a) Illustration of a sortie

(b) An operation with a combined node serving as start node (1), a combined node serving as end node (4), a drone node (3) and a truck node (2)

(c) (Depot–6–Depot), (Depot–2–1), (1–7–1), (1–5–Depot) are all feasible operations while (Depot–6–Depot), (Depot–2–1), (1–5–Depot) except (1–7–1) are all feasible sorties

Fig. 3. Drone sortie and operation (Agatz and Bouman, 2018; Murray and Chu, 2015).

Table 10
Summary of surveyed DTCO papers: routing.

Ref	Contribution	App	Drone	Truck	Sync	Role
Agatz and Bouman (2018)	M, P, H, CS	TL	SD, UD, LF	ST	Yes	SW
Bouman and Agatz (2018)	M, P, H, CS	TL	SD, UD, LF	ST	Yes	SW
Campbell and Sweeney (2017)	P, CS	TL	MD, UD, LF	ST	Yes	SW
Carlsson and Song (2017)	M, H, CS	TL	SD, UD, LF	ST	Yes	SW
Chang and Lee (2018)	M, H, CS	TL	MD, UD, LF	ST	Yes	SW
Daknama (2017)	MH, CS	TL	MD, UD, LF	MT	Yes	SW
Dayarian and Savelsbergh (2020)	M, P, H	TL	MD, CapD, LF	MT, CapT	No	TP
Dell'Amico and Montemanni (2019)	M, H, CS	TL	MD, UD, LF	ST	Yes	SW
Dukkanci and Kara (2019)	M, H, CS	TL	SD, EC	ST	Yes	DP
Ferrandez et al. (2016)	MH, H, CS	TL	MD, UD	ST	No	DP
Fikar and Gronalt (2016)	M, MH, H, CS	SM	MD, UD	MT, CapT	No	IV
Freitas (2018)	M, H, CS	TL	SD, UD, LF	ST	Yes	SW
Garone and Naldi (2011)	M, H, CS	SM	SD, LF	ST	Yes	DP
Garone et al. (2010)	M, P, H, CS	SM	SD, LF	ST	Yes	DP
Gonzalez-R et al. (2020)	M, H, CS	TL	SD, CapD, LF	ST	Yes	DP
Ha and Deville (2015)	M, H, CS	TL	SD, UD, LF	ST	Yes	SW
Ha et al. (2018)	M, H, MH, CS	TL	SD, UD, LF	ST	Yes	SW
Jeong and Song (2019)	M, E, H	TL	SD, UD, LF	ST	Yes	SW
Karak and Abdelghany (2019)	M, E, H, CS	TL	MD, LF	ST	Yes	SW
Kim and Moon (2019)	M, E, H, CS	TL	MD, UD, LF	ST	Yes	SW
Kitjacharoenchai et al. (2019)	M, E, H, CS	TL	MD, UD	MT	Yes	SW
Kundu (2017)	H, CS	TL	SD, UD, LF	ST	Yes	SW
Li et al. (2018)	H, CS	TL	MD	MT	No	DP
Luo and Liu (2017)	M, H, CS	GA	SD, LF	ST	Yes	DP
Marinelli et al. (2017)	M, H, CS	GA	SD, UD, LF	ST, CapT	Yes	SW
Mathew and Smith (2013)	M, P, CS	GA	MD, UD	MT, UT	No	DP
Mathew and Smith (2015a)	M, P, H, CS	GA	MD, EC	MT, UT	No	DP
Mathew and Smith (2015b)	P, CS	TL	SD, UD, LF	ST, UT	No	DP
Moshref-Javadi (2017)	M, H, CS	TL	MD, UD,LF	ST	Yes	SW
Murray and Raj (2019)	M, H, CS	TL	MD, UD, EC	ST	Yes	SW
Murray and Chu (2015)	M, H, CS	TL	SD, UD, LF	ST	Yes/No	SW/IV
Othman and Shurbevski (2017)	M, H	TL	SD, UD	ST	Yes	SW
Peng et al. (2018)	M, H, CS	GA	MD, LF	MT	Yes	SW
Poikonen and Golden (2020)	M, H, CS	TL	MD, CapD, LF	ST	Yes	DP
Poikonen and Golden (2019)	M, E, H, CS	TL	SD, UD, LF	ST	Yes	SW
Poikonen and Wang (2017)	P	TL	MD, UD, LF	MT, CapT	Yes	SW
Poikonen (2019)	M, P, E, H	GA	MD, UD, CapD, LF	ST	No	TP
Pugliese and Guerriero (2017)	M, H, CS	TL	MD, UD, LF	MT	Yes	SW
Sacramento et al. (2019)	M, MH, H, CS	TL	MD, UD, LF	MT	Yes	SW
Chung and Sah (2020)	M, P, H, C	TL	SD, UD, LF	ST	Yes	SW
Savuran and Karakaya (2015)	M, H, CS	GA	SD	ST	No	TP
Savuran and Karakaya (2016)	M, H, CS	GA	SD, LF	ST	No	TP
Schermer and Moeini (2018)	M, H, CS	TL	MD, UD, LF	ST, CapT	Yes	SW
Schermer and Moeini (2019a)	M, H, CS	GA	MD, UD, LF	ST, CapT	Yes	SW
Schermer et al. (2019b)	M, MH, CS	GA	MD, UD, LF	ST, CapT	Yes	SW
Tu et al. (2018)	M, H, CS	TL	MD, CapD, LF	ST	Yes	SW
Ulmer and Thomas (2018)	M, E, H, CS	TL	MD, UD, LF	MT	No	IV
Viguria et al. (2010)	H, CS	EM	MD, GF	MT, UT	Yes	SW
Wang et al. (2017)	P, H, CS	TL	MD, UD, LF	MT, CapT	Yes	SW
Wang and Sheu (2019)	M, H, CS	TL	MD, CapD, LF	MT, CapT	No	DP
Yoon (2018)	M, H, CS	TL	MD, CapD, LF	ST	Yes	SW
Yu et al. (2018)	P, H, CS	TL	SD, EC	ST, UT	Yes	DP
Yurek and Ozmutlu (2018)	M, H, CS	TL	SD, UD, LF	ST	Yes	SW

Table 11
Summary of surveyed DTCO papers: area coverage.

Ref	Contribution	App	Drone	Truck	Sync	Role
Mathew and Smith (2013)	M, P, E, CS	EM	MD, LF	MT, UT	Yes	DP
Sujit et al. (2009)	H, CS	EM	MD, LF	MT, UT, underwater	Yes	TP
Tokekar et al. (2016)	P, H, CS	AG	SD, LF	ST, UT	No	DP

Table 12
Summary of surveyed DTCO papers: scheduling

Ref	Contribution	App	Drone	Truck	Sync	Role
Boysen et al. (2018)	M, H, CS	TL	MD	ST	Yes	TP
Ham (2018)	M, H, CS	TL	MD, UD	MT	No	IV
Mbiadou Saleu et al. (2018)	M, H, CS	TL	MD, UD	ST	No	IV
Tavana et al. (2017)	M, H, CS	TL	MD, CapD	MT, CapT	No	IV

Table 13
Summary of surveyed DTCO papers: task assignment.

Ref	Contribution	App	Drone	Truck	Sync	Role
Phan and Liu (2008)	M, C	EM	MD, EqM, CapD	MT, UT	No	IV
Wu et al. (2016)	MH, H, CS, C	EM	MD,LF, EC	MT	No	IV

Table 14
Summary of surveyed DTCO papers: other problems.

Ref	Contribution	Problem	App	Drone	Truck	Sync	Role
Fawaz et al. (2017)	P, CS	Communication links	OA	MD, CC	MT	No	TP
Jia and Zhang (2017)	E, CS	Communication links	EM	MD, LF, CC	MT	No	TP
Ladosz and Oh (2018)	MH, CS	Communication links	GA	MD, EqM, CC	MT	No	TP
Oh et al. (2015)	M, H, CS	Communication links	GA	MD, LF, EqM	MT	No	TP
Sharma et al. (2017)	MH, CS	Communication links	GA	MD, CC	MT, UT	No	TP
Chowdhury et al. (2017)	M, H, CS	Facility location	SM	MD, LF, EqM, EC	MT	No	IV

vs. supporting roles, coordinating vs. independent roles) in Section 3.2. Then, we review and classify papers based on the problem specifics, as in the DO case, in Section 3.3.

3.1. Terms and definitions

We start with introducing terms and definitions used in the literature where the original abbreviation is used in the following list. Recall that most DTCO studies are based on either TSP or VRP, and, therefore, the DTCO literature can be roughly divided into TSPD and VRPD. TSPD can be further divided into several formulation types such as FSTSP, mFSTSP, PDSTSP, PDSTSP+DP, TSP-D, and Min-Cost TSP-D, which we introduce in the following. *Note that we distinguish TSP-D from TSPD in this paper.* TSPD is the term that denotes any DTCO that is based on TSP, but TSP-D is the term for TSPD that specifically uses the concept of operation, which is illustrated in the following.

- *FSTSP*: Flying side-kick traveling salesman problem (Murray and Chu, 2015)
- *mFSTSP*: Multi-drone flying side-kick traveling salesman problem (Murray and Raj, 2019)
- *PDSTSP*: Parallel drone scheduling traveling salesman problem (Murray and Chu, 2015)
- *PDSTSP+DP*: Parallel drone scheduling traveling salesman problem with drop off and pick up (Ham, 2018)
- *TSP-D*: Traveling salesman problem with drone where the concept of operation is used (Agatz and Bouman, 2018)
- *Min-Cost TSP-D*: Minimum cost TSP-D (Ha et al., 2018)
- $VRPD_{m,\alpha,k}$: Vehicle routing problem with drone (Poikonen and Wang, 2017; Wang et al., 2017) where m is the number of trucks, α is ratio of drone speed to truck speed, and k is the number of drones
- *MVDRP*: Multiple-visit drone routing problem (Poikonen and Golden, 2020)
- *MoDVRP*: Mobile depot vehicle routing problem (Hadjiconstantinou and Baldacci, 1998)
- *mTSPD*: Multiple traveling salesman problem with drones (Kitjacharoenchai et al., 2019)
- *SDDPHF*: Same-day delivery routing problem with heterogeneous fleets (Ulmer and Thomas, 2018)
- *Truck node*: A node (geographical locus) visited by a truck
- *Drone node*: A node visited by a drone
- *Combined node*: A node visited by both drone and truck
- *Start node*: A node where a drone departs from a truck to serve a customer
- *End node*: A node where a drone returns and meets the truck
- *Drone-eligible customer*: A customer who can be served by a drone based on weight and distance requirements.
- *Drone sortie:* a drone-truck combined function in which a drone departs from a truck, delivers parcel to customer, and finally returns back to the truck (Murray and Chu, 2015). Consider a tuple given by (i, j, k) as shown in Fig. 3a. The following conditions need to be fulfilled for (i, j, k) to be a sortie (Murray and Chu, 2015).
  -the start node, i, must not be the ending depot node.
  -the drone node, j, must be a drone-eligible customer node and $j \neq i$.
  -the end node, k, must be a customer node or the ending node and $k \neq j \neq i$
  -the truck may visit customers while traveling from node i to node k, while the drone only visits a single customer j.
- *Operation*: An operation consists of a start node and an end node, a non-negative number of truck nodes, and at most one drone node (Agatz and Bouman, 2018). When the operation consists of a drone node, the drone flies from the start node to the drone node and then meets the truck at the end node; meanwhile, the truck travels directly from the start node to the end node or visits customers in between. The start node and the end node can sometimes be the same node as well; in this case, the drone departs and comes back to the same node. That is, the concept of operation allows the start node and the end node to be the same, while in sorties, the start node and the end node have to be different except if start node and end node are the depot as shown in Fig. 3c; (depot–6–depot) is a feasible sortie while (1–7–1) is not.

A list of abbreviations we use in this paper to classify DTCO papers is shown in Table 9, which is in addition to the ones defined for DO. As most DTCO applications are related to delivery of items, the capacity of a drone and/or a truck can be one of the important vehicle characteristics. We use “CapT”, “UD”, and “CapD” to denote limited truck capacity, unit capacity of drone, and limited drone capacity (greater than 1 but limited), respectively. If the vehicle (either drone or truck) capacity is unlimited or not specified, none of these abbreviations is used.

3.2. DTCO research based on vehicle roles

As there are two different types of vehicles, the research focus for DTCO can be substantially different depending on their roles, which makes DTCO research fundamentally distinctive from DO research. In DTCO, either a drone or a truck may take the main role of the operation while the other vehicle takes merely a supporting role. Alternatively, both vehicles perform the same task at the same time, which can be done either independently or cooperatively. Synchronization between a drone(s) and a truck(s) can become a very important issue because it is directly related to the efficiency of the operation. Depending on the application areas, synchronization is required to, e.g., replenish items for drone delivery, replace or charge a drone battery, and perform maintenance of drone. If synchronization is required, vehicles must arrive at the predetermined location at the same time, or one vehicle needs to wait for the other vehicle at the predetermined location before the vehicle can leave the location.

The reviewed DTCP papers are summarized in Tables 10–14 where the information for synchronization requirement and vehicle roles can be found.

3.2.1. Drone and truck as synchronized working units

When drones and trucks work as synchronized working (SW) units, their roles are in general equally important. The application can be most frequently found in delivery operations in logistics. A drone can depart from a truck, delivers an item to a customer, and comes back to the truck to recharge/replace a battery and be ready for the next sortie. At the same time, the truck also delivers an item to customers while moving to the next location where both vehicles can meet.

This case can be formulated as FSTSP (Murray and Chu, 2015) or TSP-D (Agatz and Bouman, 2018; Ha et al., 2018), if there are only one drone and only one truck considered in the problem. FSTSP uses the concept of sorties while TSP-D uses the concept of operations in their formulations. The synchronization constraints in these models guarantee that a drone and a truck must arrive the rendezvous node at the same time. FSTSP and TSP-D can be extended to accommodate multiple drones and/or multiple trucks, e.g., mFSTSP (Murray and Raj, 2019) or VRPD (Poikonen and Wang, 2017; Wang et al., 2017). The mathematical models of FSTSP, TSP-D, mFSTSP, and VRPD will be introduced in more detail in Section 4.1.

Synchronization is indeed a critical issue, which is demonstrated in Murray and Chu (2015) by computational experiments, as it is not an easy task for both vehicles to arrive at a rendezvous node at the same time. A vehicle must wait for the other vehicle, and this will be a significant cost. A pseudo-node approach is proposed to resolve the synchronization issue (Chung and Sah, 2020). In FSTSP, TSP-D, mFSTSP, and some VRPDs, both drone(s) and truck (s) are required to meet at one of the specified locations (nodes in the graph, which are usually customer locations and the depot). This constraint is relaxed by adding a pseudo node where the drone and the truck can meet to eliminate the waiting time (Chung and Sah, 2020). In addition, the analysis of maximum time savings achieved by such pseudo nodes is provided (Chung and Sah, 2020). Another way to eliminate the need for synchronization is to use service hubs (Wang and Sheu, 2019), which we discuss in Section 3.2.3.

3.2.2. Independent operation of both vehicles

If all the customers are located within the drone flight range from a depot or a warehouse in a delivery problem, the need for the drone to land on a truck is eliminated (Murray and Chu, 2015) because drones can come back to the depot to replace/ charge its battery and pick up another item to be delivered. At the same time, trucks can delivery items to customers, which is independent to drone operations.

Murray and Chu (2015) formulate this problem as PDSTSP, whose objective is to minimize the makespan by finding the optimal tour of a single truck and determining the number of drones to be used. Note that Murray and Chu (2015) consider two problems in their paper: one problem that considers synchronized working units (FSTSP) and the other problem that deals with the case of independent operations of both vehicles (PSDTSP). Ulmer and Thomas (2018) also study the delivery problem where either a drone or a truck can be used to meet the customer demand for the same-day delivery. A dynamic programming approach is used to decide the acceptance or rejection of randomly arriving customer orders to meet the same-day delivery requirement. Ham (2018) extends PDSTSP to incorporate multiple trucks, multiple drones, and multiple hubs. Furthermore, drones not only deliver items to customers but also are capable of picking up items from customers. In addition to the delivery problems that are introduced above, task assignment problems are tackled using independent drones and trucks (Phan and Liu, 2008; Wu et al., 2016).

3.2.3. Drone as primary and truck as supporting working units

Drones can play a main role in a variety of operations. Indeed, drones can cover most of the problems discusses so far, which include monitoring in construction, spraying chemicals in agriculture, delivering items in logistics, searching in disaster management, connecting communication links, etc. However, as drones have limited capacity and flying range, DO can be substantially enhanced if drones can land on supporting trucks or service hubs to, e.g., recharge/replace batteries (Luo and Liu, 2017; Mathew and Smith, 2013; Mathew and Smith, 2015b; Garone et al., 2010), replenish items (for most delivery operation problems where drones have limited capacity, e.g., Agatz and Bouman, 2018; Bouman and Agatz, 2018; Campbell and Sweeney, 2017; Li et al., 2018; Wang and Sheu, 2019; Yurek and Ozmutlu, 2018), and travel together some distance with the supporting vehicle to save energy (Tokekar et al., 2016). Wang and Sheu (2019) propose VRPD with service hubs, where multiple trucks supply items to the service hubs, and drones deliver items to the customers. Multiple drones with limited flying range and capacity are considered where drones can land only on the service hubs but not on trucks. The objective is to minimize the travel cost that is the combination of the fixed truck cost and the travel cost of drones and trucks.

We categorize the DTCO as the primary-drone-and-supporting-truck problem only when trucks merely support the drones or perform supplementary tasks. Therefore, if trucks deliver a package to customers regardless of the quantity in a delivery application, then the DTCO is categorized as either synchronized working units or independent vehicles.

3.2.4. Truck as primary and drone as supporting working units

A truck works as a primary vehicle, and drones may support the truck in some particular ways. For example, ground vehicles may work as emergency vehicles (e.g., ambulance, cleaning vehicle, fire engine, utility vehicle for recovery) after disasters, and drones may provide a communication means for such ground vehicles (Fawaz et al., 2017; Jia and Zhang, 2017; Ladosz and Oh, 2018; Oh et al., 2015; Sharma et al., 2017). In Sujit et al. (2009), unmanned underwater vehicles are used to explore the ocean (primary), and drones gather data from such underwater vehicles in the most effective way by utilizing optimal tours. In the delivery problem, sometimes the truck (mobile carrier) routes are fixed with supplemental drone delivery to the customers (Boysen et al., 2018; Savuran and Karakaya, 2015; Savuran and Karakaya, 2016). In this case, the trucks are the primary vehicles because their route are given and cannot be changed, which implies that they have the priority. Drones are launched from the truck that is following its fixed route, visit as many customers as possible depending on their capacity, then return to their truck (mobile carrier). An interesting variant of this problem, where the truck is replaced with a larger aerial vehicle that does not have a fixed route, is called a mothership and drone routing problem (Poikonen, 2019). This type of problem may play an important role in some applications such as floating warehouse (McGauley, 2017), search-and-rescue (Poikonen, 2019) and delivery to island locations (Poikonen, 2019). In another problem, a truck is the only mean to deliver items to the customers with the resupply by drones (no direct drone delivery to the customers) (Dayarian and Savelsbergh, 2020).

3.3. DTCO research based on problem types

3.3.1. Routing for a set of locations

The vast majority of DTCO problems are related to routing for a set of locations. In terms of application, transportation and logistics (TL) related research, e.g., delivery of items, is most frequent. In the parcel delivery problem, drones usually carry one item per sortie (Agatz and Bouman, 2018; Bouman and Agatz, 2018; Campbell and Sweeney, 2017; Carlsson and Song, 2017; Chang and Lee, 2018; Daknama, 2017; Dell'Amico and Montemanni, 2019; Ferrandez et al., 2016; Fikar and Gronalt, 2016; Freitas, 2018; Ha and Deville, 2015; Ha et al., 2018; Jeong and Song, 2019; Kim and Moon, 2019; Kitjacharoenchai et al., 2019; Kundu, 2017; Mathew and Smith, 2013; Mathew and Smith, 2015b; Mathew and Smith, 2015a; Moshref-Javadi, 2017; Murray and Raj, 2019; Murray and Chu, 2015; Othman and Shurbevski, 2017; Poikonen and Golden, 2019; Poikonen and Wang, 2017; Pugliese and Guerriero, 2017; Sacramento et al., 2019; Chung and Sah, 2020; Schermer and Moeini, 2018; Wang et al., 2017; Ulmer and Thomas, 2018; Yurek and Ozmutlu, 2018) while trucks have unlimited or much larger capacity for carrying items. In addition, most delivery problems assume that the both vehicles are synchronized and coordinated. In summary, most DTCO delivery models assume 1) unit capacity for a drone, 2) limited flying range for a drone, 3) relatively bigger capacity for a truck, and 4) synchronized working units.

Some of the most recent papers are focusing on more general problem setting such as the one allowing drone's multiple customer visits (Gonzalez-R et al., 2020; Poikonen and Golden, 2020; Tavana et al., 2017).

There are a few papers that do now require synchronization in the DTCO delivery problem. PDSTSP (Murray and Chu, 2015) and PDSTSP+DP (Ham, 2018) consider the case where a substantial portion of customers are located close to a depot(s). Drones are used to deliver items to nearby customers while truck(s) can be used deliver items to other customers. A route(s) needs to be found for a truck(s) while scheduling for drone delivery is also an important task. The VPPD with service hubs (Wang and Sheu, 2019) is also a vehicle routing problem that does not require synchronization thanks to the use of the service hubs.

In DTCO routing, there are other articles that consider security and disaster management (Fikar and Gronalt, 2016; Garone and Naldi, 2011; Garone et al., 2010), entertainment and media (Phan and Liu, 2008), and general applications (Luo and Liu, 2017; Mathew and Smith, 2013; Mathew and Smith, 2015a; Peng et al., 2018; Savuran and Karakaya, 2015; Savuran and Karakaya, 2016). The reviewed papers are summarized in Table 10.

3.3.2. Area coverage

Either a drone or a truck can be used as a primary vehicle for area coverage operations. In both cases, the efficiency and effectiveness of operations can be enhanced with the aid of the counterpart vehicle. When a drone is the primary vehicle, ground vehicles can be used to provide a battery recharging service, to perform the maintenance of the drone, and to carry the drone to save energy and overcome the limited flight range. For example, drones are the primary vehicles to perform, e.g., a continuous surveillance operation for the given set of paths and unmanned ground vehicles are used for recharging the drones (Mathew and Smith, 2013). A drone is also a primary vehicle to take aerial pictures to classify soils and an unmanned ground vehicle is used to carry the drone to save its energy (Tokekar et al., 2016). On the other hand, when a truck is a primary vehicle, a drone can support the truck by, e.g., guiding its direction or path and gather data from trucks. In Sujit et al. (2009), autonomous underwater vehicles explore the ocean and drones are used to collect data from underwater vehicles and to guide their paths. The reviewed papers are summarized in Table 11.

3.3.3. Scheduling

DTCO scheduling problems are distinguished from the DTCO routing problems by more emphasis on drone operation scheduling with a fixed or unrelated parallel truck routing. For example, a fixed route truck only works as a take-off and landing platform, while drones' trips are scheduled to minimize the total duration of delivery tour of visiting all customers (Boysen et al., 2018). A scheduling problem for PDSTSP where multiple drones and a single truck work in parallel is solved using an iterative two-step heuristic approach (Mbiadou Saleu et al., 2018). Multiple-drone-multiple-truck cases are also considered in PDSTSP+DP (Ham, 2018), with parallel scheduling where the emphasis is on the drone operation such as sequence dependent setup or precedence relationship, e.g., drop first then pickup next at different nodes.

Trucks can also be scheduled for DTCO. Tavana et al. (2017) pose an interesting problem of DTCO in a cross-docking setting where some small items are delivered by drones from a supplier directly to a customer, while other items are delivered by trucks through the cross-docking system that is located between a supplier and a customer. This problem is formulated as a bi-objective MILP problem. Tavana et al. (2017) examine how such direct drone delivery can impact the scheduling of trucks in the cross-docking system. The reviewed papers are summarized in Table 12.

3.3.4. Task assignment

DTCO task assignment problems arise in multiple vehicle missions where inter-vehicle communications or coordination planning is required. Examples include a cooperative control framework for wildfire detection and fighting by a hierarchical UAV/UGV platform (Phan and Liu, 2008) or a coordinated planning for heterogeneous earth observations resources by hierarchical coordinated planning architecture with distributed and loosely coupled Earth observation system that includes UAV and other vehicles (Wu et al., 2016). The reviewed papers are summarized in Table 13.

3.3.5. Other problems

Other DTCO problems include communication links between drones and ground vehicles (Fawaz et al., 2017; Jia and Zhang, 2017; Ladosz and Oh, 2018; Oh et al., 2015; Sharma et al., 2017) and facility location of distribution centers for drones and trucks delivery (Chowdhury et al., 2017). DTCO communication links problems deal with vehicular density and vehicle-to-vehicle cooperation to build a efficient and effective communication network (Fawaz et al., 2017; Jia and Zhang, 2017; Sharma et al., 2017) or drone path planning or positioning under dynamic or geometrical constraints to improve the quality of communication relay (Ladosz and Oh, 2018; Oh et al., 2015). Chowdhury et al. (2017) model a logistic network for disaster relief problems to find the optimal facility locations (i.e., supply sources or distribution centers) where the emergency supplies are to be delivered by drones and trucks. The overview of the reviewed papers is summarized in Table 14.

3.4. Other considerations

In this section, we review DTCO research from the perspectives of number of drones and trucks, capacity of a drone and/or a truck, flying range of a drone, objective of the study, and model type.

3.4.1. Number of drones and trucks

A DTCO problem can have many variants based on the number of drones and trucks in consideration. We review articles based on scenarios in which there are single drone and single truck, multiple drones and single truck, single drone and multiple trucks , and multiple drones and multiple trucks.

3.4.2. Single drone and single truck

The number of drones and trucks used is an important parameter in DTCO problems. If only single drone and single truck are used, then the resulting problem is in general considered as either TSP-D (Agatz and Bouman, 2018; Ha et al., 2018) or FSTSP (Murray and Chu, 2015). TSP-D uses the concept of operations while FSTSP uses the concept of sorties to model the problem. More detailed review of the model types is provided in Section 4. In TSP-D and FSTSP, the objective is in general to minimize the tour completion time or makespan. In Ha et al. (2018), the objective is to minimize the total operating cost. When there are single drone and single truck, the problems can be any of SW, IV, DP, and TP. This implies that synchronization may or may not be required. When synchronization is required, most papers consider the case where a drone or a truck waits for the other at the predetermined customer node, while there are recent studies that allows the rendezvous of a drone and a truck en route (Marinelli et al., 2017; Schermer and Moeini, 2019a), i.e., meeting at some point in a route, which is not a customer location. Dell'Amico and Montemanni (2019) consider two versions of the problem: one in which a drone is allowed to wait at the customer location and the other in which waiting is only allowed in the flying mode. Also, most papers assume that a drone has to come back to a truck, when synchronization is required, right after it visits a customer/target/node. A natural extension to this problem is the mobile depot vehicle routing problem (MoDVRP) (Hadjiconstantinou and Baldacci, 1998) in which a drone can visit more than one targets or customers before returning to the moving carrier (truck).

3.4.3. Multiple drones and single truck

One natural extension to the single drone and single truck DTCO problem is to use multiple drones instead of a single drone to enhance DTCO even further. Murray and Chu (2015) present the PDSTSP formulation where a single truck and multiple identical drones are considered. Ham (2018) extends PDSTSP to consider k trucks (when $k = 1$, this becomes multiple-drone-one-truck case) in addition to multiple drones, and to address pick ups as well as drop offs (PDSTSP+DP). In these problems, drones launch from a depot(s), not from a truck.

A DTCO system where multiple drones can be launched from a single truck is considered (Chang and Lee, 2018; Ferrandez et al., 2016; Moshref-Javadi, 2017). Some customers are served by the truck while others are served by drones. In this system, the truck needs to wait for drones to return and does not move during that time. Unlike this system where a truck is not allowed to move to the next locations while waiting for drones to come back, another system where a truck can move to the next location is studied in the formalism of TSP with multiple drones (TSP-mD) (Yoon, 2018; Tu et al., 2018). In this system, drones can come back to the truck at a different location than the one they were launched from. A TSP-based MILP formulation is presented with a small example problem as a test instance (Yoon, 2018), and a heuristic based on the adaptive large neighborhood search is proposed to solve the TSP-mD (Tu et al., 2018).

Murray and Raj (2019) extend FSTSP by employing multiple drones as sidekicks for a delivery problem (mFSTSP), which is still formulated as MILP. However, due to the increased complexity caused by the introduction of the fleet of drones, a heuristic method that utilizes a subset of subproblems is proposed. Murray and Raj (2019) also show that increasing the number of drones exhibits diminishing margin of returns. In Campbell and Sweeney (2017), the number of trucks is fixed to one, but the number of drones can vary from one to eight. The drones meet the truck at a customer location different from the one they were launched. Therefore, synchronization is required between the two vehicles.

The multiple-drone-one-truck case may also be modeled as a nonlinear programming problem (NLP) (Chang and Lee, 2018), and the objective can be to find the centers of clusters from which drones can depart for the customers and come back to a truck. The truck itself does not make any direct deliveries to customers, and the truck's route goes through the centre of clusters.

3.4.4. Single drone and multiple trucks

To the best of our knowledge, there is no DTCO model in the literature that explicitly considers a single drone and multiple trucks case. However, this can be a special case of a multiple-drone-and-multiple-truck model.

3.4.5. Multiple drones and multiple trucks

Most DTCO problems with single drone and single truck are formulated as MILP that belongs to the class of NP-hard. It will add complexity to the already hard-to-solve problem if multiple drones and multiple trucks are considered (Wang et al., 2017; Poikonen and Wang, 2017; Pugliese and Guerriero, 2017; Kallehauge et al., 2005; Sacramento et al., 2019; Kitjacharoenchai et al., 2019; Wang and Sheu, 2019). Therefore, most multi-drone-and-multi-truck DTCO papers pay a significant attention to the computational tractability issue.

Ham (2018) considers the extension of PDSTSP (Murray and Chu, 2015) where there are multiple drones and multiple trucks (PDSTSP+DP). Unlike PSDTSP, drones can not only deliver but also pick up items to/from customers. A constraint programming is used to solve PDSTSP+DP. Ulmer and Thomas (2018) propose the same-day delivery routing problem with heterogeneous fleets (SDDPHF) of drones and vehicles, which is formulated as dynamic programming. SDDPHF is similar to PDSTSP in the sense that customers are served by either a drone or a truck, and synchronization is not required. However, in SDDPHF there are incoming customer orders, and either drones or trucks deliver the parcels to fulfill the consistently changing customer demand. That is, dynamic vehicle routing is required, which is the key factor that makes SDDPHF different than PDSTSP. A parametric policy function approximation (PFA), which is an approximate dynamic programming (ADP) approach, is used to solve the SDDPHF.

Wang et al. (2017) introduce VRPD where there are multiple trucks, each of which carries one or more drones. Drones launched from a truck must rendezvous with the same truck, and the objective of the problem is to minimize the tour completion time where both drones and trucks can serve the customers. In this paper, several worst case scenarios on how multiple drones can improve DTCO are analyzed. Poikonen and Wang (2017) extend Wang et al. (2017) to provide a more general models and proofs for the worst case scenarios of VRPD. An extension to the VRPD is also provided by Pugliese and Guerriero (2017) in which the vehicle-drone routing problem with time windows (VDRPTW) is proposed, which is a variant of the vehicle routing problem with time windows (VRPTW) (Kallehauge et al., 2005). The objective is to minimize the total transportation cost while meeting the time windows constraints provided by the customers. The model considers a fleet of trucks, each equipped with a drone, and the drone and the truck both make deliveries to the customers. The drone has to return to the same truck after serving a customer. Synchronization is required between the two vehicles.

Wang and Sheu (2019) also consider VRPD where multiple trucks, multiple drones, and their capacity constraints are considered. Interestingly, this paper uses the docking node (service hub), which is not a customer location, where drones can land and then may travel with another truck. The service hub is equipped with backup and service drones, and, therefore, synchronization is not required because if a truck arrives at the docking node before a drone, it can travel with the backup drone. The drone that will arrive later will be a subsequent backup drone. In this setting, no synchronization is required but drones and trucks still work as synchronized working units thanks to the backup drones. The objective is to minimize the travel cost.

Kitjacharoenchai et al. (2019) consider a multiple-drone-multiple-truck problem (mTSPD) where a drone can be launched from a truck and then can be retrieved by any nearby truck at a different location. An MILP formulation is provided with the objective of minimizing the makespan, and an insertion heuristics-based algorithm is presented to solve problems with the size of up to 100 customer locations.

3.4.6. Drone and truck capacity

Most DTCO delivery papers assume that a drone capacity to be one (one item per trip). A drone makes a single delivery, then comes back to a truck for refill if it is working in conjunction with a truck, see, e.g., Murray and Chu (2015), Agatz and Bouman (2018), Pugliese and Guerriero (2017), Moshref-Javadi (2017), Chang and Lee (2018), Schermer and Moeini (2018), Ferrandez et al. (2016), Wang et al. (2017), Othman and Shurbevski (2017), Campbell and Sweeney (2017), Luo and Liu (2017), Carlsson and Song (2017), Wang and Sheu (2019), or to a depot if it is working independently, see, e.g., Ham (2018), Ulmer and Thomas (2018). In addition, most studies assume the unlimited capacity for the truck but there are some papers that assume a truck to be capacitated in which we use "CapT" in the tables that show the summary of papers, see, e.g., Schermer and Moeini (2018), Wang et al. (2017), Poikonen and Wang (2017), Tavana et al. (2017). There are also some papers that consider drone capacity to be more than one (Gonzalez-R et al., 2020; Wang and Sheu, 2019; Karak and Abdelghany, 2019; Poikonen and Golden, 2020; Tavana et al., 2017), for which "CapD" is used in the tables. In particular, a multiple-visit drone routing problem (MVDRP) address the drones having greater than unit capacity because drones are assumed to visit multiple customers before they come back to a truck.

3.4.7. Flying range of a drone

A flying range for drones is an important constraint in DO and DTCO, which impacts the solution significantly. Most papers consider that drones have a limited battery capacity/flying range, see, e.g., Savuran and Karakaya (2015), Pugliese and Guerriero (2017), Moshref-Javadi (2017), Chang and Lee (2018), Schermer and Moeini (2018), Wang et al. (2017), Ulmer and Thomas (2018), Garone and Naldi (2011), Agatz and Bouman (2018), Campbell and Sweeney (2017), Poikonen and Wang (2017), Luo and Liu (2017), Ha et al. (2018), Carlsson and Song (2017), Yurek and Ozmutlu (2018), Freitas (2018), Murray and Chu (2015), Wang and Sheu (2019) where "LF" is used in the tables. This is a practical assumption, which is in general addressed by specifying drone-eligible nodes (nodes within the flying range and weight limit). Note that while most papers consider a given, fixed flying range of a drone(s), some recent studies do consider the energy consumption rate explicitly (e.g., as a function that depends on the item weight) (Dukkanci and Kara, 2019; Murray and Raj, 2019; Yu et al., 2018). There are a few papers that do not consider the battery capacity (Ferrandez et al., 2016; Ham, 2018; Othman and Shurbevski, 2017).

3.4.8. Objectives of the study

The objectives of the study can be roughly divided into three categories:

- Minimization of the tour completion time or makespan. This is the most popular objective in the literature, see, e.g., Chang and Lee (2018), Schermer and Moeini (2018), Ferrandez et al. (2016), Wang et al. (2017), Agatz and Bouman (2018), Poikonen and Wang (2017), Luo and Liu (2017), Yurek and Ozmutlu (2018), Freitas (2018), Murray and Chu (2015). One of the main reasons why drones are used in the areas such as parcel delivery is because of their ability to be faster and responsive in both DO and DTCO. In DTCO, parallel operations are made possible by utilizing two different vehicle types. Thus, the minimization of the travel/tour completion time appears to be a natural objective.
- Minimization of the total cost. While the minimization of travel time/makespan is related to the cost to some degree, it does not necessarily guarantee the cost minimization. A variety of cost factors may need to be considered such as maintenance cost, battery price, labor, etc. In addition to these traditional cost factors, there is another important factor that is associated with the waiting of one vehicle for the other in DTCO when synchronization is required (Murray and Chu, 2015). In addition to the waiting time, which can be converted to a cost, other related factors may also need to be considered in DTCO, such as parking fees for trucks, battery capacity of drones, physical or cyber attacks on drones while they are waiting, etc (Ha et al., 2018). In Wang and Sheu (2019), the objective is to minimize the travel cost that is the combination of the fixed truck cost and the travel cost of drones and trucks.
- Other objectives. There are also some other objectives such as serving customers within time windows (Pugliese and Guerriero, 2017), minimizing the latency in serving the customers (Moshref-Javadi, 2017), and maximizing the expected number of customers served the same day (Ulmer and Thomas, 2018), etc.

3.4.9. Formulation type

Different types of optimization formulations have been used for the DTCO problems. The most popular modeling technique is MILP, see, e.g., Pugliese and Guerriero (2017), Moshref-Javadi (2017), Ha and Deville (2015), Murray and Chu (2015), Tavana et al. (2017) or ILP (Agatz and Bouman, 2018), followed by dynamic programming/markov decision process (Bouman and Agatz, 2018; Ulmer and Thomas, 2018), continuous approximation (Campbell and Sweeney, 2017; Carlsson and Song, 2017), NLP (Chang and Lee, 2018), constraint programming (Ham, 2018), graph problem models (Othman and Shurbevski, 2017), and hybrid Newtons method with difference equations (Ferrandez et al., 2016).

4. Models and methodologies for DTCO

In this section, we present a more detailed review of the DTCO models. There are roughly two different DTCO models: one based on TSP and the other based on VRP. The former is usually called TSPD and the latter is commonly called VRPD. TSPD can be further divided into several different formulations: FSTSP, PDSTSP, TSP-D, Min-cost TSP-D, mFSTSP, and mTSPD depending on objectives and problem specifics. The VRP-based models are usually called

VRPD in the literature. In this paper, we use the same name convention as the original papers and provide a relatively detailed review of TSP-based and VRP-based DTCO models. As noted earlier, we distinguish TSP-D from TSPD. In addition to the TSPD and VRPD, a Markov decision process-based model is proposed for SDDPHF to address the stochastic and dynamic routing problem (Ulmer and Thomas, 2018).

We also provide a relatively detailed review of relevant heuristic methods and algorithms. Unlike other survey papers that do not usually include the details of models and algorithms, our focus in this paper is to introduce and explain the state-of-the-art DTCO optimization models and algorithms, and even suggest some directions for new models.

4.1. DTCO models

4.1.1. Single-drone-single-truck models

The single-drone-single-truck models generally belong to TSPD. We review the different formulations of TSPD for the single-drone-single-truck case in this section.

4.1.2. FSTSP formulation

Murray and Chu (2015) present a MILP formulation for DTCO, which is called FSTSP. The problem describes the optimization of single drone and single truck scenario where the objective is to minimize the tour completion time. The paper uses the actual road distance metric to calculate the distances between nodes for the truck, while Euclidean distance is used to calculate the distance between nodes for the drone. The concept of drone sorties is ised in the paper, which we introduce in Section 3.1. Based on the typical TSP formulation, the paper adds one more variable for drone, and add DTCO constraints such as synchronization, drone endurance, launch and rendezvous, and flow conservation.

The drone sortie does not allow the drone launch node to be the same as the rendezvous node, except when the launch node is the depot. The paper defines the set of tuples, P, of the form (i,j,k) where i is the launch node, j is the drone-eligible node, and k is the rendezvous node. The set P is the driver that enables the derivation of DTCO related constraints. For example, the synchronization constraints can be formulated as follows:

$$t'_i \geqslant t_i - M\left(\sum_{\substack{j=C\\ j\neq i}}\sum_{\substack{k=N_+\\ (i,j,k)\in P}} y_{ijk}\right)\forall i\in C \tag{1}$$

$$t'_i \leqslant t_i + M\left(\sum_{\substack{j=C\\ j\neq i}}\sum_{\substack{k=N_+\\ (i,j,k)\in P}} y_{ijk}\right)\forall i\in C \tag{2}$$

where t'_i and t_i are the arrival time of drone and truck at node i, respectively; M is a large number; C is the set of customer nodes; N_+ is the set of visit-eligible nodes; y_{ijk} is the binary decision variable whose value is 1 if a drone travels from the launch node i to the rendezvous node k via the drone-eligible node j. This implies that if a drone sortie is active (i.e., drone travels from i to k via j), then the drone and the truck must be synchronized at the launch node i. The rendezvous synchronization constraints can also be defined in the same fashion. Note that these synchronization constraints can be defined by use of the concept of the drone sortie, which is denoted by the set P. Note also that other DTCO related constraints such as drone endurance, track requirement to be present at the launch and rendezvous nodes, order of visitation, are defined using the drone-sortie concept.

The paper also presents an effective heuristic method to solve practical size problems as it is observed that even a small 10-customer problem takes several hours to solve using a MILP solver such as Gurobi or CPLEX. We review the heuristic in more detail in Section 4.2.

4.1.3. TSP-D and the concept of operation

Agatz and Bouman (2018) present an integer programming model for DTCO, which is called TSP-D. The nodes are divided into three categories: 1) drone node: a node visited by a drone only, 2) truck node: a node visited by a truck only, and 3) combined node: a node visited by a truck and a drone (mounted on the truck). A solution to TSP is the combination of a truck route (composed of the truck and combined nodes) and a drone route (composed of the drone and combined nodes). It is assumed that a drone's speed is α times the speed of a truck. The advantage of this assumption is that the authors are able to provide bounds on the maximum savings produced by using the DTCO delivery as compared to truck only setting. For example, it is proved that the DTCO (TSP-D) optimal solution is at most 1 + α times better than that of the TSP (truck only). The properties of the TSP-D optimal solution are also shown in this paper. For example, in the TSP-D optimal solution, a combined node may be visited more than once, which is not allowed in the FSTSP formulation.

The major advantage of this model lies in its simple formulation. The model uses the concept of operations, which we introduce in Section 3.1, where a drone is allowed to meet a truck at the same node from which it launches. Based on the set of feasible operations, denoted by O, the decision variable is x_o, a binary variable that indicates whether the operation o is included ($x_o = 1$) in the solution or not ($x_o = 0$). Using the concept of operations and the decision variable x_o, the constraints can be formulated with relative ease. For example, by $\sum_{o\in O(v)} x_0 \geqslant 1$ where $O(v)$ is the set of operations that contain node v, it can be guaranteed that all node are covered. However, unlike the FSTSP formulation which is based on the classic TSP formulation, TSP-D cannot be solved directly by solvers such as Gurobi and CPLEX because the set of operations must be properly prepared before the problem can be solved. Instead, a route first-cluster second heuristic approach based on local search and dynamic programming is proposed to find a solution. Bouman and Agatz (2018) also uses the dynamic programming approach to solve the TSP-D.

4.1.4. Min-cost TSP-D

Ha et al. (2018) extend Murray and Chu (2015) to explicitly consider the transportation costs of the drone and the truck, which is called the min-cost TSP-D. The paper uses the drone sortie concept, not the operation concept. Accordingly, the model is based on the traditional TSP formulation.

The objective is of course to minimize the operational costs, instead of the tour completion time. In particular, the min-cost TSP-D includes the total transportation cost and the waiting cost in the objective function. For the former, it is assumed that both drone and truck are associated with the transportation cost per unit distance, where the drone's unit transportation cost is expected to be cheaper due to, e.g., less energy consumption, than that of the truck. For the latter, the waiting costs of truck and drone are calculated by '$\alpha\times$ truck waiting time' and '$\beta\times$ drone waiting time', respectively, where α and β are coefficients. The drone and truck waiting times are addressed in the constraints, e.g., 'truck waiting time at node $k \geqslant$ drone arrival time at node k – truck arrival time at node k', which is one of the main differences from the formulation of Murray and Chu (2015).

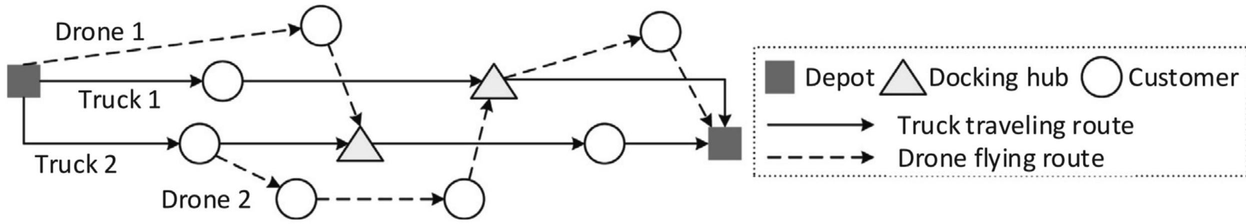


Fig. 4. Example of VRPD, Source: Wang and Sheu (2019).

Ha et al. (2018) also propose two heuristic algorithms to solve the min-cost TSP-D: greedy randomized adaptive search procedure (GRASP) and TSP local search (TSP-LS).

4.1.5. Multiple-drone-single-truck models

The above mentioned DTCO models (TSP-D and variants) include single drone and single truck in the model. It is a natural extension to include multiple drones in DTCO. In this section, we review PDSTSP (Murray and Chu, 2015), mFSTSP (Murray and Raj, 2019), and MVDRP (Poikonen and Golden, 2020).

4.1.6. PDSTSP

Murray and Chu (2015) not only present FSTSP but also PDSTSP that considers a single truck and multiple identical drones working out of a depot to deliver parcels to customers. In this model, the drones deliver items only to customers located with in a flying range from the depot and, therefore, they don't need a truck for item replenishment and battery recharging. The drones come back to the depot after each delivery. At the same time, the truck delivers items to customers along the TSP route, regardless of the flying range of the drone. Each customer is served exactly once either by the drone or by the truck. The drones and the truck work independently with no synchronization requirements, and the objective of the problem is to minimize the latest arrival time of a vehicle to the depot.

4.1.7. mFSTSP

Murray and Raj (2019) propose the multiple drone FSTSP (mFSTSP), which is an extension of Murray and Chu (2015). In this paper, a set of heterogeneous drones is introduced where each drone has its own flying time endurance and capacity while a single truck is used to work with the set of drones (synchronized working units). A truck can carry multiple drones and each drone can launch from the truck multiple times (but not from the same node). Each drone can carry one parcel at a time and is not allowed to come back to the node where it was launched from. The concept of operation is still used but the paper now considers a drone energy consumption rate when eligible sorties are to be identified. The objective is still the same: to minimize the make span, and the paper shows that increasing the number of drones results in diminishing benefits.

In terms of the modeling and formulation, the MILP formulation is carried over from Murray and Chu (2015) but a number of variables and constraints are added to address drone timing, truck timing, and sequencing conditions. For example, to prevent overlapping sorties, the drone launch time of the next sortie must be greater than equal to the drone arrival time to the end node of the previous sortie.

4.1.8. MVDRP

Poikonen and Golden (2020) propose a multiple-visit drone routing problem (MVDRP) where a single truck and k drones (kMVDRP) are considered. In this model, drones are allowed to carry multiple heterogeneous items, which implies that they may visit several different customer locations before coming back to the truck to recharge/replace the battery and pick up the new packages. The truck serves as a mobile depot (drone primary) and does not deliver packages to customers. To address the relationship between heterogeneous packages and drone endurance (flying range/time), a drone energy drain function is introduced. In this paper, an operation is defined as a set of actions involving the launch and retrieval of all drones at the launch and rendezvous nodes. At the launch node, multiple drones (all or part of the drones the truck is carrying) can be launched from the truck. After the launch of drones is completed, the truck in only allowed to move to the rendezvous node, which implies that it cannot launch another drone in between. The kMVDRP model is based on the concept of an operation, which leads to rather simple formulation. To solve kMVDRP, a route-transform-shortest path heuristic algorithm is proposed.

4.1.9. Multiple-drone-multiple-truck models

The final step of DTCO model generalization is to consider multiple drones and multiple trucks for which several variants are studied: multiple drone PDSTSP (Ham, 2018), VRP with drones using service hubs (Wang and Sheu, 2019), and multiple FSTSP (mFSTSP) (Kitjacharoenchai et al., 2019).

4.1.10. PDSTSP+DP

Ham (2018) extends PDSTSP proposed by Murray and Chu (2015) to incorporate multiple trucks in addition to multiple drones. In this paper, drones not only deliver items to customers but also are capable of picking up items from customers. A fleet of drones and a fleet of truck with multiple depots are considered in this paper for an operational excellence. A constraint programming approach is used to solve this problem (PDSTSP with drop off/pick up).

4.1.11. VRPD with service hubs

Wang and Sheu (2019) propose the capacitated VRP (CVRP)-based DTCO model, implying that the model becomes a traditional CVRP if drones are removed, where multiple trucks and multiple drones with limited flying range and capacity are considered. This model has some unique features and assumptions. First, drones cannot land on trucks at the customer locations. Instead, there are designated service hubs (docking nodes) where drones can land. Second, synchronization is not required because there are some backup drones at the service hubs. Third, drones can travel with another truck that is different than the ones they were launched from. Any truck can pick up any drone at the service hub as long as the flying range and capacity constraints are satisfied. The example of VRPD is illustrated in Fig. 4. The objective is to minimize the travel cost that is the combination of the fixed truck cost and the travel cost of drones and trucks. Because of these unique features and assumptions, the model does not require the concept of drone sortie nor operation.

The model can be formulated in two ways in Wang and Sheu (2019): the arc-based and path-based formulations. The arc-based formulation is derived from CVRP and it contains a large number of constraints that handles the special requirements of drone and truck travel such as flow conservation, flying endurance, and capacity of drones and trucks. Such constraints can be effectively handled and the model can be presented in more compact form if the path-based formulation is used. To reformulate, the feasible truck and drone paths, along with their associated costs, are identified first and the new decision variables are introduced to indicate whether a particular drone/truck path is included in the final selection. To make sure drones paths are feasible, some theoretical study is given. A branch-and-price algorithm is presented to solve the path-based model.

4.1.12. mTSPD

Kitjacharoenchai et al. (2019) consider a multiple-drone-multiple-truck problem where a drone can be launched from a truck and then can be retrieved by any nearby truck at a different location. Only one drone can be launched or retrieved at one customer location. The model in this paper, called a multiple traveling salesman problem with drones (mTSPD), can be considered as an extension of FSTSP (Murray and Chu, 2015), which implies that it employs the concept of the drone sortie. In addition, a drone is not allowed to come back to its launch node, which is a typical drone sortie assumption. An MILP formulation is provided with the objective of minimizing the makespan. In general, the formulation of mTSPD (Kitjacharoenchai et al., 2019) is similar to that of mFSTSP (Murray and Raj, 2019) because both are the extensions of FSTSP (Murray and Chu, 2015). The main differences between mTSPD and mFSTSP include the number of trucks (single truck for mFSTSP while multiple trucks for mTSPD) and the number of drone launches and retrievals (multiple launches and retrievals for mFSTSP while one at a time at each location for mTSPD). An insertion heuristics-based algorithm is presented in Kitjacharoenchai et al. (2019) to solve mTSPD problems with the size of up to 100 customer locations.

4.1.13. SDDPHF

Ulmer and Thomas (2018) propose SDDPHF, formulated as dynamic programming, to to fulfill the consistently changing customer demand by either drones or trucks. That is, in SDDPHF a fleet of trucks and a fleet of drones deliver items to customers located in the service area on an on-demand basis during the fixed time frame.

In Ulmer and Thomas (2018), both drones and trucks are initially located at the depot, and they are capable of making multiple trips back and forth from the depot to the customer locations. Of course, drones differ from trucks with respect to capacity, speed, charging requirement, travel speed/range, etc. As is typical to dynamic programming methods, SDDPHF determines whether or not to accept the customer order as soon as it arrives. Once accepted, the delivery is assigned to either a drone or a truck. Therefore, there are three decisions: 1) rejection of order, 2) order assigned to a drone, and 3) order assigned to a truck. Depending on these decisions, systems states such as arrival time of vehicles and routes information are updated, and the reward is also updated accordingly. The objective is to maximize the total expected reward. A parametric policy function approximation (PFA), which is an approximate dynamic programming (ADP) approach, is used to solve the SDDPHF.

4.2. DTCO methodologies

Various solution methodologies have been proposed for DTCO. We divide them into four categories: heuristics, metaheuristics, exact methods, and continuous approximation.

4.2.1. Heuristics

Due to the NP-hard nature of DTCO problems, it is not practical to use off-the-shelf MILP solvers such as Gurobi or CPLEX for the larger instances of the problem. This leads to the popularity of heuristics in solving the DTCO problems (Agatz and Bouman, 2018; Garone et al., 2010; Garone and Naldi, 2011; Mathew and Smith, 2015b; Savuran and Karakaya, 2015; Ha and Deville, 2015; Tokekar et al., 2016; Wu et al., 2016; Ponza, 2016; Ferrandez et al., 2016; Fikar and Gronalt, 2016; Carlsson and Song, 2017; Daknama, 2017; Kundu, 2017; Chang and Lee, 2018; Murray and Chu, 2015; Schermer and Moeini, 2018; Schermer and Moeini, 2019a; Reinelt, 1994; Ha et al., 2018; Sujit et al., 2009; Yurek and Ozmutlu, 2018).

In this regard, Murray and Chu (2015) introduce a route and reassign heuristic for the FSTSP problem where there are single drone and single truck for DTCO. The heuristic starts with solving a TSP for which different TSP solution methodologies (Reinelt, 1994) may be explored. Next, the heuristic selects drone-eligible customer nodes and removes them from the truck route, and, then, serves them using a drone while keeping in mind the savings achieved for each removal and assignment. The time savings achieved by removing some customer j can be calculated using another algorithm dedicated for such task. Similarly, the cost of inserting some customer j into a truck route and a drone route, respectively, can be evaluated using dedicated algorithms.

Murray and Raj (2019) extend the FSTSP to consider multiple heterogeneous drone, which is called mFSTSP. As mFSTSP involves a number of additional constraints to consider drone timing, truck timing, and sequencing conditions, it becomes more complex than FSTSP, which necessitates a more effective heuristic algorithm. To address this, a three-phase algorithm is proposed. In the first phase, customers are partitioned into two different sets: drone eligible customers and truck customers. The minimum number of truck customers is determined and initialized in this phase. In the second phase, drone sorties are generated and routes for drones and truck are determined. In the third phase, a special MILP is solved to determine the timing of drone launch, recovery, and service activities, as well as the drone queuing sequences.

Agatz and Bouman (2018) present a route first-cluster second heuristic approach to find a solution. The first stage is to find the TSP solution (truck only), which is the same as the first stage of Murray and Chu (2015). In the second stage where a TSP-D tour is constructed from the TSP solution, two different heuristics are proposed: a greedy partitioning heuristic and an exact partitioning algorithm. As the two heuristics rely on the TSP solution and a good initial TSP solution does not guarantee a good TSP-D solution, several different TSP initial solution can be used, which is called iterative improvement procedures.

Ha et al. (2018) present two heuristic algorithms to solve the min-cost TSP-D: GRASP and TSP-LS. GRASP is divided into two steps: construction step and local search step. In the construction step, a split algorithm is used to construct a TSP-D tour based on a TSP tour. That is, the truck only solution must be found in advance, which is called a giant tour. To build the giant tour, k-nearest neighbor, k-cheapest neighbor, and random insertion algorithms are used. In the local search step, new operators (e.g., relocation operator, remove operator, two exchange operator) are used adapted from the traditional ones. TSP-LS is adapted from Murray and Chu (2015), which has the different cost savings calculation algorithm to address the waiting time cost. The computational results show that GRASP outperforms TSP-LS in terms of quality of solutions, while the TSP-LS is significantly faster than GRASP in terms of speed of generating the solutions.

Schermer and Moeini (2019a) propose Variable Neighborhood Search (VNS)-based heuristic algorithm to VRPD that is formulated as MILP. In addition, some valid inequalities are used to help reduce computation time when the problem is solved using commercial solvers.

Wang and Sheu (2019) present the branch-and-price algorithm to solve the path-based model of VRPD. The set of customers is divided into the two subsets: the ones within the flying range of drones from the depot and others. Drone and truck optimal routes are then found to serve the first and second subset, respectively, which become an initial solution for the branch-and-price algorithm. The pricing sub-problem finds a route for a truck or a drone from the origin to the destination with the minimum reduced cost. A special case of the pricing sub-problem is the constrained shortest-path problem, which is solved by a modified pulse algorithm because it is known to outperform a label correcting algorithm.

4.2.2. Metaheuristics

A metaheuristic, a higher-level procedure to find a good solution with few or no assumptions about the problem being optimized, is also proved to be effective for several DTCO problems (Ferrandez et al., 2016; Fikar and Gronalt, 2016; Freitas, 2018; Ladosz and Oh, 2018; Ponza, 2016; Sacramento et al., 2019; Sharma et al., 2017; Wu et al., 2016).

For example, Ponza (2016) uses the simulated annealing (SA) approach to solve the single-drone-single-truck DTCO problem. The analysis shows that problems of the size up to 200 customers can be solved within 200 seconds using the SA metaheuristic. For a deeper understanding of SA, readers may refer to Busetti (2003). Freitas (2018) present a hybrid general variable neighborhood search (HGVNS) metaheuristic, which is based on the complimentary characteristics of a drone and a truck to make deliveries. In HSVNS, a MIP solver is initially used to obtain a TSP optimal tour. The TSP solution is then converted to a TSP-D solution using a metaheuristic known as general variable neighborhood search (GVNS).

4.2.3. Exact methods

Most DTCO problems are based on TSP and/or VRP, which are known to be NP-hard. Therefore, it is hard to solve the DTCO problems using exact methods, especially when the problem size is large. However, there are still several studies to focus on developing exact methods, as it has great potential to provide insights into the problem. Yurek and Ozmutlu (2018) develop a decomposition-based iterative algorithm that solves a single-drone-single-truck TSP-D problem up to 12 customers to optimality within 15 min. In contrast, the solution time of commercial solvers such as CPLEX and Gurobi for a 10 customer DTCO problem formulated using the state-of-the-art mathematical models can be several hours (Murray and Chu, 2015). However, when the size of the problem is increased beyond 12 customers, the solution time using their approach increases significantly.

Practical problems are expected to be much larger than a 12 customer problem. Accordingly, Bouman and Agatz (2018) present a three-pass approach (exact method) for TSP-D, which can solve larger instances of the problems to optimality than other exact methods found in the literature. In the first pass, the well-known Bellman-Held-Karp algorithm to solve TSP (Bellman, 1961; Held and Karp, 1962) is adapted to find the shortest truck paths for each start node, end node, and all truck nodes covered by the path. In the second pass, the efficient (least costly) operations are obtained. In the third pass, the optimal sequence of efficient operations is deteremined.

4.2.4. Continuous approximation

Continuous approximation (CA) techniques replace the numerical methods by analytical techniques, and the detailed data is replaced by concise summaries (Daganzo, 2005; Carlsson and Song, 2017). The problem can be reduced into a smaller set of parameters. Then, the impact of these parameters on the outcome of the problem can be determined. Assuming that a continuous distribution of customer location is given, analytical formulas are derived to calculate the expected delivery cost and time. In a similar work, Campbell and Sweeney (2017) solve the CA models to obtain important design parameters such as optimal numbers of drones per truck, and analyze whether the DTCO based delivery method provides a lower cost than the truck only method for different scenarios.

5. Barriers to DO and DTCO implementation

Despite the recent surge of interests on DO and DTCO research, a number of existing or potential barriers still need to be addressed before practical implications can be made. Since a drone is the core of DTCO, a large portion of the barriers share the concerns with DO itself. In this section, we review the DO and DTCO implementation barriers discussed in the literature. The barriers can be categorized into a few groups based on the characteristics of issues: regulation (e.g., privacy, security, safety, etc.) and sustainability (e.g., environment, technology, socio-economics, etc.). Table 15 summarizes the identified barriers.

5.0.5. Privacy issues

Drones may be seen as a serious threat to privacy by the general public. Drones are rapidly evolving into a smaller but more functional device with various sensing and communicating technologies. In particular, a surveillance drone, either individually or as part of fleet, is expected to be present almost anywhere for traffic management (Akram et al., 2017), pro- or post-event management (Bracken et al., 2014), surveillance against crime (e.g., police and border patrol) (Finn and Wright, 2012), nature conservation (Sandbrook, 2015), etc. It is natural that the general public may feel the presence of drones very uncomfortable or may consider them as an infringement of privacy if surveillance drones are hovering around them.

Mass data collection via drones can be worrisome. For example, in search-and-rescue operations and surveillance operations, drones may have to take random pictures without permission, which may be taken as 'search without warrant' (Villasenor, 2014). Small drones may make the concern worse because it is very difficult to see them in the sky, and people may not notice even when they are observed by the drones. Regulations for drone surveillance operations are already in act or under discussion (Bracken et al., 2014).

5.0.6. Security issues

Communication is a critical part for a drone or a fleet of drones both in manual (e.g., control signal) and autonomous (e.g., GPS signal) control and operations. Many drones are also expected to transmit collected time-sensitive data through communication links rather than saving it until they return to the base. Despite the continuous effort to protect the communication protocol such as security framework or cryptographic schemes (Akram et al., 2017), drones are always exposed to various types of cyber attacks and can become vulnerable as long as they are communicating through the air.

The compromised communication issues are naturally connected to the concerns about using the drones for cyber-physical attacks to both private and public sectors (Akram et al., 2017; Solodov et al., 2018). An attack to the drone itslef may also be possible by, e.g., fake GPS signals or interference in control (Clarke and

Table 15
Barriers to implementation.

Main criteria	Instances	References
1. Privacy	Surveillance against privacy related legislation	Finn and Wright (2012), Bracken et al. (2014), Akram et al. (2017), Sandbrook (2015)
	Mass data collection	Bracken et al. (2014), Villasenor (2014)
2. Security	Data security	Akram et al. (2017), Sandbrook (2015), Solodov et al. (2018)
	Cyber-physical attacks	Akram et al. (2017), Clarke and Moses (2014), Rao et al. (2016), Solodov et al. (2018)
	Identification of non-authorized drones	Anbaroğlu (2017)
3. Safety	Regulatory concerns to the general public	Clarke and Moses (2014), Dalamagkidis and Valavanis (2008)
	Risk of accidents	Clarke and Moses (2014), Lidynia and Philipsen (2017), Rao et al. (2016), Sandbrook (2015)
	Airspace safety	Dalamagkidis and Valavanis (2008), Kwon and Kim (2017), Rao et al. (2016), Ryan (2018), Villasenor (2014)
4. Environment	Wildlife disruption	Chang and Chundury (2017), Kwon and Kim (2017)
	CO_2 emissions	Goodchild and Toy (2018)
	Pollution (noise, visual, etc.)	Kwon and Kim (2017)
5. Technology	Performance (flight range, battery life, routing network, carrying capacity, weather)	Agatz and Bouman (2018), Anbaroğlu (2017), Bracken et al. (2014), Gupta and Jain (2016), Hallermann (2013)
	Flight control (air collision, obstacle avoidance)	Dalamagkidis and Valavanis (2008)
	Countering adversary threats	Solodov et al. (2018)
6. Socio-economics	Economy and employment	Boucher (2016), Kwon and Kim (2017)
	Public perception and acceptance	Boucher (2016), Bracken et al. (2014), Chang and Chundury (2017), Clothier et al. (2015), Kwon and Kim (2017), Lidynia and Philipsen (2017), Yoo et al. (2018)

Moses, 2014; Rao et al., 2016). Some ways to prevent drone attacks can be done by identification of unauthorized drones, drone hackers, and routes of such drones (Anbaroğlu, 2017).

Another concern is the usage of collected and leaked data. If the private data is sold without permission to a commercial entity, shared in the social networks, and gathered by national security agencies, it could lead to another serious issue that is related to civil liberties (Sandbrook, 2015). If the collected data is about sensitive facilities, the security issue can be more critical because it can be used for both cyber and physical attacks (Solodov et al., 2018).

5.0.7. Safety issues

In general, safety issues of drones are coupled with the security issues because insecure control of drone, whether from malfunction or hacking, may cause accidents by falling into the ground (Clarke and Moses, 2014; Lidynia and Philipsen, 2017; Rao et al., 2016; Sandbrook, 2015) or by a collision in the air (Dalamagkidis and Valavanis, 2008; Kwon and Kim, 2017; Rao et al., 2016; Ryan, 2018; Villasenor, 2014). A proliferation of drones may make this issue more complicated because not only the chances but also the causes of accidents may increase in proportion to the number and types of drones. The use of different altitudes for different types of air vehicles would not be a complete solution because a collision may happen during landing or takeoff (Kwon and Kim, 2017; Ryan, 2018). Therefore, there is a continuous need of considering extensive scenarios for regulations and corresponding training programs to address the anticipated safety issues (Clarke and Moses, 2014; Dalamagkidis and Valavanis, 2008).

5.0.8. Environmental issues

Drones may have a negative impact on physiological health of wildlife by increasing stress level due to the noise (unique buzzing sounds) when the drones fail to keep the distance (Chang and Chundury, 2017). If wild animals are exposed to such environment for a long time, it could lead to wildlife disruption because such impact may be particularly serious with animals that are pregnant or raising the young (Kwon and Kim, 2017). There is also possibility of drones to hit birds and other wildlife animals (Chang and Chundury, 2017). As drones are expected to become more widely used, they would fill the sky similar to how vehicles are on the roads (Kwon and Kim, 2017). This may cause both visual (e.g., shadows) and sound (e.g., buzzing noise) pollution to the general public, as the drones would be seen everywhere leading to a phenomenon called full skies. Drone operation is also not free from CO_2 emission issues. Electricity to recharge batteris may be generated from burning fossil fuels. In addition, fossil fuel-powered trucks may also be used in DTCO. In contrast to the general belief that delivery drones are much more environmentally friendly than conventional trucks, drones may cause more emissions especially when the delivery distance is very long (Goodchild and Toy, 2018).

5.0.9. Technological issues

Drone specifications such as the flight range, battery life, and carrying capacity limit the operational boundary of DO and DTCO (Agatz and Bouman, 2018; Anbaroğlu, 2017; Bracken et al., 2014; Gupta and Jain, 2016; Hallermann, 2013). Current DTCO research seeks solutions with such technical limitations as constraints. If a breakthrough in technology resolves such technical barriers, the potentiality of DO and DTCO can be greatly expanded in many application area.

Technological issues are often closely connected to security and safety issues as well. Whether it is from a malfunction or an intended operation, any accident from technical problems may result in consequences that may compromise security and/or safety. Therefore, technological considerations in DO and DTCO also need to give serious attention to security and safety (Solodov et al., 2018).

Research papers published on the DO- and DTCO-based delivery systems do not usually give enough attention to the obstacle avoidance technology because this may need to be addressed more in detail at the application level. Most commercial drone manufacturers have been adopting the sense-and-avoid (SAA) technology to make their drones safer. However, the integration of drones into the national airspace system would require more strict regulations made by systematic approaches (Dalamagkidis and Valavanis, 2008). One research direction would be to use the artificial intelligence (AI) and deep learning methods to identify obstacles, which also would require a cutting edge sensor technology.

5.0.10. Socio-economic aspects

New technologies such as autonomous drones and autonomous trucks may replace a number of human jobs and may cause economic issues such as mass unemployment or polarized economy (Kwon and Kim, 2017). There will be opportunities for new skilled jobs for DO and DTCO while the number of old replaceable jobs (such as truck drivers) may decrease (Boucher, 2016). Drone delivery combined with truck operations will reduce the need for truck drivers, and accelerate the radical transformation of logistics industry (Krok, 2018; Stenson, 2017). Therefore, adopting the new technology needs to be agreed upon between diverse economic stakeholders by appropriately considering and interpreting the anticipated potential impacts. Various issues that may affect the public perception and acceptance must be discussed and addressed in advance (Boucher, 2016; Bracken et al., 2014; Chang and Chundury, 2017; Clothier et al., 2015; Kwon and Kim, 2017; Lidynia and Philipsen, 2017; Yoo et al., 2018).

6. Future research areas

In this section, our goal is to identify possible research directions based on the literature survey provided in the previous sections. We discuss topics such as uncertainty, operational constraints, methodology enhancement, and energy and environmental concerns.

6.1. Incorporating uncertainty

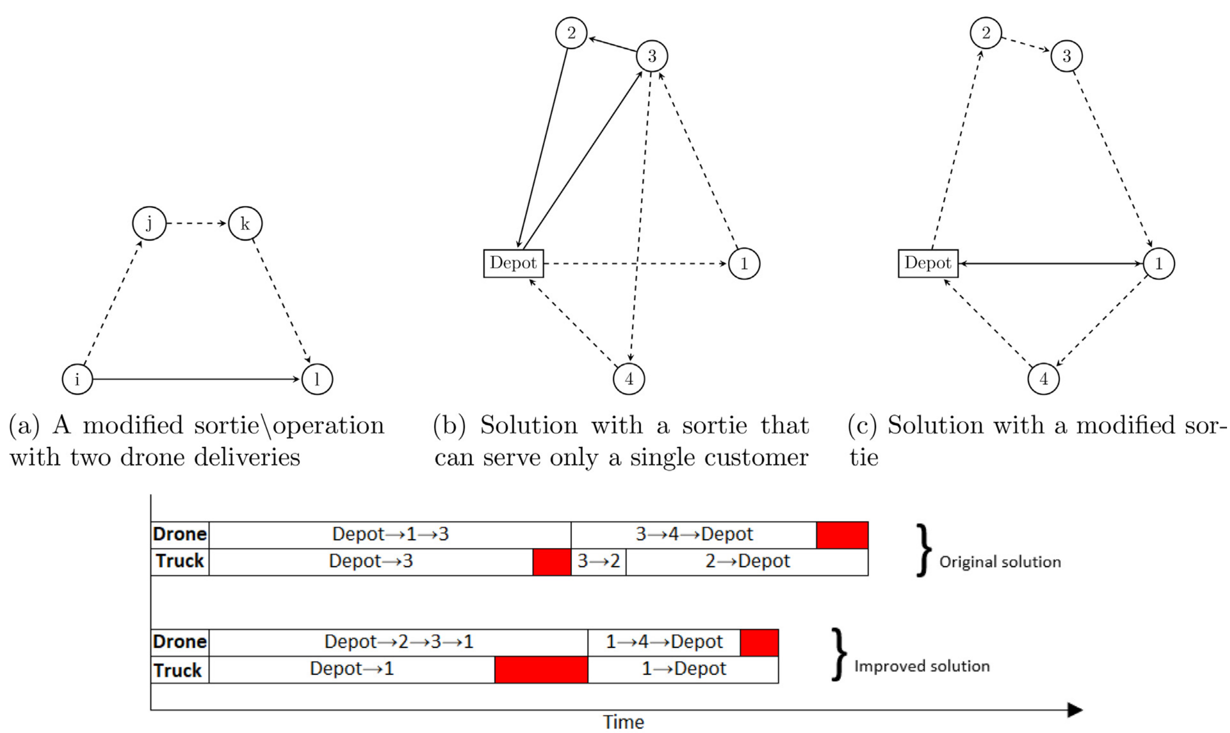
There is always uncertainty in the air traffic and ground road networks. The uncertainty can be in the form of traffic conditions including accidents, natural disasters such as earthquakes and hurricanes, and man-made calamities such as riots, protests, political disturbances, etc. In addition, drone travel may be affected by weather conditions such as extreme temperatures, precipitation, fog, humidity, and wind. In particular, the battery life, flying range, and drone speed may be impacted by these factors.

Such uncertain factors may greatly impact drone safety and security. In addition, in the presence of uncertainty, the synchronization between drones and trucks may become much more difficult task. This implies that uncertainty may seriously impact the economy of DO and DTCO. However, this important uncertainty issues are not considered enough in the literature. To address the uncertainty, data mining, machine learning and AI methods as well as stochastic optimization including robust optimization, stochastic programming, and dynamic programming should be explicitly used to plan DO and DTCO.

6.2. Relaxing operational constraints

Most DTCO models in the literature consider various operational constraints. For example, a drone can depart from and rendezvous with a truck at some fixed locations. A drone can serve only one customer. A truck must wait for a drone to come back at the launch node. The customer demand is given and all the items are ready at the depot. These are only a few of many operational constraints and assumptions. While these constraints are needed for modeling purposes, they may limit the effectiveness of DO and DTCO. In addition, considering the speed at which DO and DTCO relevant technology and infrastructure are developing, some of such operational constraints may not make sense in the near future. Therefore, relaxing some of the operational constraints can be one of the important future research directions.

In the literature, most DTCO problems assume that all items are ready to be picked up at the depot(s), and also assume no addi-



(a) A modified sortie\operation with two drone deliveries (b) Solution with a sortie that can serve only a single customer (c) Solution with a modified sortie

(d) Comparison of delivery schedules (Red box: waiting time)

Fig. 5. Modified sortie/operation for multiple drone visits.

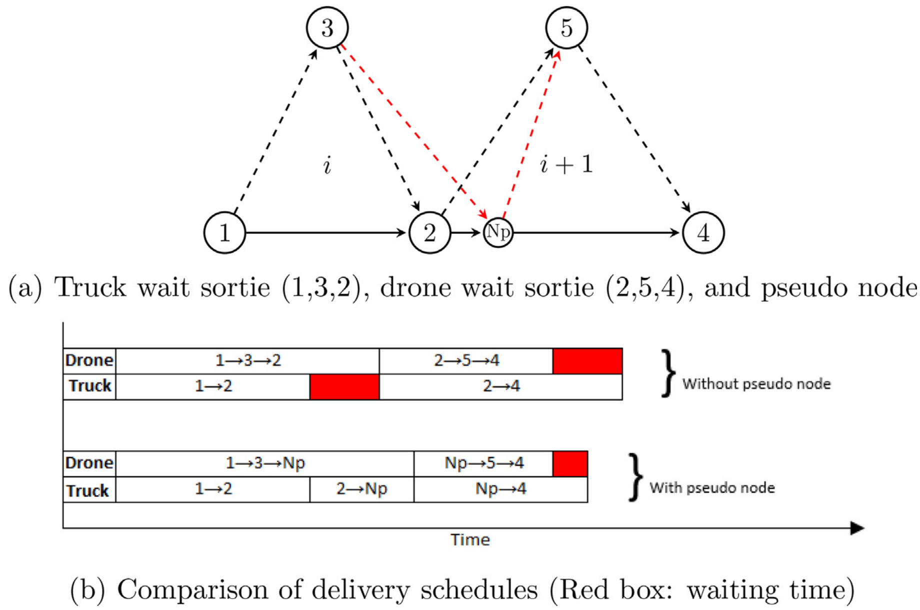


Fig. 6. Impact of pseudo node in DTCO.

tional customer demand and no item replenishment at the depot. However, as Amazon Prime Air demonstrates (Johnson, 2017), one of the greatest benefits of using drones can be the quick delivery on demand. This necessitates the need for dynamic routing problem for DTCO, which would be a very interesting topic for future research. Indeed, the same-day delivery problem using drones is studied by Ulmer and Thomas (2018) where customers order items over the course of the day, and either drones or trucks deliver the items. A parametric policy function approximation (PFA), which is an approximate dynamic programming (ADP) approach, is used to solve the problem. While this paper is the first to consider heterogeneous vehicles (trucks and drones) for the same-day delivery using dynamic routing, there are still ample opportunities for further improvements. For example, as this paper does not capture the characteristics of heterogeneous customers, the introduction of methods that can deal with different customers would be one way to improve the paper. In addition, the relaxation of drone's unit capacity assumption as well as enhanced solution algorithms would also be potential future works.

One assumption that may need to be relaxed quickly is the unit capacity of drones, because drones are becoming more capable at a fast rate. It will be interesting to see how the solutions change when a drone can serve more than one customer in a single *sortie* or *operation* as shown in Fig. 5a. Fig. 5b and c show how this drone capacity relaxation affect the optimal solutions. The improvement in total delivery time of the example is illustrated in Fig. 5d. Multi visit drone problem (MVDRP) is already addressed in Poikonen and Golden (2020) with some limitations. For example, a truck is not allowed to launch another drone before it recovers all the drones previously launched. In addition, only single truck is considered with multiple drones. The more generalized version of Poikonen and Golden (2020) to consider multiple trucks and free launch/recovery of drones at any node/time can be an interesting future research topic because that is what actually needs to be done at practice.

Finally, we emphasize one important operational constraint: drone launch and recovery location assumption. Most of the reviewed DTCO papers that require drone launch and recovery assume that the launch and recovery can only be done at certain locations such as the customer node and/or the depot, which is the main cause for asynchronization between drones and trucks. There are recent studies that allow the rendezvous of a drone and a truck at some locations in a route that are not customer locations. This type of problem is called Vehicle Routing Problem with Drones and En Route Operations (VRPDERO) (Marinelli et al., 2017; Schermer and Moeini, 2019a), which is formulated as MILP (Schermer and Moeini, 2019a). If we allow drones and trucks to meet each other at any point in the network, the synchronization issue may be completely resolved, which has potential to greatly enhance the economic aspect of DTCO.

In more detail, one way to resolve this problem is by creating a pseudo node where a drone and a truck can meet simultaneously, as illustrated in Fig. 6. The pseudo node may be constructed in a parking lot, a rest area, or even a road assuming that a truck can retrieve a drone while driving. Recently, UPS showcased the drone-truck delivery system (UPS, 2019) in which the driving truck received the returning drone from a customer location. Therefore, constructing a pseudo node within a road is absolutely feasible at the technology level at least.

Fig. 6 shows a pair of drone sorties where the original pair of sorties is given as $\{(1,3,2),(2,5,4)\}$. In this example, the truck waits at Note 2 while the drone waits at node 4, as shown in Fig. 6a. The red boxes represent the waiting time. The waiting time can be reduced if the drone and truck meet simultaneously at the pseudo node N_p instead of meeting at node 2, as illustrated in Fig. 6a. Incorporating the pseudo node has potential to greatly improve DTCO. The method of finding optimal pseudo node locations and the analysis of performance improvement could be a very interesting future research topic.

6.3. Improving modeling techniques and solution methodologies

Most DTCO problems are formulated as ILP or MILP, which are known to be NP-hard. The small DTCO problems, e.g., up to 10 customers, may be solved using exact algorithms within a reasonable time frame. For relatively larger problems, exact algorithms may not work and commercial solvers such as CPLEX and Gurobi will experience the curse of dimensionality. Considering that the commercial application of DTCO is imminent, the development of effective and efficient heuristic algorithms is essential. Unfortunately, aa DTCO adds more complexity to already hard-to-solve TSP and VRP models, the state-of-the-art methods developed for TSP and VRP may not work well for DTCO problems.

The DTCO was first formulated as FSTSP in 2015 (Murray and Chu, 2015), and several heuristic methods have been proposed since 2015, which are extensions of TSP and/or VRP solution methods. These include route and re-assign (Murray and Chu, 2015), three-phase (customer partition, sortie generation, and timing) (Murray and Raj, 2019), route first-cluster second (Agatz and Bouman, 2018), GRASP and TSP-LS (Ha et al., 2018), branch-and-price (Wang and Sheu, 2019), etc. However, there still remain a myriad of opportunities to develop more effective and efficient heuristic algorithms.

There is also a possibility to develop dynamic programming-based heuristic methods (Bouman and Agatz, 2018). Since the effectiveness of dynamic programming relies on the substructure of the problem, one promising direction might be to develop a method to identify the operations in which one vehicle waits excessively for another vehicle. As they are far from efficient (i.e., bad operations), these sorties or operations can be excluded in the next step, which can reduce some solution time. Note that if the number of locations a truck visits is restricted while a drone is visiting other customers, the solution time can be greatly decreased Bouman and Agatz (2018). However, as this restriction clearly limits the practical application, the relaxation of this restriction could be a good future research topic.

Although most solution approaches in the literature focus on the DTCO problems with single drone and single truck, there is also a need to extend these for multiple drones and multiple trucks. As the number of trucks and drones increases, the DTCO problems will become increasingly difficult to solve with traditional approaches. Using simulation studies to find the optimal number of drone and truck combination for real life scenarios may be a practical research direction. To this end, simulation studies may compare different drone and truck combinations in a relatively short amount of time, and help save time in searching for a feasible solution space by a sensitivity analysis.

There is also a need to find the correlation between the truck route in the DTCO problem and the optimal TSP tour, which may provide important insights to build heuristics for the DTCO problems.

6.4. Energy and environmental studies

While environmental and energy concerns continue to grow, it is a general perception that drones produce less pollution than trucks. However, recent research shows that the drones have carbon dioxide emissions advantage over trucks for shorter flight distances or when the delivery route has only a few recipients. For longer distances or if the delivery route has many recipients, then the trucks could become a more environmentally friendly alternative as they can carry more items in a single trip (Goodchild and Toy, 2018). This kind of analysis also needs to be explored in combination with aforementioned improved solution techniques since the energy and environmental factors in the objective function may change the scope of entire problems.

6.5. Mixed-fleet arc routing problems

VRP concerns a route mapping between nodes, which is the basis for most DO and DTCO routing problems surveyed in this paper. An arc routing problem (ARP) focuses on mapping a route to cover the arcs or edges, e.g., streets or road segments. The objective of ARP is in general to minimize the makespan or the amount of dead mileage (covering the same arc more than once or covering arcs that need not be covered), while fully encompassing all the demand arcs. In ARPs, each demand arc must be completely traversed by a service vehicle. In addition, between the two demand arcs that are not connected to each other by another demand arc, a vehicle must follow non-demand arcs in a network (Hertz, 2005; Dror, 2012; Corberán and Laporte, 2015; Mourão and Pinto, 2017).

Most ARP studies are based on the assumption that a service vehicle follows ground roadways. If an aerial drone is used as a service vehicle, which is called a drone ARP (D-ARP), new opportunities and challenges follow. In D-ARP, drones depart from and return to a depot, and are assumed to be able to fly directly any two points in a network, whose cost can be represented by the Euclidean distance on a complete graph. Because the requirement of following ground arcs is relaxed, a better solution can be obtained in D-ARP.

There are only a few papers that explicitly study D-ARP (Chow, 2016; Campbell et al., 2018), mainly because of its complexity in modeling and algorithm development. Chow (2016) tackles a stochastic dynamic D-ARP for traffic monitoring while Campbell et al. (2018) propose a polygonal approximation approach to solve a length-constrained D-ARP (with single drone) where drone flying costs are defined by the Euclidean distances. No research has addressed a length-constrained multi-drone ARP.

A natural extension to D-ARP is the drone-truck (DT) ARP, which has never been addressed in the literature except Chung (2020) in which a new drone arc excursion modeling approach is proposed. This will be fundamentally different and significantly more challenging than the traditional ARPs such as the Chinese postman problem and the rural postman problem, because drones can fly directly from one point to other point in a network without following ground arcs while trucks have to follow such ground arcs. In addition, a drone may serve only part of an arc, due to its limited capacity and footprint (length constrained), and/or potential benefits from multiple routes covering the entire arc. The shape of arc must be taken into consideration, unlike the traditional ARPs. Furthermore, a drone may launch from one truck and return to another truck if beneficial, while synchronization between drones and trucks will play a significant role. All in all, this unprecedented, DT-ARP poses significant opportunities and challenges simultaneously, and will require completely new modeling and algorithmic methods.

7. Conclusion

This paper surveys the optimization methods for DO and DTCO research with a more focus on DTCO. As discussed earlier, drones are one of the emerging technologies that provide opportunities and challenges simultaneously. In particular, some applications areas that are suffering from, e.g., high labor cost, dangerous working environment, and inaccessibility can greatly benefit from the drone deployment, which include wildlife monitoring, disaster management, emergency medicine delivery, inspection of infrastructure, etc. To maximize such potential benefits, a well planned drone operations with the aid of the state-of-the-art optimization methods is a definite prerequisite.

We note that the effectiveness and efficiency of DO can be significantly enhanced if drones are combined with other vehicles, e.g., trucks. However, the research on DTCO is still in its initial phase, and it will take some time for the research to mature. Therefore, the investigation into the current status of the DTCO research can be crucial to understand the state of the art and suggest future directions.

References

Agatz, N., Bouman, P., Schmidt, M., 2018. Optimization approaches for the traveling salesman problem with drone. Transp. Sci. 52 (4), 965–981.

Akram, R.N., Markantonakis, K., Mayes, K., Habachi, O., Sauveron, D., Steyven, A., Chaumette, S., 2017. Security, privacy and safety evaluation of dynamic and static fleets of drones. In: Digital Avionics Systems Conference (DASC). IEEE, pp. 1–12.
Albert, A., Leira, F.S., Imsland, L., 2017. UAV path planning using MILP with experiments. Model. Identif. Control 38 (1), 21–32.
Alemayehu, T.S., Kim, J.-H., 2017. Efficient nearest neighbor heuristic TSP algorithms for reducing data acquisition latency of UAV relay WSN. Wireless Personal Commun. 95 (3), 3271–3285.
Ali, K., Nguyen, H.X., Vien, Q.-T., Shah, P., Raza, M., 2020. Deployment of drone-based small cells for public safety communication system. IEEE Syst. J.
Altmann, A., Niendorf, M., Bednar, M., Reichel, R., 2014. Improved 3D interpolation-based path planning for a fixed-wing unmanned aircraft. J. Intell. Robot. Syst. 76 (1), 185–197.
Alzenad, M., El-Keyi, A., Lagum, F., Yanikomeroglu, H., 2017. 3-d placement of an unmanned aerial vehicle base station (UAV-bs) for energy-efficient maximal coverage. IEEE Wireless Commun. Lett. 6 (4), 434–437.
Anbaroğlu, B., 2017. Parcel delivery in an urban environment using unmanned aerial systems: a vision paper. ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci. 4, 73.
Andrei, M., 2017. UB engineer sees drones as more than eyes in the sky for disaster response. http://www.buffalo.edu/ubnow/stories/2017/07/drones-disaster-response.html. [Online; accessed 30-March-2019].
Aufgebauer, K., 2016. The future has landed, thanks to delivery drones. https://goglobal.dhl-usa.com/blog/shipping/the-future-has-landed-thanks-to-delivery-drones/. [Online; accessed 20-July-2018].
Avellar, G., Pereira, G., Pimenta, L., Iscold, P., 2015. Multi-UAV routing for area coverage and remote sensing with minimum time. Sensors 15 (11), 27783–27803.
Babel, L., 2017. Curvature-constrained traveling salesman tours for aerial surveillance in scenarios with obstacles. Eur. J. Oper. Res. 262 (1), 335–346.
Bae, J., Rathinam, S., 2015. Approximation algorithm for a heterogeneous vehicle routing problem. Int. J. Adv. Robot. Syst. 12 (8), 113.
Balampanis, F., Maza, I., Ollero, A., 2017. Area partition for coastal regions with multiple UAS. J. Intell. Robot. Syst. 88 (2–4), 751–766.
Bandeira, T.W., Coutinho, W.P., Brito, A.V., Subramanian, A., 2015. Analysis of path planning algorithms based on travelling salesman problem embedded in UAVs. In: 2015 Brazilian Symposium on Computing Systems Engineering (SBESC), IEEE, pp. 70–75.
Barna, R., Solymosi, K., Stettner, E., 2019. Mathematical analysis of drone flight path. J. Agric. Inf. 10 (2), 15–27.
Barrientos, A., Colorado, J., Cerro, J.D., Martinez, A., Rossi, C., Sanz, D., Valente, J., 2011. Aerial remote sensing in agriculture: a practical approach to area coverage and path planning for fleets of mini aerial robots. J. Field Robot. 28 (5), 667–689.
Bellingham, J., Tillerson, M., Richards, A., How, J.P., 2003. Multi-task allocation and path planning for cooperating UAVs. In: Cooperative Control: Models, Applications and Algorithms. Springer, pp. 23–41.
Bellman, R.E., 1961. Dynamic Programming Treatment of the Traveling Salesman Problem. RAND Corporation.
Benkoski, S.J., Monticino, M.G., Weisinger, J.R., 1991. A survey of the search theory literature. Naval Res. Logist. 38 (4), 469–494.
Bhardwaj, A., Sam, L., Martín-Torres, F.J., Kumar, R., et al., 2016. UAVs as remote sensing platform in glaciology: present applications and future prospects. Remote Sens. Environ. 175, 196–204.
Bortoluzzi, F., 2019. How switzerland and the us are preparing for a drone future. https://www.swissinfo.ch/eng/opinion_how-switzerland-and-the-us-are-preparing-for-a-drone-future/45045100. [Online; accessed 21-June-2019].
Boucher, P., 2016. You wouldn't have your granny using them: drawing boundaries between acceptable and unacceptable applications of civil drones. Sci. Eng. Ethics 22 (5), 1391–1418.
Bouman, P., Agatz, N., Schmidt, M., 2018. Dynamic programming approaches for the traveling salesman problem with drone. Networks 72 (4), 528–542.
Boyer, K.K., Prud'homme, A.M., Chung, W., 2009. The last mile challenge: evaluating the effects of customer density and delivery window patterns. J. Business Logist. 30 (1), 185–201.
Boysen, N., Briskorn, D., Fedtke, S., Schwerdfeger, S., 2018. Drone delivery from trucks: drone scheduling for given truck routes. Networks 72 (4), 506–527.
Bracken, C., Lyon, R.D., Mansour, M.J., Molnar, A., Saulnier, A., Thompson, S., Adams, G., Masoodi, M., Sharpe, J., 2014. Surveillance Drones: Privacy Implications of the Spread of Unmanned Aerial Vehicles (UAVs) in Canada. Surveillance Studies Centre: Queen's University, Kingston, UK, 30.
Buchmueller, D., Green, S.A., Kalyan, A., Kimchi, G., 2018, February 8. Communications and landings of unmanned aerial vehicles on transportation vehicles for transport. US Patent App. 15/785,886.
Burgess, M., 2016. DHL's delivery drone can make drops quicker than a car. http://www.wired.co.uk/article/dhl-drone-delivery-germany/. [Online; accessed 19-July-2018].
Busetti, F., 2003. Simulated Annealing overview. http://www.aiinfinance.com/saweb.pdf. [Online; accessed 12-June-2018].
Çakící, F., Ergezer, H., Irmak, U., Leblebicioğlu, M.K., 2016. Coordinated guidance for multiple UAVs. Trans. Inst. Measure. Control 38 (5), 593–601.
Campbell, J.F., Corberán, Á., Plana, I., Sanchis, J.M., 2018. Drone arc routing problems. Networks 72 (4), 543–559.
Campbell, J.F., Sweeney, D., Zhang, J., 2017. Strategic design for delivery with trucks and drones. Supply Chain Anal. Rep. SCMA 04.
Caraballo, L.E., Díaz-Báñez, J.M., Maza, I., Ollero, A., 2017. The block-information-sharing strategy for task allocation: a case study for structure assembly with aerial robots. Eur. J. Oper. Res. 260 (2), 725–738.
Carlsson, J.G., Song, S., 2017. Coordinated logistics with a truck and a drone. Manage. Sci. 64 (9), 3971–4470.
Chang, V., Chundury, P., Chetty, M., 2017. Spiders in the sky: user perceptions of drones, privacy, and security. In: Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems, pp. 6765–6776.
Chang, Y.S., Lee, H.J., 2018. Optimal delivery routing with wider drone-delivery areas along a shorter truck-route. Expert Syst. Appl. 104, 307–317.
Chen, H., Wang, X.-M., Li, Y., 2009. A survey of autonomous control for UAV. International Conference on Artificial Intelligence and Computational Intelligence 2, 267–271.
Chen, M., Hu, Q., Fisac, J.F., Akametalu, K., Mackin, C., Tomlin, C.J., 2017. Reachability-based safety and goal satisfaction of unmanned aerial platoons on air highways. J. Guid. Control Dyn. 40 (6), 1360–1373.
Choi, D.H., Kim, S.H., Sung, D.K., 2014. Energy-efficient maneuvering and communication of a single uav-based relay. IEEE Trans. Aerosp. Electron. Syst. 50 (3), 2320–2327.
Choi, H.-J., Kim, Y.-D., Kim, H.-J., 2011. Genetic algorithm based decentralized task assignment for multiple unmanned aerial vehicles in dynamic environments. Int. J. Aeronaut. Space Sci. 12 (2), 163–174.
Chow, J.Y., 2016. Dynamic UAV-based traffic monitoring under uncertainty as a stochastic arc-inventory routing policy. Int. J. Transp. Sci. Technol. 5 (3), 167–185.
Chowdhury, S., Emelogu, A., Marufuzzaman, M., Nurre, S.G., Bian, L., 2017. Drones for disaster response and relief operations: a continuous approximation model. Int. J. Prod. Econ. 188, 167–184.
Chung, S.H., Kwon, C., 2020. Drone-truck Arc Routing Problems. Working paper.
Chung, S.H., Sah, H., Lee, J., 2020. Pseudo node insertion method for synchronization in drone-truck combined operations. Transp. Res. C Emerg. Technol. under review
Claesson, A., Bäckman, A., Ringh, M., Svensson, L., Nordberg, P., Djärv, T., Hollenberg, J., 2017. Time to delivery of an automated external defibrillator using a drone for simulated out-of-hospital cardiac arrests vs emergency medical services. Jama 317 (22), 2332–2334.
Clarke, R., 2014. Understanding the drone epidemic. Comput. Law Secur. Rev. 30 (3), 230–246.
Clarke, R., Moses, L.B., 2014. The regulation of civilian drones' impacts on public safety. Comput. Law Secur. Rev. 30 (3), 263–285.
Clothier, R.A., Greer, D.A., Greer, D.G., Mehta, A.M., 2015. Risk perception and the public acceptance of drones. Risk Anal. 35 (6), 1167–1183.
Coelho, B.N., Coelho, V.N., Coelho, I.M., Ochi, L.S., Zuidema, D., Lima, M.S., da Costa, A.R., et al., 2017. A multi-objective green UAV routing problem. Comput. Oper. Res. 88, 306–315.
Cohen, I., Epstein, C., Shima, T., 2017. On the discretized Dubins traveling salesman problem. IISE Trans. 49 (2), 238–254.
Corberán, Á., Laporte, G., 2015. Arc routing: problems, methods, and applications. SIAM.
Coutinho, W.P., Battarra, M., Fliege, J., 2018. The unmanned aerial vehicle routing and trajectory optimisation problem, a taxonomic review. Comput. Ind. Eng. 120, 116–128.
Daganzo, C.F., 2005. Logistics Systems Analysis. Springer Science & Business Media.
Daknama, R., Kraus, E., 2017. Vehicle routing with drones. arXiv preprint arXiv:1705.06431.
Dalamagkidis, K., Valavanis, K.P., Piegl, L.A., 2008. On unmanned aircraft systems issues, challenges and operational restrictions preventing integration into the national airspace system. Prog. Aerosp. Sci. 44 (7–8), 503–519.
Darbari, V., Gupta, S., Verma, O.P., 2017. Dynamic motion planning for aerial surveillance on a fixed-wing UAV. In: 2017 International Conference on Unmanned Aircraft Systems (ICUAS), IEEE, pp. 488–497
Dayarian, I., Savelsbergh, M., Clarke, J.-P., 2020. Same-day delivery with drone resupply. Transp. Sci. To appear
Dektas, M., 2018. Workhorse group receives patent for HorseFly delivery truck-launched drone package delivery system. https://www.prnewswire.com/news-releases/workhorse-group-receives-patent-for-horsefly-delivery-truck-launched-drone-package-delivery-system-300623140.html. [Online; accessed 22-July-2018].
Dell'Amico, M., Montemanni, R., Novellani, S., 2019. Drone-assisted deliveries: new formulations for the flying sidekick traveling salesman problem. arXiv preprint arXiv:1905.13463.
Dickey, M.R., 2018. Autonomous delivery drone startup Matternet raises $16 million round led by Boeing's venture arm. http://techcrunch.com/2018/06/26/autonomous-delivery-drone-startup-matternet-raises-16-million-round-led-by-boeings-venture-arm/. [Online; accessed 19-July-2018].
Dille, M., Singh, S., 2013. Efficient aerial coverage search in road networks. In: AIAA Guidance, Navigation, and Control (GNC) Conference, p. 5094.
Dorling, K., Heinrichs, J., Messier, G.G., Magierowski, S., 2017. Vehicle routing problems for drone delivery. IEEE Trans. Syst. Man Cybern. Syst. 47 (1), 70–85.
Dror, M., 2012. Arc Routing: Theory, Solutions and Applications. Springer Science & Business Media.
Dukkanci, O., Kara, B.Y., Bektas, T., 2019. The drone delivery problem. Tolga, The Drone Delivery Problem (January 10, 2019)
Enright, J.J., Savla, K., Frazzoli, E., Bullo, F., 2009. Stochastic and dynamic routing problems for multiple uninhabited aerial vehicles. J. Guid. Control Dyn. 32 (4), 1152–1166.

Ergezer, H., Leblebicioglu, K., 2013. Path planning for UAVs for maximum information collection. IEEE Trans. Aerosp. Electron. Syst. 49 (1), 502–520.
Evers, L., Barros, A.I., Monsuur, H., Wagelmans, A., 2014. Online stochastic UAV mission planning with time windows and time-sensitive targets. Eur. J. Oper. Res. 238 (1), 348–362.
Fawaz, W., Atallah, R., Assi, C., Khabbaz, M., 2017. Unmanned aerial vehicles as store-carry-forward nodes for vehicular networks. IEEE Access 5, 23710–23718.
Ferrandez, S.M., Harbison, T., Weber, T., Sturges, R., Rich, R., 2016. Optimization of a truck-drone in tandem delivery network using k-means and genetic algorithm. J. Ind. Eng. Manage. 9 (2), 374.
Fikar, C., Gronalt, M., Hirsch, P., 2016. A decision support system for coordinated disaster relief distribution. Expert Syst. Appl. 57, 104–116.
Finn, R.L., Wright, D., 2012. Unmanned aircraft systems: surveillance, ethics and privacy in civil applications. Comput. Law Secur. Rev. 28 (2), 184–194.
Freitas, J.C., Penna, P.H.V., 2018. A variable neighborhood search for flying sidekick traveling salesman problem. arXiv preprint arXiv:1804.03954.
Furini, F., Persiani, C.A., Toth, P., 2016. The time dependent traveling salesman planning problem in controlled airspace. Transp. Res. B Methodol. 90, 38–55.
Garone, E., Naldi, R., Casavola, A., 2011. Traveling salesman problem for a class of carrier-vehicle systems. J. Guid. Control Dyn. 34 (4), 1272–1276.
Garone, E., Naldi, R., Casavola, A., Frazzoli, E., 2010. Cooperative mission planning for a class of carrier-vehicle systems. In: 49th IEEE Conference on Decision and Control (CDC). IEEE, pp. 1354–1359.
Golabi, M., Shavarani, S.M., Izbirak, G., 2017. An edge-based stochastic facility location problem in UAV-supported humanitarian relief logistics: a case study of Tehran earthquake. Nat. Haz. 87 (3), 1545–1565.
Gonzalez-R, P.L., Canca, D., Andrade-Pineda, J.L., Calle, M., Leon-Blanco, J.M., 2020. Truck-drone team logistics: a heuristic approach to multi-drop route planning. Transp. Res. C Emerg. Technol. 114, 657–680.
Goodchild, A., Toy, J., 2018. Delivery by drone: an evaluation of unmanned aerial vehicle technology in reducing CO2 emissions in the delivery service industry. Transp. Res. D Transp. Environ. 61, 58–67.
Gottlieb, Y., Shima, T., 2015. UAVs task and motion planning in the presence of obstacles and prioritized targets. Sensors 15 (11), 29734–29764.
Gramajo, G., Shankar, P., 2017. An efficient energy constraint based UAV path planning for search and coverage. Int. J. Aerosp. Eng. 2017.
Guerrero, J.A., Bestaoui, Y., 2013. UAV path planning for structure inspection in windy environments. J. Intell. Robot. Syst. 69 (1–4), 297–311.
Guerriero, F., Surace, R., Loscri, V., Natalizio, E., 2014. A multi-objective approach for unmanned aerial vehicle routing problem with soft time windows constraints. Appl. Math. Model. 38 (3), 839–852.
Gupta, L., Jain, R., Vaszkun, G., 2016. Survey of important issues in UAV communication networks. IEEE Commun. Surv. Tutorials 18 (2), 1123–1152.
Ha, Q.M., Deville, Y., Pham, Q.D., Ha, M.H., 2015. Heuristic methods for the traveling salesman problem with drone. arXiv preprint arXiv:1509.08764.
Ha, Q.M., Deville, Y., Pham, Q.D., Hà, M.H., 2018. On the min-cost traveling salesman problem with drone. Transp. Res. C Emerg. Technol. 86, 597–621.
Hadjiconstantinou, E., Baldacci, R., 1998. A multi-depot period vehicle routing problem arising in the utilities sector. J. Oper. Res. Soc. 49 (12), 1239–1248.
Haidari, L.A., Brown, S.T., Ferguson, M., Bancroft, E., Spiker, M., Wilcox, A., Ambikapathi, R., Sampath, V., Connor, D.L., Lee, B.Y., 2016. The economic and operational value of using drones to transport vaccines. Vaccine 34 (34), 4062–4067.
Hallermann, N., Morgenthal, G., 2013. Unmanned aerial vehicles (UAV) for the assessment of existing structures. IABSE Symposium Report, vol. 101. International Association for Bridge and Structural Engineering, pp. 1–8.
Hallett, R., 2018. Workhorse Horsefly autonomous drone package delivery pilot underway in Cincinnati. https://www.prnewswire.com/news-releases/workhorse-horsefly-autonomous-drone-package-delivery-pilot-underway-in-cincinnati-300649076.html. [Online; accessed 19-June-2018].
Ham, A.M., 2018. Integrated scheduling of m-truck, m-drone, and m-depot constrained by time-window, drop-pickup, and m-visit using constraint programming. Transp. Res. C Emerg. Technol. 91, 1–14.
Haugen, J., Imsland, L., 2015. Monitoring an advection-diffusion process using aerial mobile sensors. Unmanned Syst. 3 (03), 221–238.
Hawkins, A.J., 2019. UPS will use drones to deliver medical supplies in North Carolina. https://www.theverge.com/2019/3/26/18282291/ups-drone-delivery-hospital-nc-matternet. [Online; accessed 30-March-2019].
Held, M., Karp, R.M., 1962. A dynamic programming approach to sequencing problems. J. Soc. Ind. Appl. Math. 10 (1), 196–210.
Hertz, A., 2005. Recent trends in arc routing. In: Graph Theory, Combinatorics and Algorithms. Springer, pp. 215–236.
Ho, D.-T., Grøtli, E.I., Sujit, P., Johansen, T.A., Sousa, J.B., 2015. Optimization of wireless sensor network and uav data acquisition. J. Intell. Robot. Syst. 78 (1), 159–179.
Ho, H.-M., Ouaknine, J., 2015. The cyclic-routing UAV problem is pspace-complete. In: International Conference on Foundations of Software Science and Computation Structures. Springer, pp. 328–342.
Hong, I., Kuby, M., Murray, A., 2015. A deviation flow refueling location model for continuous space: a commercial drone delivery system for urban areas. In: Advances in Geocomputation: Geocomputation 'The 13th International Conference'. Springer, pp. 125–132.
Huang, C., Yang, Z., Kong, Y., Chen, P., Yang, X., Cheng, K.-T.T., 2018. Through-the-lens drone filming. In: 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, pp. 4692–4699.
Jawhar, I., Mohamed, N., Al-Jaroodi, J., Agrawal, D.P., Zhang, S., 2017. Communication and networking of UAV-based systems: classification and associated architectures. J. Network Comput. Appl. 84, 93–108.
Jeong, H.Y., Song, B.D., Lee, S., 2019. Truck-drone hybrid delivery routing: payload-energy dependency and no-fly zones. Int. J. Prod. Econ. 214, 220–233.
Ji, X., Wang, X., Niu, Y., Shen, L., 2015. Cooperative search by multiple unmanned aerial vehicles in a nonconvex environment. Math. Probl. Eng. 2015.
Jia, S., Zhang, L., 2017. Modelling unmanned aerial vehicle base station in ground-to-air cooperative networks. IET Commun. 11 (8), 1187–1194.
Jiang, X., Zhou, Q., Ye, Y., 2017. Method of task assignment for UAV based on particle swarm optimization in logistics. In: Proceedings of the 2017 International Conference on Intelligent Systems, Metaheuristics & Swarm Intelligence, ACM, pp. 113–117
Jin, Z., Shima, T., Schumacher, C.J., 2006. Optimal scheduling for refueling multiple autonomous aerial vehicles. IEEE Trans. Robot. 22 (4), 682–693.
Johnson, L., 2017. 9 things you need to know about the Amazon Prime Air drone delivery service. http://www.digitalspy.com/tech/feature/a820748/amazon-prime-air-drone-delivery-service/. [Online; accessed 18-July-2018].
Kahale, E., Castillo, P., Bestaoui, Y., 2014. Minimum time reference trajectory generation for an autonomous quadrotor. In: 2014 International Conference on Unmanned Aircraft Systems (ICUAS), pp. 126–133.
Kallehauge, B., Larsen, J., Madsen, O.B., Solomon, M.M., 2005. Vehicle Routing Problem with Time Windows. Springer US, Boston, MA, pp. 67–98.
Karak, A., Abdelghany, K., 2019. The hybrid vehicle-drone routing problem for pick-up and delivery services. Transp. Res. C Emerg. Technol. 102, 427–449.
Karaman, S., Inalhan, G., 2008. Large-scale task/target assignment for UAV fleets using a distributed branch and price optimization scheme. IFAC Proc. Vol. 41 (2), 13310–13317.
Kastrenakes, J., 2017. UPS has a delivery truck that can launch a drone. http://www.theverge.com/2017/2/21/14691062/ups-drone-delivery-truck-test-completed-video/. [Online; accessed 19-July-2018].
Kelleher, K., 2019. UPS, Matternet delivering medical samples in North Carolina using drones. https://www.auvsi.org/industry-news/ups-matternet-delivering-medical-samples-north-carolina-using-drones. [Online; accessed 12-June-2019].
Khosiawan, Y., Nielsen, I., 2017. Indoor UAV scheduling with restful task assignment algorithm. arXiv preprint arXiv:1706.09737.
Khoufi, I., Laouiti, A., Adjih, C., 2019. A survey of recent extended variants of the traveling salesman and vehicle routing problems for unmanned aerial vehicles. Drones 3 (3), 66.
Kim, J., Morrison, J.R., 2014. On the concerted design and scheduling of multiple resources for persistent UAV operations. J. Intell. Robot. Syst. 74 (1–2), 479–498.
Kim, J., Song, B.D., Morrison, J.R., 2013. On the scheduling of systems of UAVs and fuel service stations for long-term mission fulfillment. J. Intell. Robot. Syst. 70 (1–4), 347–359.
Kim, S., Moon, I., 2019. Traveling salesman problem with a drone station. IEEE Trans. Syst. Man Cybern. Syst. 49 (1), 42–52.
Kim, S.J., Lim, G.J., Cho, J., Côté, M.J., 2017. Drone-aided healthcare services for patients with chronic diseases in rural areas. J. Intell. Robot. Syst. 88 (1), 163–180.
Kim, Y.C., Lee, Y.H., Cho, S.-Y., Hur, S., 2016. Strategy and further researches for operation of drone logistics system. In: The Korean Operations Research and Management Science Society Conference, pp. 2376–2387.
Kitjacharoenchai, P., Ventresca, M., Moshref-Javadi, M., Lee, S., Tanchoco, J.M., Brunese, P.A., 2019. Multiple traveling salesman problem with drones: mathematical model and heuristic approach. Comput. Ind. Eng. 129, 14–30.
Krakowczyk, D., Wolff, J., Ciobanu, A., Meyer, D.J., Hrabia, C.-E., 2018. Developing a distributed drone delivery system with a hybrid behavior planning system. In: Joint German/Austrian Conference on Artificial Intelligence (Künstliche Intelligenz). Springer, pp. 107–114.
Krok, A., 2018. Hyundai's self-driving truck completes first highway jaunt in South Korea. https://www.cnet.com/roadshow/news/hyundai-self-driving-truck-first-highway-trip/. [Online; accessed 25-August-2018].
Kundu, A., Matis, T.I., 2017. A delivery time reduction heuristic using drones under windy conditions. In: IIE Annual Conference. Proceedings, pp. 1864–1869.
Kunze, O., 2016. Replicators, ground drones and crowd logistics a vision of urban logistics in the year 2030. Transp. Res. Procedia 19, 286–299.
Kwon, H., Kim, J., Park, Y., 2017. Applying LSA text mining technique in envisioning social impacts of emerging technologies: the case of drone technology. Technovation 60, 15–28.
Ladosz, P., Oh, H., Chen, W.-H., 2018. Trajectory planning for communication relay unmanned aerial vehicles in urban dynamic environments. J. Intell. Robot. Syst. 89 (1–2), 7–25.
Lanillos, P., Gan, S.K., Besada-Portas, E., Pajares, G., Sukkarieh, S., 2014. Multi-UAV target search using decentralized gradient-based negotiation with expected observation. Inf. Sci. 282, 92–110.
Lawler, E.L., Lenstra, J.K., Kan, A.R., Shmoys, D.B., et al., 1985. The traveling salesman problem: a guided tour of combinatorial optimization, vol. 3. Wiley, New York.
Le Thi, H.A., Nguyen, D.M., Dinh, T.P., 2012. Globally solving a nonlinear UAV task assignment problem by stochastic and deterministic optimization approaches. Optim. Lett. 6 (2), 315–329.
Lee, J., 2017. Optimization of a modular drone delivery system. In: 2017 Annual IEEE International Systems Conference (SysCon), IEEE, pp. 1–8.
Levin, A., 2018. FedEx, Alphabet and Uber win drone sweepstakes lost by Amazon. https://www.bloomberg.com/news/articles/2018-05-09/drone-tests-from-

deliveries-to-farming-unveiled-by-government. [Online; accessed 19-July-2018].
Levin, A., 2019. Google spinoff's drone delivery business first to get faa approval. https://www.bloomberg.com/news/articles/2019-04-23/alphabet-s-drone-delivery-business-cleared-for-takeoff-by-faa. [Online; accessed 21-June-2019].
Li, D., Wang, X., Sun, T., 2016. Energy-optimal coverage path planning on topographic map for environment survey with unmanned aerial vehicles. Electron. Lett. 52 (9), 699–701.
Li, Y., Chen, H., Er, M.J., Wang, X., 2011. Coverage path planning for UAVs based on enhanced exact cellular decomposition method. Mechatronics 21 (5), 876–885.
Li, Y., Zhang, G., Pang, Z., Li, L., 2018. Continuum approximation models for joint delivery systems using trucks and drones. Enterprise Inf. Syst., 1–30
Lidynia, C., Philipsen, R., Ziefle, M., 2017. Droning on about drones–acceptance of and perceived barriers to drones in civil usage contexts. In: Advances in Human Factors in Robots and Unmanned Systems. Springer, pp. 317–329.
Lin, J., 2018. Meet China's growing fleet of automated delivery drones. http://www.popsci.com/china-drone-deliveries/. [Online; accessed 19-August-2018].
Lin, S., 1965. Computer solutions of the traveling salesman problem. Bell Syst. Tech. J. 44 (10), 2245–2269.
Liu, X.F., Guan, Z.W., Song, Y.Q., Chen, D.S., 2014. An optimization model of UAV route planning for road segment surveillance. J. Central South Univ. 21 (6), 2501–2510.
Luo, Z., Liu, Z., Shi, J., 2017. A two-echelon cooperated routing problem for a ground vehicle and its carried unmanned aerial vehicle. Sensors 17 (5), 1144.
Ma, F., Karaman, S., 2017. On sensing, agility, and computation requirements for a data-gathering agile robotic vehicle. arXiv preprint arXiv:1704.02075.
Mackle, C., Bond, R., Torney, H., Mcbride, R., McLaughlin, J., Finlay, D., Biglarbeigi, P., Brisk, R., Harvey, A., Mc Eneaney, D., 2020. A data-driven simulator for the strategic positioning of aerial ambulance drones reaching out-of-hospital cardiac arrests: a genetic algorithmic approach. IEEE J. Transl. Eng. Health Med.
Marin, L., 2016. The humanitarian drone and the borders: unveiling the rationales underlying the deployment of drones in border surveillance. In: The Future of Drone Use. Springer, pp. 115–132.
Marinelli, M., Caggiani, L., Ottomanelli, M., Dell'Orco, M., 2017. En route truck–drone parcel delivery for optimal vehicle routing strategies. IET Intell. Transp. Syst. 12 (4), 253–261.
Mathew, N., Smith, S.L., Waslander, S.L., 2013. A graph-based approach to multi-robot rendezvous for recharging in persistent tasks. In: 2013 IEEE International Conference on Robotics and Automation (ICRA), IEEE, pp. 3497–3502.
Mathew, N., Smith, S.L., Waslander, S.L., 2015a. Multirobot rendezvous planning for recharging in persistent tasks. IEEE Trans. Robot. 31 (1), 128–142.
Mathew, N., Smith, S.L., Waslander, S.L., 2015b. Planning paths for package delivery in heterogeneous multirobot teams. IEEE Trans. Autom. Sci. Eng. 12 (4), 1298–1308.
Maza, I., Ollero, A., 2007. Multiple UAV cooperative searching operation using polygon area decomposition and efficient coverage algorithms. In: Distributed Autonomous Robotic Systems, vol. 6, Springer, pp. 221–230.
Mbiadou Saleu, R.G., Deroussi, L., Feillet, D., Grangeon, N., Quilliot, A., 2018. An iterative two-step heuristic for the parallel drone scheduling traveling salesman problem. Networks 72 (4), 459–474.
McGauley, J., 2017. Amazon's Next Grand Plan: Blimp-sized, Floating Warehouses. Thrillist.
Mersheeva, V., Friedrich, G., 2012. Routing for continuous monitoring by multiple micro UAVs in disaster scenarios. In: Proceedings of the 20th European Conference on Artificial Intelligence. IOS Press, pp. 588–593.
Miao, Y., Zhong, L., Yin, Y., Zou, C., Luo, Z., 2017. Research on dynamic task allocation for multiple unmanned aerial vehicles. Trans. Inst. Measure. Control 39 (4), 466–474.
Moon, S., Oh, E., Shim, D.H., 2013. An integral framework of task assignment and path planning for multiple unmanned aerial vehicles in dynamic environments. J. Intell. Robot. Syst. 70 (1–4), 303–313.
Moon, S.-W., Shim, D.H.-C., 2009. Study on path planning algorithms for unmanned agricultural helicopters in complex environment. Int. J. Aeronaut. Space Sci. 10 (2), 1–11.
Moshref-Javadi, M., 2017. Optimization Modeling and Analysis of Customer-Centric Delivery Logistics. Ph. D. thesis, Purdue University.
Moshref-Javadi, M., Lee, S., 2017. Using drones to minimize latency in distribution systems. In: IIE Annual Conference. Proceedings, pp. 235–240.
Mourão, M.C., Pinto, L.S., 2017. An updated annotated bibliography on arc routing problems. Networks 70 (3), 144–194.
Mozaffari, M., Saad, W., Bennis, M., Debbah, M., 2016. Efficient deployment of multiple unmanned aerial vehicles for optimal wireless coverage. IEEE Commun. Lett. 20 (8), 1647–1650.
Mufalli, F., Batta, R., Nagi, R., 2012. Simultaneous sensor selection and routing of unmanned aerial vehicles for complex mission plans. Comput. Oper. Res. 39 (11), 2787–2799.
Murray, C., Raj, R., 2019. The multiple flying sidekicks traveling salesman problem: parcel delivery with multiple drones. Available at SSRN 3338436.
Murray, C.C., Chu, A.G., 2015. The flying sidekick traveling salesman problem: optimization of drone-assisted parcel delivery. Transp. Res. C Emerg. Technol. 54, 86–109.
Nedjati, A., Izbirak, G., Vizvari, B., Arkat, J., 2016. Complete coverage path planning for a multi-UAV response system in post-earthquake assessment. Robotics 5 (4), 26.
Nex, F., Remondino, F., 2014. UAV for 3D mapping applications: a review. Appl. Geomat. 6 (1), 1–15.
Nguyen, J.L., Lawrance, N.R., Fitch, R., Sukkarieh, S., 2016. Real-time path planning for long-term information gathering with an aerial glider. Auton. Robots 40 (6), 1017–1039.
Niu, S., Zhang, J., Zhang, F., Li, H., 2015. A method of UAVs route optimization based on the structure of the highway network. Int. J. Distrib.Sensor Networks 12, (12) 359657.
Nonami, K., 2007. Prospect and recent research & development for civil use autonomous unmanned aircraft as UAV and MAV. J. Syst. Des. Dyn. 1 (2), 120–128.
Ny, J., Feron, E., Frazzoli, E., 2011. On the dubins traveling salesman problem. IEEE Trans. Autom. Control 57 (1), 265–270.
Oh, G., Kim, Y., Ahn, J., Choi, H.-L., 2018. Task allocation of multiple uavs for cooperative parcel delivery. In: Advances in Aerospace Guidance, Navigation and Control. Springer, pp. 443–454.
Oh, H., Kim, S., Tsourdos, A., White, B.A., 2014. Coordinated road-network search route planning by a team of UAVs. Int. J. Syst. Sci. 45 (5), 825–840.
Oh, H., Shin, H.-S., Kim, S., Tsourdos, A., White, B.A., 2015. Cooperative mission and path planning for a team of UAVs. Handbook Unmanned Aerial Vehicles, 1509–1545.
Ong, T., 2017. The first autonomous drone delivery network will fly above Switzerland starting next month. https://www.theverge.com/2017/9/20/16325084/matternet-autonomous-drone-network-switzerland/. [Online; accessed 19-July-2018].
Ortiz, A., Kingston, D., Langbort, C., 2013. Multi-UAV velocity and trajectory scheduling strategies for target classification by a single human operator. J. Intell. Robot. Syst. 70 (1–4), 255–274.
Othman, M.S., Shurbevski, A., Nagamochi, H., 2017. Routing of carrier-vehicle systems with dedicated last-stretch delivery vehicle. J. Inf. Process. 25, 1–16.
Otto, A., Agatz, N., Campbell, J., Golden, B., Pesch, E., 2018. Optimization approaches for civil applications of unmanned aerial vehicles (UAVs) or aerial drones: a survey. Networks 72 (4), 411–458.
Peng, K., Lin, F., Chen, B.M., 2017. Online schedule for autonomy of multiple unmanned aerial vehicles. Sci. China Inf. Sci. 60, (7) 072203.
Peng, K., Liu, W., Sun, Q., Ma, X., Hu, M., Wang, D., Liu, J., 2018. Wide-area vehicle-drone cooperative sensing: opportunities and approaches. IEEE Access 7, 1818–1828.
Penicka, R., Faigl, J., Vána, P., Saska, M., 2017. Dubins orienteering problem. IEEE Robot. Autom. Lett. 2 (2), 1210–1217.
Peters, J.R., Bertuccelli, L.F., 2016. Robust task scheduling for multi-operator supervisory control missions. J. Aerosp. Inf. Syst. 13, 393–406.
Phan, C., Liu, H.H., 2008. A cooperative UAV/UGV platform for wildfire detection and fighting. In: Asia Simulation Conference-7th International Conference on System Simulation and Scientific Computing, 2008. ICSC 2008, IEEE, pp. 494–498.
Phung, M.D., Quach, C.H., Dinh, T.H., Ha, Q., 2017. Enhanced discrete particle swarm optimization path planning for UAV vision-based surface inspection. Autom. Construct. 81, 25–33.
Poikonen, S., Golden, B., 2019. The mothership and drone routing problem. INFORMS J. Comput. To appear.
Poikonen, S., Golden, B., 2020. Multi-visit drone routing problem. Comput. Oper. Res. 113, 104802.
Poikonen, S., Golden, B., Wasil, E.A., 2019. A branch-and-bound approach to the traveling salesman problem with a drone. INFORMS J. Comput. 31 (2), 335–346.
Poikonen, S., Wang, X., Golden, B., 2017. The vehicle routing problem with drones: extended models and connections. Networks 70 (1), 34–43.
Ponza, A., 2016. Optimization of drone-assisted parcel delivery. Master's thesis, Università degli Studi di Padova, Italy
Porter, J., 2019. Google's wing drones approved to make public deliveries in australia. https://www.theverge.com/2019/4/9/18301782/wing-drone-delivery-google-alphabet-canberra-australia-public-launch. [Online; accessed 21-June-2019].
Pugliese, L.D.P., Guerriero, F., 2017. Last-mile deliveries by using drones and classical vehicles. In: International Conference on Optimization and Decision Science, pp. 557–565
Pugliese, L.D.P., Guerriero, F., Zorbas, D., Razafindralambo, T., 2016. Modelling the mobile target covering problem using flying drones. Optim. Lett. 10 (5), 1021–1052.
Raap, M., Meyer-Nieberg, S., Pickl, S., Zsifkovits, M., 2017. Aerial vehicle search-path optimization: a novel method for emergency operations. J. Optim. Theory Appl. 172 (3), 965–983.
Raap, M., Zsifkovits, M., Pickl, S., 2017. Trajectory optimization under kinematical constraints for moving target search. Comput. Oper. Res. 88, 324–331.
Rao, B., Gopi, A.G., Maione, R., 2016. The societal impact of commercial drones. Technol. Soc. 45, 83–90.
Rathinam, S., Sengupta, R., 2006. Lower and upper bounds for a multiple depot UAV routing problem. In: 2006 45th IEEE Conference on Decision and Control. IEEE, pp. 5287–5292.
Reinelt, G., 1991. Tsplib-a traveling salesman problem library. ORSA J. Comput. 3 (4), 376–384.
Reinelt, G., 1994. The traveling salesman: computational solutions for TSP applications. Lecture Notes in Computer Science, vol. 840, Springer-Verlag, Berlin Heidelberg.
Roberge, V., Tarbouchi, M., Labonté, G., 2013. Comparison of parallel genetic algorithm and particle swarm optimization for real-time UAV path planning. IEEE Trans. Ind. Inf. 9 (1), 132–141.

Ryan, M., 2018. Amazon proposes drone highway as it readies for flying package delivery. http://www.forbes.com/sites/ryanmac/2015/07/28/amazon-proposes-drone-highway-as-it-readies-for-flying-package-delivery/#20b33b4d2fe8/. [Online; accessed 19-July-2018].
Sacramento, D., Pisinger, D., Ropke, S., 2019. An adaptive large neighborhood search metaheuristic for the vehicle routing problem with drones. Transp. Res. C Emerg. Technol. 102, 289–315.
Saeed, A., Abdelkader, A., Khan, M., Neishaboori, A., Harras, K.A., Mohamed, A., 2017. On realistic target coverage by autonomous drones. arXiv preprint arXiv:1702.03456.
Sahingoz, O.K., 2014. Generation of bezier curve-based flyable trajectories for multi-UAV systems with parallel genetic algorithm. J. Intell. Robot. Syst. 74 (1–2), 499–511.
Sancí, S., İşler, V., 2011. A parallel algorithm for UAV flight route planning on gpu. Int. J. Parallel Program. 39 (6), 809–837.
Sandbrook, C., 2015. The social implications of using drones for biodiversity conservation. Ambio 44 (4), 636–647.
Sandvik, K.B., Lohne, K., 2014. The rise of the humanitarian drone: giving content to an emerging concept. Millennium 43 (1), 145–164.
Sanjab, A., Saad, W., Başar, T., 2017. Prospect theory for enhanced cyber-physical security of drone delivery systems: a network interdiction game. IEEE International Conference on Communications (ICC), pp. 1–6.
Sathyan, A., Ernest, N.D., Cohen, K., 2016. An efficient genetic fuzzy approach to UAV swarm routing. Unmanned Syst. 4 (02), 117–127.
Savkin, A.V., Huang, H., 2020. Navigation of a network of aerial drones for monitoring a frontier of a moving environmental disaster area. IEEE Syst. J. in press.
Savla, K., Frazzoli, E., Bullo, F., 2005. On the point-to-point and traveling salesperson problems for dubins' vehicle. In: Proceedings of the 2005, American Control Conference, 2005, IEEE, pp. 786–791.
Savla, K., Frazzoli, E., Bullo, F., 2008. Traveling salesperson problems for the dubins vehicle. IEEE Trans. Autom. Control 53 (6), 1378–1391.
Savuran, H., Karakaya, M., 2015. Route optimization method for unmanned air vehicle launched from a carrier. Lect. Notes Software Eng. 3 (4), 279–284.
Savuran, H., Karakaya, M., 2016. Efficient route planning for an unmanned air vehicle deployed on a moving carrier. Soft Comput. 20 (7), 2905–2920.
Schermer, D., Moeini, M., Wendt, O., 2018. Algorithms for solving the vehicle routing problem with drones. In: Asian Conference on Intelligent Information and Database Systems. Springer, pp. 352–361.
Schermer, D., Moeini, M., Wendt, O., 2019a. A hybrid vns/tabu search algorithm for solving the vehicle routing problem with drones and en route operations. Comput. Oper. Res. 109, 134–158.
Schermer, D., Moeini, M., Wendt, O., 2019b. A matheuristic for the vehicle routing problem with drones and its variants. Transp. Res. C Emerg. Technol. 106, 166–204.
Seifried, K., 2019. The traveling salesman problem with one truck and multiple drones. Available at SSRN 3389306.
Sharma, V., Srinivasan, K., Kumar, R., Chao, H.-C., Hua, K.-L., 2017. Efficient cooperative relaying in flying ad hoc networks using fuzzy-bee colony optimization. J. Supercomput. 73 (7), 3229–3259.
Shetty, V.K., Sudit, M., Nagi, R., 2008. Priority-based assignment and routing of a fleet of unmanned combat aerial vehicles. Comput. Oper. Res. 35 (6), 1813–1828.
Shu, C., 2017. Flytrex launches an autonomous on-demand drone delivery service in Iceland's capital. http://techcrunch.com/2017/08/23/flytrex-launches-an-autonomous-on-demand-drone-delivery-service-in-icelands-capital/. [Online; accessed 20-July-2018].
Snow, C., 2019. Amazon's Drone Delivery Plans: What's Old, What's New And When? https://www.forbes.com/sites/colinsnow/2019/06/17/amazons-drone-delivery-whats-old-whats-new-and-when/#6a2eadbf35f9. [Online; accessed 18-June-2019].
Solodov, A., Williams, A., Al Hanaei, S., Goddard, B., 2018. Analyzing the threat of unmanned aerial vehicles (UAV) to nuclear facilities. Secur. J. 31 (1), 305–324.
Song, B.D., Kim, J., Kim, J., Park, H., Morrison, J.R., Shim, D.H., 2014. Persistent UAV service: an improved scheduling formulation and prototypes of system components. J. Intell. Robot. Syst. 74 (1–2), 221–232.
Song, B.D., Kim, J., Morrison, J.R., 2016. Rolling horizon path planning of an autonomous system of UAVs for persistent cooperative service: MILP formulation and efficient heuristics. J. Intell. Robot. Syst. 84 (1–4), 241–258.
Song, B.D., Park, K., Kim, J., 2018. Persistent UAV delivery logistics: MILP formulation and efficient heuristic. Comput. Ind. Eng. 120, 418–428.
Song, X., Hu, S., 2017. 2D path planning with dubins-path-based A$*$ algorithm for a fixed-wing UAV. In: 2017 3rd IEEE International Conference on Control Science and Systems Engineering (ICCSSE), IEEE, pp. 69–73
Staff, D., 2019. Dayton college partners with NC university on drone research, training. https://www.bizjournals.com/dayton/news/2019/03/29/dayton-college-partners-with-nc-university-on.html. [Online; accessed 30-March-2019].
Statt, N., 2017. Alphabet's Project Wing drones will deliver burritos to Australian homes. https://www.theverge.com/2017/10/16/16486208/alphbet-google-project-wing-drone-delivery-testing-australia. [Online; accessed 21-June-2018].
Stenson, H., 2017. Volvo pioneers autonomous, self-driving refuse truck in the urban environment. https://www.volvogroup.com/en-en/news/2017/may/news-2561936.html. [Online; accessed 20-June-2018].
Stipanović, D.M., Inalhan, G., Teo, R., Tomlin, C.J., 2004. Decentralized overlapping control of a formation of unmanned aerial vehicles. Automatica 40 (8), 1285–1296.
Sujit, P., Ghose, D., 2004. Search using multiple UAVs with flight time constraints. IEEE Trans. Aerosp. Electron. Syst. 40 (2), 491–509.
Sujit, P., Ghose, D., 2010. Two-agent cooperative search using game models with endurance-time constraints. Eng. Optim. 42 (7), 617–639.
Sujit, P., Saripalli, S., Sousa, J.B., 2014. Unmanned aerial vehicle path following: a survey and analysis of algorithms for fixed-wing unmanned aerial vehicless. IEEE Control Syst. 34 (1), 42–59.
Sujit, P., Sousa, J., Pereira, F.L., 2009. UAV and AUVs coordination for ocean exploration. In: Oceans 2009-Europe, IEEE, pp. 1–7
Sundar, K., Rathinam, S., 2017. Algorithms for heterogeneous, multiple depot, multiple unmanned vehicle path planning problems. J. Intell. Robot. Syst. 88 (2–4), 513–526.
Tavana, M., Khalili-Damghani, K., Santos-Arteaga, F.J., Zandi, M.-H., 2017. Drone shipping versus truck delivery in a cross-docking system with multiple fleets and products. Expert Syst. Appl. 72, 93–107.
Tisdale, J., Kim, Z., Hedrick, J.K., 2009. Autonomous UAV path planning and estimation. IEEE Robot. Autom. Mag. 16 (2), 35–42.
Tokekar, P., Vander Hook, J., Mulla, D., Isler, V., 2016. Sensor planning for a symbiotic UAV and UGV system for precision agriculture. IEEE Trans. Robot. 32 (6), 1498–1511.
Torabbeigi, M., Lim, G.J., Kim, S.J., 2020. Drone delivery scheduling optimization considering payload-induced battery consumption rates. J. Intell. Robot. Syst. 97 (3), 471–487.
Torres, M., Pelta, D.A., Verdegay, J.L., Torres, J.C., 2016. Coverage path planning with unmanned aerial vehicles for 3d terrain reconstruction. Expert Syst. Appl. 55, 441–451.
Toth, P., Vigo, D., 2002. The vehicle routing problem. SIAM
Tse, D., Viswanath, P., 2005. Fundamentals of Wireless Communication. Cambridge University Press.
Tseng, C.-M., Chau, C.-K., Elbassioni, K.M., Khonji, M., 2017. Flight tour planning with recharging optimization for battery-operated autonomous drones. CoRR, abs/1703.10049
Tu, P.A., Dat, N.T., Dung, P.Q., 2018. Traveling salesman problem with multiple drones. In: Proceedings of the Ninth International Symposium on Information and Communication Technology, ACM, pp. 46–53
Tu, Y.-H., Phinn, S., Johansen, K., Robson, A., Wu, D., 2020. Optimising drone flight planning for measuring horticultural tree crop structure. ISPRS J. Photogramm. Remote Sens. 160, 83–96.
Ulmer, M.W., Thomas, B.W., 2018. Same-day delivery with heterogeneous fleets of drones and vehicles. Networks 72 (4), 475–505.
UPS, 2019. Drone meets delivery truck. https://www.ups.com/us/es/services/knowledge-center/article.page?kid=cd18bdc2. [Online; accessed 9-October-2019].
Van Blyenburgh, P., 1999. UAVs: an overview. Air Space Eur. 1 (5–6), 43–47.
Venkatachalam, S., Sundar, K., Rathinam, S., 2017. Two-stage stochastic programming model for routing multiple drones with fuel constraints. arXiv preprint arXiv:1711.04936.
Viguria, A., Maza, I., Ollero, A., 2010. Distributed service-based cooperation in aerial/ground robot teams applied to fire detection and extinguishing missions. Adv. Robot. 24 (1–2), 1–23.
Villasenor, J., 2014. Drones and the future of domestic aviation [point of view]. Proc. IEEE 102 (3), 235–238.
Wang, X., Poikonen, S., Golden, B., 2017. The vehicle routing problem with drones: several worst-case results. Optim. Lett. 11 (4), 679–697.
Wang, Z., Sheu, J.-B., 2019. Vehicle routing problem with drones. Transp. Res. B Methodol. 122, 350–364.
Weinstein, A., Schumacher, C., 2007. UAV scheduling via the vehicle routing problem with time windows. In: AIAA Infotech@ Aerospace 2007 Conference and Exhibit, p. 2839.
Wen, T., Zhang, Z., Wong, K.K., 2016. Multi-objective algorithm for blood supply via unmanned aerial vehicles to the wounded in an emergency situation. PLOS One 11, (5) e0155176.
Woods, B., Punnen, A., Stephen, T., 2017. A linear time algorithm for the 3-neighbour travelling salesman problem on a Halin graph and extensions. Discr. Optim. 26, 163–182.
Wu, G., Pedrycz, W., Li, H., Ma, M., Liu, J., 2016. Coordinated planning of heterogeneous Earth observation resources. IEEE Trans. Syst. Man Cybern. Syst. 46 (1), 109–125.
Xia, J., Wang, K., Wang, S., 2019. Drone scheduling to monitor vessels in emission control areas. Transp. Res. B Methodol. 119, 174–196.
Xu, J., Solmaz, G., Rahmatizadeh, R., Turgut, D., Boloni, L., 2016. Internet of things applications: animal monitoring with unmanned aerial vehicle. arXiv preprint arXiv:1610.05287.
Xu, S., Doğançay, K., Hmam, H., 2017. Distributed pseudolinear estimation and UAV path optimization for 3d aoa target tracking. Signal Process. 133, 64–78.
Yang, Y., Minai, A., Polycarpou, M., 2002. Decentralized cooperative search in UAV's using opportunistic learning. In: AIAA Guidance, Navigation, and Control Conference and Exhibit, p. 4590.
Yao, P., Wang, H., Ji, H., 2017. Gaussian mixture model and receding horizon control for multiple UAV search in complex environment. Nonlinear Dyn. 88 (2), 903–919.
Yoo, W., Yu, E., Jung, J., 2018. Drone delivery: factors affecting the public's attitude and intention to adopt. Telemat. Inf. 35 (6), 1687–1700.

Yoon, J.J., 2018. The traveling salesman problem with multiple drones: an optimization model for last-mile delivery. Master's thesis, Massachusetts Institute of Technology.
Yu, K., Budhiraja, A.K., Tokekar, P., 2018. Algorithms for routing of unmanned aerial vehicles with mobile recharging stations. In: 2018 IEEE International Conference on Robotics and Automation (ICRA), IEEE, pp. 1–5.
Yurek, E.E., Ozmutlu, H.C., 2018. A decomposition-based iterative optimization algorithm for traveling salesman problem with drone. Transp. Res. C Emerg. Technol. 91, 249–262.
Zhang, C., Kovacs, J.M., 2012. The application of small unmanned aerial systems for precision agriculture: a review. Precision Agric. 13 (6), 693–712.
Zorbas, D., Pugliese, L.D.P., Razafindralambo, T., Guerriero, F., 2016. Optimal drone placement and cost-efficient target coverage. J. Network Comput. Appl. 75, 16–31.